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"Enhancement of Business Intelligence Platforms Through Artificial Intelligence: Applications to Supply Chain and Logistics Management"

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La Storia Infinita

Una vita comincia e una finisce
e in tutte c'è la mappa della via
giusta che tutte le rotte unisce
per riportarmi sempre a casa mia

la roccaforte e porto sicuro
di braccia benevole, uniti, insieme
la mia guida, Itaca per me, Nessuno,
la rosa dell'archè di Anassimene.

Questa casa non è fatta di mura
ma di spiriti forti ed assiomi,
e son chiavi per sentirli vicino

in ogni impresa e contro sorte oscura,
Lorena, Luca e Matteo, i loro nomi,
e poi Gianni, Gina, Noemi Ardolino.

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Abbreviations Index:

- **ABM:** Agent based model.
- **AGV:** Automated Guided Vehicles.
- **AI:** Artificial intelligence.
- **ANN:** Artificial neural network.
- **API:** Application programming interface.
- **ART:** Adaptive resonance theory.
- **ASF:** Apache software foundation.
- **B2B:** Business to business (referred to a certain market).
- **B2C:** Business to consumer (referred to a certain market).
- **BFP:** Bayesian fractional polynomial.
- **BI:** Business intelligence.
- **CC:** Cloud computing.
- **CCM:** Customer churn model.
- **CCN:** Convolutional neural network.
- **DB:** Database.
- **DNN:** Deep neural network.
- **DQM:** Data quality management.
- **DRL:** Deep reinforced learning.
- **DSS:** Decision support systems.
- **DT:** Decision trees.
- **DW:** Data warehouse.
- **e.g. :** for example ("exempli gratia").
- **et al. :** and others ("et alii").
- **FAS:** Fuzzy Ant System.
- **FDA:** Food and drug administration.
- **FMEA:** Failure mode effect analysis.
- **GA:** Genetic algorithms.
- **HR:** Human resources.
- **i.e. :** meaning what, specification ("id est").
- **IM:** Inventory management
- **IMA:** Inventory management assistant.
- **IoT:** Internet of things.
- **IT:** Information technology.
- **LGV:** Laser guided vehicles.
- **MAS:** Multi-agent system.
- **MDM:** Master Data Management.
- **ML:** Machine learning.
- **NLP:** Natural language processing.
- **NP:** Nondeterministic polynomial.
- **ODS:** Operational data store.
- **OEM:** Original equipment manufacturers.
- **R&D:** Research and development.
- **RDD:** Resilient distributed dataset.
- **RF:** Random forest.
- **RST:** Rough set theory.
- **SC:** Supply chain.
- **SCM:** Supply chain management.
- **SKU:** Stock keeping unit.
- **SVM:** Support vector machine.
- **TSP:** Travelling salesman problem.
- **WHO:** World health organization.
- **WIP:** Work in process.

Pictures Index:

Introduction:

Artificial intelligence is not a new concept either in science or in mass culture. It is a theme that has managed to fascinate many brilliant minds in the world of cinema and literature, leading to the production of numerous works over the years, capable of engaging and exciting a huge number of people. Some of the most illustrious examples include Andy & Larry Wachowski with their masterpiece “The Matrix”, Isaac Asimov with his series of novels “The Foundation Cycle” and Masamune Shirow’s “Ghost in the Shell”. Despite the amount of works, people involved and debates on the subject, very few people actually have a true and concrete idea of what artificial intelligence actually is and what its real potential and capabilities are today. On this subject, there is as much interest as there is confusion. Putting the fantasy aside, artificial intelligence is a technology that, since from its early stages, has demonstrated its validity and the concrete potential to the point that many scholars and experts had announced several times over the years that the revolution was imminent. So far, this has not yet happened, but given the recent successes in areas where this technology had long struggled to operate effectively and efficiently, such as the recognition and generation of text, images and even audio and video, it seems that the tipping point may indeed be getting closer to be realized. Another factor that helps to support this thesis is the fact that the renewed interest, thus no longer limited to researchers alone, has not only involved the general public, but also organizations (which are increasingly beginning to invest and experiment with applications of this type) and, above all, institutions, which not only have an interest in the technology itself, but have begun to address issues such as regulations to be enforced and the protection of privacy linked to the development and diffusion of AI. For this reason, this paper will investigate the application of artificial intelligence to business intelligence and the respective platforms, with a view to supply chain management and logistics. More in detail, the aim is to assess the feasibility and the possible concrete benefits that artificial intelligence can bring to this field, to underline and clarify the operating logics and the fundamental basic concepts, and, in case, outline a possible cause that is slowing down or limiting its development and diffusion. To this end, we will proceed with an analysis of the scientific literature on the subject, looking in particular for case studies of real applications as evidence of the actual effectiveness and validity of these techniques. The work will be structured in 4 chapters. In the first, the current market situation will be outlined, looking for the main expected market trends to depict what will be the scenario of tomorrow.

In the second chapter the focus will be on business intelligence, starting from its evolution over time, and then concentrating on briefly reconstructing the architecture and operating logics typical of the current state of the art of business intelligence systems. The third chapter will be devoted to artificial intelligence. In particular, the aim is to try to understand what is actually meant by the term "AI", not from a mathematical or programming point of view, but from a qualitative perspective. It is important to specify that the aim of this chapter is not to be exhaustive regarding the existing AI techniques, but to deal with the most relevant ones in the field of SCM & logistics. Although less specialistic, such an approach is important from a business perspective because, by understanding "how algorithms think" and their requirements, it is also possible to understand how to interface with them and how they can be successfully applied and exploited to real advantage. The chapter concludes by bringing at least one case study of a successful application of artificial intelligence to a process for each business activity. Finally, Chapter 4 will be the concluding chapter of the entire paper, and it will be focused on case studies of the application of AI to business intelligence, together with the final conclusions that will synthesize what has been learnt in the previous chapters.

Before starting it's important to make a few clarifications regarding the approach and the methodology applied for the following paper. The research started from a pool of sources provided by Professor Weiper, as an initial starting point, and others found independently. Subsequently, the research was carried out by searching a range of contents at the TH Köln library and then on the web, first by following the links and cross-references in the previous contents and then through a broader search. In the choice of publications, preference was given based on recency and amount of citations. In addition, for some aspects, knowledge gained during lectures and the various courses taken during the Bachelor's and Master's degree course was used, with appropriate indication in the notes.

Lastly, there are a few sources that can't be considered as "academic", even if still trustable and valuable, but this has to be specified for the sake of transparency. The most important example is the research of the BARC institute, since it was the study that inspired the entire work. This study was chosen because, although it does not claim to be incontrovertible and exhaustive, it gives a general idea. In fact, it is based on a sample of more than 2300 companies, divided between "users" (the majority, about two thirds of the total respondents), consultants and IT service providers. The companies were selected to have a diversified sample in terms of their production sector, company size, degree of innovation and adoption of IT technologies (“best-in-class” and “laggards”) and geographic location (although Europe and North America remain the majority). In addition, for each company, several people were questioned, each of whom plays a different role (including, but not limited to, IT, finance, controllers and managers). The result consists of a ranking of the areas in which the various company figures expect to concentrate their efforts and investments. Each of which is then analyzed in detail to represent the different responses for each of the above categories. Finally, a comparison is presented between the scenarios formulated by companies and the scenarios expected by consultancies and vendors, highlighting the main similarities and differences regarding the two overall visions. This study is to be considered as the starting point and inspiration for the work.

Chapter 1) Artificial Intelligence and Business Intelligence Coming Closer

In the following chapter we are going to broadly outline the current situation in which the world of industry finds itself at the "macro" level, trying to identify the main forces that are driving its evolution, and then move on to how this is being translated into needs and requirements by companies and managers from a more "micro" or more concrete point of view. In particular we are going to focus purely on the aspect of data and the needs in terms of management, analysis and use in order to make decisions, trying to emphasize why they are important in the current and future context. Finally, will be discussed the topic of artificial intelligence, more specifically what will be its impact on this aspect within organizations and why it is considered by some to be an inevitable and, above all, beneficial advent.

1.1) What is driving the Modern Industry's Development

We are now witnessing to the "4th Industrial revolution" or "Industry 4.0", which is a concept that aims to describe the rapid change in industry, manufacturing and technology led by the increasing connectivity, digitalization, automation and social patterns change in the 21st century [1]. Among the most fundamental shifts taking place in how the global supply network, production and logistics operate, one of the most impacting of companies operativity is a large scale machine-to-machine communication and IoT (Internet of Things) [2]. There are 3 major forces driving manufacturing transformation and development today [3]:

- **Integrated operations:** from equipment and machinery effectiveness and efficiency to inventory traceability and supplier collaboration, IoT insights can give the manufacturers the power to optimize the performances with a data driven approach.
- **The agile supply chain:** markets nowadays require both quick responses and continuous innovation while guaranteeing quality in a global network. The agile supply chain is an approach that can allow companies to respond to those market needs and help to contain the related costs.

- **Connected consumer:** customers, nowadays, are more empowered than ever, thanks to their ability to have easily access to a lot of information. To win their attention and loyalty it's crucial for manufacturers to understand their behavior, develop the right products and to find new and better ways to engage them and establish a solid and profitable relation.

To ensure the compliance of these goals, Analytics are playing a key role for companies and their weight to ensure the competitiveness can only increase over time. By 2020 one third of manufacturing supply chains were expected to apply analytics-driven cognitive capabilities to increase their cost efficiency on average by 10%, and 60% of manufacturers to rely on the support of digital platforms for as much as 30% of their overall revenue [4]. This prospective is not limited to the bigger companies, since is expected an increase of the investments for midsize enterprises in this sector, increasing the volume of data and analytics processed by machines to increase over the half of the total amount by 2022 [5]. IDC identified four of the most notable changes in the industry over the next few years [4]:

- Redefining how organizations design, deliver and monetize products and services
- Developing customized experiences for customers, employees and partners
- Increasing coordination and collaboration between IT and "shop floor level" business users ("ecosystem" concept)
- Changing the nature of workflow and operations in terms of people, processes, and technology and their integration

In this context it is clear that, in the near future, the success of business will be strictly related not only to the ability to correctly design and manage the entire supply chain and all its processes, but also to the capability to collect, process and analyze data for producing valuable information, able to drive the decision process of the company itself. In other words, for more and more organizations it's increasing the need to develop the capability to derive value from data [6].

1.2) Top Trending Topics in the BI field

In order to draw a picture of tomorrow's companies, it's important to understand how the main external forces that are driving modern industry development are actually translated into internal transformation. Having a clear idea of the trend topics that are capturing the attention of the companies, it's fundamental to have an idea of what are going to be the main fields of investments and sources of innovation for the near future. In this context, three main fields of interest for companies have been identified into which the main trends can be grouped [6]:

- **"Organization":** they are mainly oriented toward the directional-organizational-cultural aspect of the company. Although less concrete than the others, they should not be underestimated as they form the basis for the successful implementation of procedures and techniques. If something is not fully understood, cooperation by the members of the company in order to make procedures and tools work effectively fails, compromising success as well as the benefits that could be obtained.
- **"Procedure":** these are trends whose impact is geared toward bringing about change in terms of procedures and workflow within the company. Thus, they are more practical and directly affecting staff and at multiple hierarchical levels.
- **"Tools and systems":** here we are talking about trends that relate precisely to specific processes and the systems and tools that aim to support them. As mentioned earlier, they are critical but doomed to fail (in adoption) and be shelved if not properly supported at the organizational and procedural level. Very frequently the failure of an evolution to succeed occurs when managers aim directly to implement new systems without first considering those two aspects.

1.2.1) "Organization" Trends

The main trends of this field are three: "Master data & Data Quality Management (DQM)", "Data culture, governance and discovery" and "Analytics teams and Data labs". Each of them is discussed in detail in the following section.

Master data & Data Quality Management (DQM)

This is felt as the most important and urgent topic by the companies, because every model or system that aims to support information transactions and data-driven decision making, funds its reliability on the quality of the data taken as input (never forget the "garbage-in-garbage-out" rule). Vendors of systems tend to consider this aspect as less important, but mainly because the struggle of fixing problems and dealing with errors and mistakes caused by a low quality of data gravitates directly on companies [6]. For this reason, before proceeding with the implementation of new tools, managers want to establish a good foundation, in order to secure the functionality of the systems by ensuring to provide the desired data quality to drive futures developments. Gartner's definition of Master Data Management (MDM) is "*technology-enabled discipline in which business and IT work together to ensure the uniformity, accuracy, stewardship, semantic consistency and accountability of the enterprise's official shared master data assets. Master data is the consistent and uniform set of identifiers and extended attributes that describes the core entities of the enterprise including customers, prospects, citizens, suppliers, sites, hierarchies, and chart of accounts*". The critical success factors for sustainable high data quality are [6]:

- Defined roles and responsibilities
- Quality assurance processes
- Continuous monitoring of the health of a company's data
- Awareness and transparency: everyone has to be involved and correctly informed

It appears clear that the main scope of Master Data and Data Quality Management is not only to define criteria, techniques and guidelines able to identify, collect, store and process data able to provide correct and valuable information, but, primarily, to promote an internal development in terms of organization and processes that can adapt effectively to the company's specific needs while being able to evolve through time. The priority of this topic [6], even with a few differences, it's recognized by all the companies, no matter the size, the sector in which they operate or the fact that a company is considered a "laggard" or the "best-in-class", according to surveys. The only exception seems to be the North America, in which, despite the fact that much importance is given to Master Data and DQM, even more than other areas, this topic it's not ranked as the most important.

Data Culture, Governance and Discovery

Top managements believe that data is going to be the key driver for successful decisions, effective and efficient processes, in other words the source of tomorrow's competitive advantage. To pursue the goal of a data driven decision making in business processes, "Master Data & DQM" and technological investments are necessary requirements, but not sufficient for success without the diffusion of a "Data Culture" within the company itself. All employees must be involved and has to be created a culture of constant and open interaction with data. The foundation needed to achieve the goal are described as [6]:

- **Data strategy:** long-term vision that defines the technology, people, processes and rules required to manage an organization's information assets and how it will bring value to the company [7].
- **Leadership:** the management of resources, both human and financial, priorities and responsibilities to implement and develop the data structure inside the company.
- **Governance:** setting internal standards for data policies, that apply to how data is collected, stored and processed [8].
- **Literacy:** constant and continuous formation of all the users.
- **Communication:** clear definition of the procedures, systems and the protocols to achieve a correct, efficient and effective collection, storage and flow.
- **Access:** define, assign and monitor the authorizations for accessing, using and modifying data, in order to comply to safety and privacy requirements.

"Data strategy", "Data Culture" and "Data Governance" are strictly interrelated and create the base of the new information concept. Traditionally, each business function and process had to create, collect and communicate information to reach predetermined goals. In this situation, data and information are a mere tool to support the correct functioning of business processes. This means that they have to adapt to fit the operations and their necessities as much as possible. Instead the new approach is based on the idea that the success and competitive advantage in modern days market comes from the ability to satisfy the needs of the customers, both "external", which means consumers or other companies, and "internal" (other users, company's functions or business units) [9]. The natural consequence of this paradigm is that information becomes the key value driver for every process, causing the need to develop an organic and organized structure that is able to collect, process, store and communicate data on which decision will be taken, in order to adapt the market offer and business processes to effectively and efficiently satisfy the customers. In other words, being able to capture correct information means being able to capture value for the company, and that's the final purpose of "Data Strategy", "Data Culture" and "Data Governance".

This leads to the last point: "Data discovery and Visualization". As previously said, data is going to be one of the most valuable assets for tomorrow's company. The main issue is that data doesn't have intrinsic value, but only when it can be used to produce information that is correct, accurate, relevant, accessible and delivered to the right person at the right time. This means that it's critical to be effective and efficient to find patterns, clusters, trends and outliers inside data useful for making decisions. Three functional areas must be covered [6]:

- **Data preparation:** "raw data", coming from a wide range of sources, has to be connected, cleaned, enriched and shaped to be in the correct form to be used as input for BI and analytics.
- **Data discovery:** data, after being processed and stored, has to be analyzed and explored, in order to find information (pattern, clusters, relations, trends, etc.).
- **Data Visualization:** to make correct decisions, information has to be interpreted by users. To avoid misleading evaluations and wrong conclusions, after being processed, data has to be presented in a way that can facilitate true comprehension.

As reported by vendors, "Data Discovery" remains one of the top priorities in the agenda of many customers, and it's evolving along two axes. Firstly, vendors provide data discovery based on a governed platform to allow business users to share and use each other's assets, aiming to deliver trusted results across the enterprise. On the other hand, more recently, the development is moving towards automated insight and discovery, allowing to reduce the time required for information acquisition from data that can be relevant for decision making [6].

Analytics Teams & Data Labs

"Data science" is a term that groups many methodological principles and techniques from many different disciplines, based on the scientific method, that has the goal of interpreting and extracting knowledge from data [10] [11]. Every organization has different and specific needs, so internal data scientists have to work to research and develop the best possible solutions to maximize the company's performances. To this purpose, companies, mainly the bigger ones, are increasingly feeling the need of data labs, which are separate organizational units specifically designed to conduct the design of data science projects in a space that is aside of established processes and operations. This trend slowed down after the rise of cloud solutions, since the investment for these teams could hardly compete with the services provided by specialized vendors. However, investments in staff that has an adequate formation in data science field is still crucial for companies in the middle of the digital transformation, especially if they aim to integrate analytics with machine learning [6].

1.2.2) "Procedure" Trends

In this part are going to be analyzed trends that are involving, at least in part, business processes and procedures, keeping, of course, a perspective oriented to data, analytics and their impact.

Data Preparation by Business Users

In a volatile environment as it is today's market, achieving an agile data preparation can have a lot of impact on the realization of an actual data driven decision making. Data preparation includes various activities that may include profiling, cleaning, filtering, structuring and enriching data, in order to convert raw data into valuable assets. Firstly, the collaboration between development resources in IT an business users has to be guaranteed, to ensure high efficiency and quality. Then, the agility should be achieved by assigning tasks as shaping and enrichment of data to business users, to reduce the time required by the traditional "waterfall approach". To help non specialists to achieve the proposed objectives in terms of processing speed and accuracy, "easy-to-use" and intuitive tools able to ensure a sophisticated user guidance are needed, paired with "machine-learning-led automation" to support exploring, filtering and processing huge amounts of data in little time [6].

Integrated Platforms for Performance Management

Decision making, especially in a volatile environment, ask to take complex decisions based on data, so characteristics such as transparency and efficiency are among the most felt priorities. Since years, companies are asking for "seamless" integration between performance management, planning and analytics functionalities to support their decisions, both on short and long term. This is the most stable and relevant trend emerged from BARC institute's study.

This integration is vital because using the same data for day-to-day control, planning, financial consolidation and reporting means more consistency and reliability of decisions, and the effort in this direction has empirically proved to bring those benefits. The integration of planning and analytics functionalities, especially in the field of predictive scenarios and forecasting, is considered very important by managers, bringing conspicuous investments in research. Vendors believe that the market will soon be ready for the next step, which should be the implementation of artificial intelligence and machine learning for improving forecasting, planning and monitoring capabilities, and for this reason they are starting to implement these features within the solutions they offer to their customers [6].

Embedded BI & Analytics

Embedded Business Intelligence (BI) is defined as *"the integration of self-service business intelligence tools into commonly used business applications. BI tools support an improved user experience with visualizations, real-time analysis and interactive reporting. A dashboard can be provided within the application to display relevant data or various charts, graphs and reports can be generated for instant review"* [12]. This technology enables users, in every business process, to derive rapidly and autonomously relevant information without the need to involve the IT department, allowing more people within the organization to have easier access to data on which base their actions. It appears clear that this topic is strictly related to "real-time analytics". This, however, despite bringing the benefits related to "data-driven decision making", leads companies to face new challenges. From an organizational and "governance" perspective, it must be defined the role of BI and analytics, the composition and the responsibilities of the related teams. Then, regarding the "data strategy" point of view, it's important to determine the mix of tools and the capabilities they must own to accomplish the objectives. Finally, on the "operativity" side, companies need to face "make-or-buy" decision in terms of solutions and applications of embedded functions.

1.2.3) “Tools and Systems” Trends

The third and final part consist of an analysis of tools and systems that can be reasonably considered desirable future implementations within organizations.

Self-Service Analytics

In traditional, or “guided”, analytics end-users are dependent on ITs and data analysts, while, when using self-service analytics, users can work with data and create dashboards and reports on their own, enabling them to develop more relevant contents suitable for their specific needs. This doesn’t mean that business users do not require IT or BI and analytics experts, in fact their role as enhancers, monitors and system supporters is fundamental and undisputed. Self-service BI and analytics allow business users to answer urgent questions in autonomy, and basing decisions and problem-solving on solid evidence. To do so, they communicate insights and results via quicker and more efficiently prepared visualizations, reports and dashboards. This is based on a “Bottom-Up” logic, in which users can bring their experience about needs and necessities from every day’s work to contribute to the effectiveness of the overall system. This topic is not new to companies, and many of them adopted, at least in part, these types of systems, but still it’s drawing a lot of attention and high demand, especially among the “best-in-class” organizations [6].

Data Warehouse Modernization

In this new context, old data warehouses are proving themselves inadequate. They have become too complex to support agile development, or too expensive to have their functionality extended to accommodate modern analytics requirements. Not to mention the fact that those systems were not designed and optimized to run and support the way analytics is currently moving forward, so in the direction of exploration, operational processing and real-time analysis. This evolution in terms of core needs means that it’s necessary a modernization of the systems, especially in terms of architecture and approach [6].

The traditional data warehouse ETL concept (Extract-Transform-Load) can be visualized, as shown [13][14]:

- **Data sources:** data is collected by multiple sources that can be both internal and external.
- **Staging area:** The raw data is stored in this layer, waiting to be filtered and pre-processed in the integration layer.
- **Warehouse:** the data coming from the previous layers is transferred to the warehouse, where the data is arranged into hierarchical groups, or "dimensions", and into "facts".
- **Data marts:** (not always present, especially in older architectures) contain a copy of data from the warehouse that is already organized, pre-processed and tailored for a specific purpose accessible to specific categories of users [15] [16].

This system doesn't perform well when dealing with huge amounts of semi-structured or unstructured data, which nowadays are essential to produce relevant information for decision making. In the early years of this century, new concepts of architecture were created to overcome the problem, leading to new enterprise data management schemes, for example "data lakes". To visualize the concept of "data lake" it helps the depiction of Dixon: "*whilst a data warehouse seems to be a bottle of water cleaned and ready for consumption, then "Data Lake" is considered as a whole lake of data in a more natural state*" [17]. A definition by an architectural point of view can be [18]: "*A data lake uses a flat architecture to store data in its raw format. Each data entity in the lake is associated with a unique, i.e. identifier and a set of extended metadata, and consumers can use purpose-built schemas to query relevant data, which will result in a smaller set of data that can be analyzed to help answer a consumer's question*". This system proved to be much more scalable and flexible than "traditional" systems and are more suitable to support real-time analytics, since processing data in a warehouse system requires time, and machine learning. Of course, this comes with higher costs and complexity, since it's much easier for non-data scientist or experts to deal with data that has been already filtered and pre-processed for a specific purpose. To be able to work with unprocessed data, is required not only to be familiar with the visualization and interpretation of the presented data, but users need certain knowledge, skills and tools to manage unprocessed data and be able to produce the information needed for the purpose [19]. Usually, this type of architecture is paired with the adoption of cloud systems, and it's starting to be adopted by vendors themselves (Microsoft Azure, AWS). Some vendors have similar solutions with different names (for example IBM propose a “data fabric” [20] system), but the main concept, even if realized with some differences, it’s the same: to propose a system optimized to deal with structured, unstructured and semi-structured data, and so to support the new evolution of analytics and the application of artificial intelligence (will be treated more in detail in Chapter 2).

Analytics on Real-Time Data

If companies want to establish a real “data-driven decision making”, they have to develop the capability to have at disposal real-time relevant data that can concretely help in problem solving situations. One of the most important limitations, according to users of BI systems, comes from the query performance. “Real-time analytics” refers to an almost immediate response in terms of provision, processing and visualization of information about business processes and operations. This can be translated, technically, into alerts activation directly to the dashboards of the users that should be involved for the resolution (with the related possibility to “drill down” or receive a report with all the information the users need) or by triggering pre-automated events to counter the possible negative effects [6]. To achieve this, two sub-systems have to work together: a “back-end” part, that should operate a continuous monitoring of the operations, and a “front-end” visual part, that has to be designed in a way that can easily draw the attention of the users and provide them all the necessary information to operate the decisions quickly and based on solid evidence, optimizing the overall performance of the company. This is an important chance of the main purpose of Business Intelligence, since it’s switching from a static and descriptive tool, to a dynamic and proactive system to guide business processes.

Still, there are some practical problems that give hard times to users. In the traditional approach, KPIs and thresholds have to be set in advance, but usually they fail to be sufficiently accurate and quick to respond to relevant changes (not to mention that usually they need to be adjusted or modified through time) and the problem of false positives remains very challenging to solve. For the next future, experts believe that machine learning may be very helpful to improve the precision and the reliability of these systems, with a better outliers, pattern and trend recognition. Experimentation in this field is already being led, not only limited to alerts and triggers, but also oriented to automated insights (augmented analytics) able to bring to the users all the information needed to understand the problem and quickly act consequently [6].

This means that the future development doesn't aim to settle to predictive analysis, but to prescriptive ones, able to propose solutions and guide users in problem-solving.

Data Catalogs

A "Data catalogue" of a database consist in metadata that stores the definitions of all database objects, accessible via SQL standards [21] [22]. Metadata must be systematically collected, updated, linked and analyzed, for a correct and complete understanding of data. This is actually very important and felt by companies because the lack of available and detailed documentation is essential to preserve knowledge and to ease the work of both data analysts, to avoiding repeating time consuming work that has already been done, and data consumers, allowing a better understanding, trusting and usage of data. This requires an organizational change, because maintaining a data catalogue require active and continuous effort, that has to be included in the topics related to data governance, quality and strategy. Technology can be helpful, especially for time consuming tasks, as ingesting, processing and linking huge amounts of metadata. This is another field in which machine learning can play a key role in tomorrow's companies [6].

Augmented Analytics, Advanced Analytics and AI

Advanced analytics uses machine learning, mathematical models and statistical algorithms and tools to generate new information from data. These methods are able to identify patterns, trends, correlations and dependencies that may be hidden in data and bring them to the attention of the users. It's already been proven that these algorithms can be very effective, even more than humans, in "data discovery", if properly trained and implemented. By now, the responsibility of interpreting data and making decisions still goes entirely to people, but for the future the aim is to automate at least a part of specific decisions processes.

The spread of libraries with "ready-to-use" machine learning algorithms paired with an appropriate availability of data from one side and the diffusion of cloud systems, in many of which vendors are actually starting to implement themselves those algorithms to be used by their customers, is bringing artificial intelligence to have a huge jump forward in terms of business process applications [6]. This is motivated by the fact that companies have to deal with enormous amounts of data, impossible to be analyzed entirely by users. Furthermore, the huge investments on digitalization require that data is exploited to extract as much value as possible.

It appears clear that, to achieve an actual "data-driven decision making", machine learning and artificial intelligence has to play a key role, producing "real-time" reliable and relevant information from the huge mole of data produced by every business process.

Tableau's definition of "Augmented analytics" is the following: *"Augmented analytics is a class of analytics powered by artificial intelligence (AI) and machine learning (ML) that expands the human ability to interact with data in context. We use AI to make analytics accessible, so more people can confidently explore and interact with data to make meaningful decisions. From automated modeling to guided natural language queries, augmented analytics capabilities can help organizations leverage their growing datasets and deliver insights to a broader business audience"* [23]. It's possible to say that augmented analytics are a sub-division of "advanced analytics" that aim to combine human capabilities with business intelligence, machine learning and self-service analytics, becoming the tool that can definitely lead the evolution from predictive analysis ("what will happen in the future?") to prescriptive analysis ("what are the best/most effective actions to maximize our success in the future?") [24], by providing automated insights with relevant information whenever is needed to a user to make a decision, helping the users in data discovery, analysis and decisions, especially for non-data scientist users. This last aspect it's the "game changing" feature because it enables the possibility to benefit from the advantages of machine learning even users that are not specifically trained to develop, deploy and deeply understand this technology. Many vendors are working to implement this in their Business Intelligence solutions (for example AutoML by Qlik).

1.3) Emerging needs, critical factors and future perspectives

For the near future, as seen in the trend overview, the external market forces are translating themselves in very important transformations on the way to conduct business. Data and information is evolving from being a cost, necessary to a correct functioning of processes within the company and along the supply chain, to be the backbone asset on which build the value stream for the company itself.

1.3.1) Lesson Learned from Trends' Analysis

A direct consequence of this new way of thinking and concepting data as something fundamental and pervasive within organizations to face future markets volatility and risks, is the fact that almost everyone will have to deal with data in every day's work in order to establish a "data-driven decision making". This leads to three different implications. Firstly, data culture gains a lot of importance, since trust, effort and support by all people within the organization is critical for the overall success and performances of the tools and technologies applied. People should understand the importance and the motivation behind the change, allowing them to follow or even to directly contribute to it. Then, it's very important to acquire specialized professional figures on one side, and on the other to correctly form the existing personnel, since people need to have the correct knowledge and instruments ("data literacy") to work in the new environment that is going to be created. Last but not least, companies have to provide the adequate tools to guarantee help and support in accessing, processing, communicating and analyzing useful and relevant data, in order to produce valuable information on which base day to day decisions (real-time, self-service and augmented analytics).

According to Gregor, Martin, Fernandez, Stern, & Vitale (2006) [25], technological investments, to be effective, have to bring benefits in four different dimensions: strategic, transactional, informational and transformational. Naturally, these benefits are bounded with change, sometimes even radical, that has to be embraced in order to obtain and indulge those benefits. "Strategic" benefits can lead to an alteration of the way the company competes or the nature of the goods offered to the market. On the other hand, "transactional" benefits are the ones that can transform the operational management and the cost structure of the business. It's possible to consider these benefits as "external", since they have impact on the company's inputs and outputs. On the contrary, the other two types of benefits can be considered as “internal”, because they impact on the structure and procedure within the company, more in detail this means the communications and decision-making, when talking about “informational” benefits, and organizational layout and capacity when considering the “transformational” ones.

This is confirmed by the interest and importance given in strategic and organizational aspects seen in the pervious overview. In fact, this transformation, to be effective, has to be supported by a proper structure and governed accordingly to the value, both in terms of importance for competitive advantage and in terms of investments of capital and resources. The importance given by the majority of the companies in the BARC study to these topics it’s a clear sign that these aspects within organizations is still lacking in terms of implementation and feel that more effort should be put on creating or enforcing a solid base of culture, governance, management, structure and infrastructure on which to place the next steps.

1.3.2) The Future of Industry

These transformations will lead to two major changes in the concept of industry and business that can be summarized with “Servitization & Platform economy”, as “external” evolution, and “Smart factories”, regarding the “internal” evolution.

The term “Servitization” [26] refers to a business model innovation, that gained lots of importance in the last 20 years, that aims to switch from selling physical products to offering a combination of products and services. In most of the cases, the property of the products is not transferred to the customer, but is kept by the company, changing the idea of “product as an output” with the idea of “product as a service”, becoming an asset and an investment for the company, and so becoming the interface through which the value is delivered to the customers. Among the many advantages of this system, the most relevant are [27]:

- **Margins defense:** can protect the company’s offer by the competition (differentiation).
- **Growth:** its proven that services can lead to increasing the sales and to a more stable revenue flow.
- **Strict relationship:** services lead to more strict relationships, allowing companies to collect more information about customers.
- **Loyalty:** services are less interchangeable that products.

This concept can be considered strictly bounded with another relatively new trend, which is "platform economy". Platforms can be online application or technology frameworks. Professor Carliss Y. Baldwin and Dr C. Jason Woodard developed a general definition of economic platforms: "*a set of stable components that support variety and evolvability in a system by constraining the linkages among the other components*"[28]. On the other hand, Woodard and Baldwin, in abstract terms, referred to platforms from an architectural point of view as: "*a system partitioned into a set of core components with low variety and a complementary set of peripheral components with high variety*" [28]. According to PWC, tomorrow's companies that want to keep their competitive performances, have to face some major issues: strategy has to move from a physical product vision to a "product and services hybrid", the firm needs to build its own platform and has to invest with the aim of leading, or at least not lagging, in technology and, finally, the timing to accomplish all the previous objectives has to be right to avoid being cut out of the market [29]. It appears clear that the platform economy is going to be the key aspect to realize and optimize the "Servitization" of future business. The term "smart factories" is a term coined by German government in the context of "Industry 4.0" [30]. The original vision describes a production environment that can organize autonomously manufacturing and logistics, without human intervention. Even if this idea can be considered fascinating, its realization seems, even optimistically, very far in the future. More realistically in the near future the term will be nearer to the "digital twin" concept. The technical base is actually very similar: a "cyber-physical system", which means that there is a digital representation of a physical object characterized by a two-way connection between them, so data and information flow from the object to the twin and the other way around. The digital model, fed with data from the physical object, can represent the aspects of interest of the physical object and realize simulations and predictions useful to optimize and influence the performances of the object. This has already capture lots of attention in industry environment and has already been successfully applied by some companies, as General Electric and Rolls Royce [31]. Business intelligence is moving along this path, in fact, companies have increasing interest to evolve BI systems from a tool that can help the reporting and financial consolidation, to a system not only able to give a real time depiction of business processes and operations, but also to provide indications and insights on critical aspects useful to face with an objective evidence challenges and problems as they emerge, as it can be learnt by the BARC study and by Qlik insights [3] [6].

1.3.3) The Role of AI

In this scenario, it's clear that artificial intelligence can play a key role in the future of industry. By now, for the majority of the companies, is not the top priority, but the field for a major spread of this technology is getting prepared. Data strategy, culture and governance paired with the modernization of systems and architecture of data management are preparatory steps, especially considering the future perspective of tomorrow's company. To realize those scenarios and ensure market competitiveness will be critical the ability to access, process, exploit and react to the information that lies within the huge amount of data that firms are going to deal with. The KPI that will drive competitive advantage are going to be the speed of response, so the time that goes from the moment in which data is collected and the moment in which it can be effectively used for decision making, and the reliability of the models and information derived by data, both in terms of accuracy and resilience, all this paired to the ability to fully understand the meaning and the implications of it. AI will play a double role in business intelligence. Firstly, it can improve the effectiveness of data discovery and analysis, helping to scout relevant and solid information that, otherwise, wouldn't be taken into account, and secondly, can reduce the time needed for analysis and processing by automating at least part of these tasks, bringing to the attention of the users exactly what they need to perform at best. Many vendors of business intelligence systems are starting to implement AI tools in their solutions (for example, AutoML by Qlik). The combination of AI with BI platforms aims to revolutionize the concept of business intelligence itself, evolving from a facilitator or staff role to be the key holder of the value stream of the company, becoming the guiding function that is able to produce and deliver to the right person in the right moment the information necessary to conduct and optimize every business process. The idea is to move the main purpose from cost control and financial reporting to being able to real-time monitor the business processes with the aim to perform simulations and analysis that can produce the necessary information and early identify the critical factors to determine, with sufficient confidence, the best actions to take in order to optimize performances and outcomes.

Chapter 2) BI In Supply Chain Management and Logistics: State of the Art of the Technologies

This chapter will analyze the concept of business intelligence (BI) as a business function, starting with its evolution through the years and then trying to picture the actual state of the art. Literature and information in regard don't follow a unique standard, and, sometimes, terms are changed for academic or marketing purposes, depending on which aspect goes the main focus. Usually, the term "data science" is used when the focus is over software and programming, "controllership" when concentrating on costs and management, and "business intelligence" when is privileged the marketing aspect or the decision making and insight capacity aspects. It's important to specify that each of those terms refers to a wider field of knowledge, but the modern conception of business intelligence as a business process, characterized by techniques, principles, logics and technologies, is an eclectic and integrated discipline, that needs to take into consideration many different aspects of business and technology to correctly work.

Nowadays Business Intelligence (BI) it's a term that includes strategies, methodologies and technologies that are used within companies to collect, manage and analyze operations' information [32]. The core value that BI can bring to the company is the ability to produce relevant information, based on which it's possible to make decisions and react accordingly to the objectives set for a certain time horizon [33]. Another similar definition was given by Hans Peter Luhn (researcher at IBM): "*the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal*" [34]. Again, the same concept can be expressed as: "*about how to capture, access, understand, analyze and turn one of the most valuable assets of an enterprise - raw data - into actionable information in order to improve business performance*" [35]. Even though BI, as it is concepted today, it is a fairly new topic, it's possible to trace the emerging and the evolution of this concept through the years and see how it changed to adapt to the economical and industrial environment. It can be noticed that, especially in the early stages its evolution, BI can be considered as strictly related to the accounting function and "controller's" role.

2.1) Evolution of BI as a Function

In this section will follow an analysis of the evolution of Business Intelligence as a function and as a business process, concentrating on how the external environment's evolution affected companies. To this purpose, is possible to consider Business Intelligence as an entity that, firstly, was born as an activity of the accounting function, and then, when it became more structured and systematic, became an actual process, until achieving an actual independence, as a concept, when the effort required and the importance acquired became a fundamental asset for organizations.

2.1.1) The Early Days of Industry

During the second industrial revolution (1800) emerged with strong relevance the need to determine systematic and scientific rules and practices to manage a company, a need arisen by the increasing complexity of organization and processes required by the operations (the integrated set of functions and processes that allow to offer a certain product or service to a customer [9]). A major contribution was given by Taylor, which was among the pioneers of company's organization elaborating the "functional theory", in which he underlined the importance of a precise hierarchical subdivision of specific roles, tasks and responsibilities. In this optic, management issues and decisions have a strong bond with the organizational ones, enforcing the correlation between business administration, management and control [36]. Based on Taylor's theories, Fayol focused on the first actual elaboration of an organizational model for company's administration. He located 6 different types of functions (or categories) [37]:

- Technical-productive
- Commercial: acquiring inputs and selling the products
- Financial
- Safety
- Accounting (and reporting)
- Administration-Direction: guide, coordination and control of the business

In this picture, the accounting functions are the most related with the general administration and had the double role of tracking and monitoring the company's assets and to fulfill accounting duties. In other words, it had a fundamental role in business administration, working as supervisor and surveillance mechanism, with the aim of maximizing the economical wealth of the company [38]. In this period two different approaches rose up. From one side there was the "Anglo-Saxon school", which had a deep and precise separation between accounting duties and surveillance of operation's management, in terms of roles, responsibilities and organization. On the other side, there was Besta's conception, in which there was not such a distinction between planning and control, and so had a more organic and merged vision of the two processes. In both cases, despite starting from different perspectives on the subject, they shared a substantial similarity in the revolutionary theoretical content, and consist of understanding that the control, as a process, has a strict correlation with the directional functions, making it a fundamental tool for business administration [39].

Despite the importance and the innovation brought by these two approaches in the first years of the 18^{th} century, it's not even close to the conception of modern days BI, as a distinguished discipline and process, but it was still considered as an aspect of business direction with the role of verification and restriction of non-aligned actions within the firm, so the main focus was on corporate asset situation and management, which means the interest was centered of financial and accounting data and measures.

2.1.2) Post WWII Industry

Around 1920 to the '80 the World could witness to the third industrial revolution. In the technology field, the two main drivers were the birth and the development of electronics at first, and then informatics and computers, while in the economic dimension there was a progressive switch from the national state conception to a global economy. This was a huge change in the environment in which enterprises were competing, leading to a progressive transformation to adapt to the new situations. Of course, this brought a new and wider array of needs that should be satisfied in order to maintain competitiveness, and the organs of control, which saw their status evolving from a service function within the company, to a staff organ. This was a symptom of the change of main purpose, and therefore also to the role, of the function: from accounting recognition mainly, even if not limited to, to absolve law and regulations' obligations, to assist the firm's direction in the formulation of the management politics to guide, and eventually adjust, the actions over the business processes in the future fiscal periods [40]. In those years new tools appeared, such as budgeting, reporting and analytical accounting, developed to answer to the new necessities. It is possible to say that this is the period in which a first form of Business Intelligence was actually born, as a set of systematic activities made by the "Controllership" function, recognized as a separate entity and no more as part of the general direction [40]. The focus switched from asset monitoring to costs and investments. In other words, the perspective moved its centrality from the "stock", therefore a static picture of company's status, to more "dynamic" aspects of business, so its operative (costs and revenues) and strategic (investments) performances. Administration evolved from a perspective of "management for the number", focused on the conservation and production of wealth and economic assets, to a "management by the number", so focusing on the evaluation and control of operations management efficiency and effectiveness [41]. However, the link with business capital monitoring, typical of the previous conception, is still central, in fact the interest is still almost entirely on reporting financial and accounting data, underlining the staff role (provider of specialized advisory and support, "outside" the hierarchical function scheme of the company [42]) played towards the general direction and top management. Still, tasks, objectives and roles started to be defined more specifically and organically, determining a changing point in terms of growing importance of this function, even if its core value had a mainly operative nature: data had to be "manually" collected among every company's function and business unit, processed, analyzed, reported and aggregated accordingly to the role of each recipient. More in general the main role was the design, management and implementation of accounting and information instruments. The economic environment in which companies competed was characterized to a relatively low complexity and great economic expansion (after WWII until the late '70s), so the main issue was centered to cost management optimization and efficiency and effectiveness control [40]. It is in this period, precisely in 1958 that Hans Peter Luhn, a German researcher of IBM, created the term "business intelligence".

2.1.3) The Modern Evolution of BI

From 1980, waves of radical changes in the social-economic environment led progressively to a new paradigm in the market. Many agree that this transition reached a turning point firstly with the oil crisis in 1973, starting a period in which cyclical crisis can suddenly strike with little advising signals but with great impact on global economy, to which companies have to adapt quickly to avoid huge losses or even failure. At the same time, market structure changed a lot. In the Business-to-Business market, technological innovation brought a growing need for specialized knowledge and solutions, due to the higher technology content and complexity of both production processes and products. Meanwhile, especially in the Business-to-Consumer environment of the “First World Countries”, competition reached very high levels and market needs for non-essential goods differentiate and stratified. The traditional approach to marketing, focusing on the sales of standard goods to the entire potential demand was no more beneficial, so companies moved to a more customer-center perspective.

The STP model (“Segmentation-Targeting-Positioning”) suggests an analytic and systematic approach to the market: the first step should be the segmentation, which means to apply a method that allow to divide the set of potential customers in a certain number of groups characterized by a similar consumer behavior within them. Then comes the “targeting” phase, in which managers conduct a multicriteria analysis to determine to which segments direct the effort, and so, the offer. Finally, in the “positioning” phase, the characteristics and the specifications of the offer are determined based on the profile of customer that represents the targeted segments. This method suggests to concentrate the effort in a relatively smaller set of homogeneous customer among whom reach a higher success ratio by proposing a tailored (and more difficult to emulate) offer [43]. On the other hand, in an environment with strong competition, costs reduction is essential. Progressively, firms moved more and more of the early production phases in developing countries. Only registered offices and the higher value operations (for example final assembly and design) and functions (for example R&D, finance) were the ones that hardly got delocalized, leading to a worldwide spread of the facilities. The company is not considered anymore as a stand-alone entity, but as part of a supply network in which relations and information flow is fundamental for the benefit and success of every player. The Supply Chain Management is based on the division of labor along the supply chain, leading companies to focus on the core competencies and capabilities, reduce vertical integration and to fewer but more important and strong relationships [44]. This evolution has been pushed by the strong competition in a worldwide economy, shorter life cycle products that require short time-to-market and high customer expectations, all this while achieving profitability objectives [45]. This caused a very important change of enterprises’ paradigm: success is no more driven by efficiency, but by the ability to make good decisions in a high uncertainty environment, in being able to quickly adapt to change and to concretize the decisions taken, and to an effective logistic, so being able to deliver rapidly and efficiently the goods to the customers, both external (actual customers) and internal (other supply chain’s actors) [46]. It appears clear that, in this context, information becomes a critical aspect and a fundamental value driver for companies, since without proper information is almost impossible to make correct decisions. These phenomena mined the traditional rigid, hierarchical and bureaucratic organization control and management systems, privileging a more horizontal, flexible and process/product centered organization structure, to satisfy the peculiar needs of each business unit and for each geographical area subdivision. In this context, business intelligence acquires importance for the planning process for the long term, but even for the mid and short term as well. The planning process nowadays takes into consideration many variables, even “out of control” elements that have to be continuously monitored and measured by collecting and processing data. Business intelligence widens its scope and can be considered as an important business function, since is no more limited to financial reporting, but has the responsibility to collect, generate and provide the information that is fundamental for the modern conception’s workflow [40]. This means that business intelligence has to deal not only with non-financial data, but also with more unstructured types of data, especially for short-term decision making support. This pervasive approach allows business intelligence to play a key role in the feedback loop at the base of business strategy: not only facilitates the implementation at the operational level, but also contributes to determine and re-formulate the strategy based on the evolution of the situation and the events. Managing the information in means managing the relationships between the different actors within the enterprise [47].

Since productivity and efficiency, even if still necessary, are no more enough to be successful and profitable on the market, but, nowadays, managers focus on characterizing skills and factors that are unique and specifical. The objective is to create and offer almost impossible to emulate or substitute, and business intelligence has to provide the knowledge and the information required for this task. Many authors theorized on this new strategical support aspect of BI and control, for example Kaplan and Norton, creators of the Balanced Scorecard. They concentrated their work on enriching the reporting systems with other types of measures and data, in addition to those of an accounting and financial nature, expanding the perspective of the system itself and moving from an internal orientation, no longer adequate and sufficient, useful only for accounting and financial analysis, to a more integrated perspective: being able to use business and process information to guide decisions and actions [48]. To achieve this is fundamental to establish a system and a procedure that can guarantee a quick and effective collection, processing, distribution and presentation of information (from data), the more accurate, correct and relevant as possible.

In conclusion, let's analyze the most important changes over time in this field. From being a set of activities that were performed occasionally, upon specific request or in case of special needs, mostly of accounting or financial interest, evolved to a structured, systematic process that plays an important role not only for short-term management and planning, but also in long-term and strategy formulation. Technology played a fundamental role in the evolution of BI's concept. In the early stages, people had to manually collect, analyze and produce the information required, and that was a very time consuming and costly activity. With time, and the spread of computer, each function or business process could collect data and prepare reports on their situation. Controllers in charge of business intelligence had to work as middle managers between the top management and the operational functions to ensure that the process took place on time and produced the data of interest in an established form, and then they had to prepare, process and analyze data in order to produce the information and the insights useful to managers in order to make decisions. In this phase the focus was not limited to financial and accounting aspects, even if it was still the main part. With the spread of centralized systems and database, and then with cloud systems, many aspects of the process of collecting and pre-processing of data have been automated. It's possible to appreciate that technology was important for two different reasons. Firstly, the time required to process a certain amount of data was highly reduced over time, and this means that the cost of producing information quickly scaled over time. The second reason impacts on the human aspect: the employees can focus more on more valuable activities, such as analyzing and interpreting data and making decisions, so reducing the "time-to-act" in a data-driven logic. Soon, the implementation of new technologies, such as artificial intelligence, aims to improve in terms of speed, accuracy and pattern seeking, the analyzing processes of BI. Employees work passed from consisting almost entirely on collecting and processing data to interpretation, decision making and process optimization.

The original role was to produce data and information to monitor the capital aspect of a company so, in other words, "ex-post monitoring". Then the main focus moved from stock to flow measures, in particular to accounting, finance and costs, assuming a "correction and adjustment" and "coordination" purpose. In the end, the field of interest was expanded, including a vast set of data, especially non-financial, semi-structured and even unstructured data from many different sources, with the aim of producing information for decision making, but not only limited to the accounting and top management functions, but also for every single function and process within the organization. This meant a progressive evolution from a descriptive role, to a predictive role, aiming to forecast the future situation, based on which companies make plans and decisions to adapt and try to optimize their future results. The future evolution of BI has, as objective, to cover a leading and prescriptive role, so not only being able to produce trustworthy future forecasting, but also to identify the key values and levers to activate to achieve the planned results. Note that changing role doesn't mean that BI abandoned certain activities, it only means that changed the key value brought to the company.

2.2) Today's State of the Art of BI Platforms

In the previous section it's been pictured the environmental evolution that led to the creation and development of BI as a business function, why its importance grew over time and how the core values and the main objectives changed along with business needs, "pulled" by external forces, such as the evolution of business and markets. But there's another phenomenon that contributed to "push" from inside the evolution of business intelligence, which is the technological development. More in particular, the key role was played by internet and the digitalization. Over time the information systems of the companies evolved, in every activity, function and processes, to improve the overall efficiency and effectiveness. Many different companies developed and offered on the market software solutions with this purpose, leading to the digitalization of organizations, starting from the bigger firms and then gradually spreading to the medium-size and, finally, to the smaller ones. These software solutions can be classified with many different criteria, for example by using a process-centered criteria there are:

- **ERP (Enterprise Resource Plan):** this term, coined by Gartner Group in the '90s [49], refers to a management software that integrates every aspect strictly related to the supply, production, storage, logistic, sales and accounting [50]. These types of software was designed to automate certain operations (for example the invoicing process), reducing the overall processing and communication time and supporting the optimization of the resource planning (e.g. raw materials orders or production capacity allocation), aiming to minimize inventories and WIP (i.e. Work-In-Process).
- **CRM (Customer Relationship management):** it's a systematic process by which an organization manage its customers and the relations with them. This is achieved by a continuous and methodical data collection, processing and analysis. The idea at the base of this approach is that the knowledge produced by collection information regarding the

customers can be used to increase the value (ultimately in monetary terms) that the company is able to extract from customers, both in the short and long term [51]. On the market is possible to find many software solutions to support this specific business process (e.g. “Salesforce”, “Microsoft Dynamics 365”, “SAP CEC Suite”, “Oracle CX Cloud”, and many others).

- **SCM (Supply Chain Management):** describes a category of software that supports the activity of supply chain management, mainly regarding the field of demand forecasting and managing orders, marketing and logistics. Typically, ERP systems are designed to manage processes and operations within the company, while SCM aim to optimize the interface between partners along the supply chain.
- **MES (Manufacturing Execution System):** many companies adopted software and systems with the purpose of optimizing the production. These systems manage orders, progress and warehousing with a direct link with machineries (PLC/SCADA), allowing managers to monitor the production and to produce useful information to optimize processes and planning of capacity and resources [52].

These systems are designed with a modular architecture, allowing a progressive implementation over time of different modules, so that a company can spread the investment on a wider time interval and proceed gradually with the transformation. Very soon, companies passed from a situation in which business data was scarce to the exact opposite, so having to deal with a huge amount of data, more than what they were able to manage. This situation was the perfect field for business intelligence and shows the importance of the correct background to be effective: BI can bring advantage to companies only if they already have a functional and efficient digital base, from which obtain the amount of data necessary as input of a business intelligence application. It’s important to remind that it’s not sufficient to have a huge amount of data, but also that data can potentially bring valid information (the “Data Quality” concept discussed in the first chapter).

In terms of technology business intelligence’s mission is “to transform data and information in knowledge”. Data is a set of values that describe a fact [53] [54], that can be obtained in different ways, such as measurement, observation, query or analysis, usually represented by numbers or characters and that can be processed. Processing and interpretation of data produce information. “*Knowledge is structured and organized information that has developed inside* *of a cognitive system or is part of the cognitive heritage of an individual*" [55]. According to the definition of the Fraunhofer institute, a cognitive system, whose definition can be applied but not restricted to individuals, is characterized by the ability to understand, learn and make decisions. Business intelligence as a technology serves to this purpose within organizations.

A business intelligence tool is a software application that acquires, processes and manipulates masses of data that it receives from one or multiple sources (database, libraries or archives) and produces reports, parameters, indicators, plots and similars. These outputs, like the inputs, are constantly updated. Not only, but users can easily adapt ad configurate them in order to realize insights according to their needs, roles and situations, without requiring a direct action from systems' administrators. For technical and technological reasons, as well as for reasons of availability and security, the BI tools don't work and manipulate the original data from the database source, but with a copy those data transferred "real time" to the tool's database.

2.2.1) Base Concepts of BI's Architecture:

In this section will be recalled a few key concepts that are going to be cited in the following part of the chapter and are introduced before going in detail for the sake of a better clarity and to ease the further explanation without the need to interrupt the discourse to pause and explain the meaning of terms, ensuring a more linear exposition.

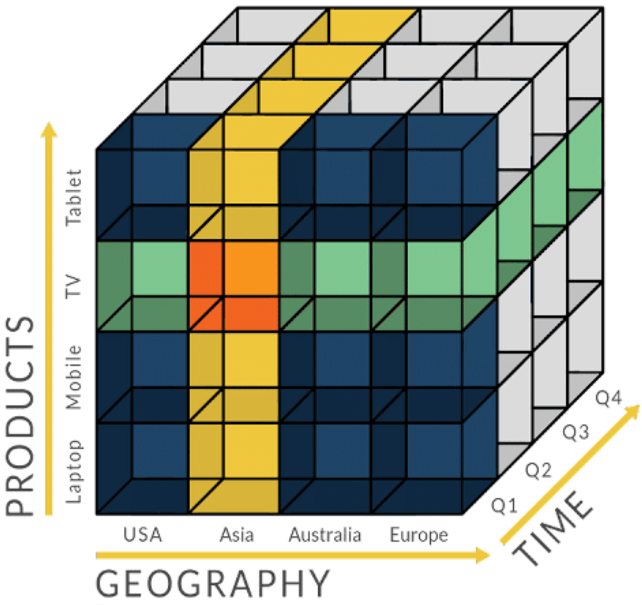
Relational Database:

Nowadays, when talking about databases, the concept of relationality is implicit. A relational database is based on the concept of "entity-relationship" in the representation of data. This is justified by the fact that, to understand a phenomenon, a list of descriptive characteristics (dimensions) is not enough, but one also needs to know how they interact in determining it. Therefore, instead of listing the ways in which each record is expressed in a single table, the information content is divided into several tables, each containing dimensions that are closely related, linked together in accordance with the relationships determined. This, in concrete terms, is achieved using keys. A primary key is a unique identifier of a given row in a table, hence of a record. By calling up keys in the rows of other tables, it is possible to reconstruct the phenomenon of interest by means of "entity – relation" logic. This has the advantage of a lower memory occupation for the same amount of data and greater robustness against errors (in the event of an error and subsequent correction, due to the way the complex is structured, it will be applied instantaneously to all records involved), allows faster and more efficient search and filtering operations and opens up the possibility of conducting operations on the data to generate information [56].

Multi-Dimensional Data (Hypercube Representation):

Within relational databases, data are stored and processed using the hypercube structure. To understand that is necessary to picture a N dimensional cube, and each dimension is a vector with its own cardinality (number of possible ways of expressing that record along that dimension itself) that describes an aspect of the data. This representation is particularly convenient since it enables the possibilities to perform specific operation on data that allow the extraction of information from the database [56]. In the following picture (Figure 1) it is possible to have a 3D visual example of the obtained data structure.

Figure 1: Example of a 3D hypercube data structure



Source: *Margaret Rouse, "Olap-3d-cube.png" olap.com, 2018*

Query:

With this term is meant a command written in a specific language by a user that has the specific purpose to extract some specific information from a relational database (in this case the standard is SQL, Structured-Query-Language). The relational structure is fundamental to conduct the query's operations, which are performed interfacing with the DBMS (Database-Management-System). SQL is a declarative language, which means that it specifies properties and characteristics relating to the data to be manipulated, not the extraction process.

There are many different commands that can be used for creating a query, but it’s possible to divide them in 6 main types:

- **Selection:** allows to extract data and visualize it in a dedicated table.
- **Insertion:** can add records that respond to specific rules or characteristics to an existing table.
- **Updating:** allows one or more fields of existing records to be modified.
- **Deleting:** allows to delete one or more records that respond to determined criteria.
- **Cross-checking/Pivot:** allow to analyze data by crossing specified fields of the records, obtaining a matrix.
- **Creation:** allow the creation of new tables.

Of course, it’s possible to perform logically connected queries (e.g. connected with “and”/“or” logic operators) or to program a query that is filtered by another one. Other operations, such as grouping or basic mathematical operations, are also possible. This is how database and data are processed at lower level (it’s required to know how to write and to perform queries), by interfacing almost directly with the system [57] [58].

2.2.2) BI Software Architecture

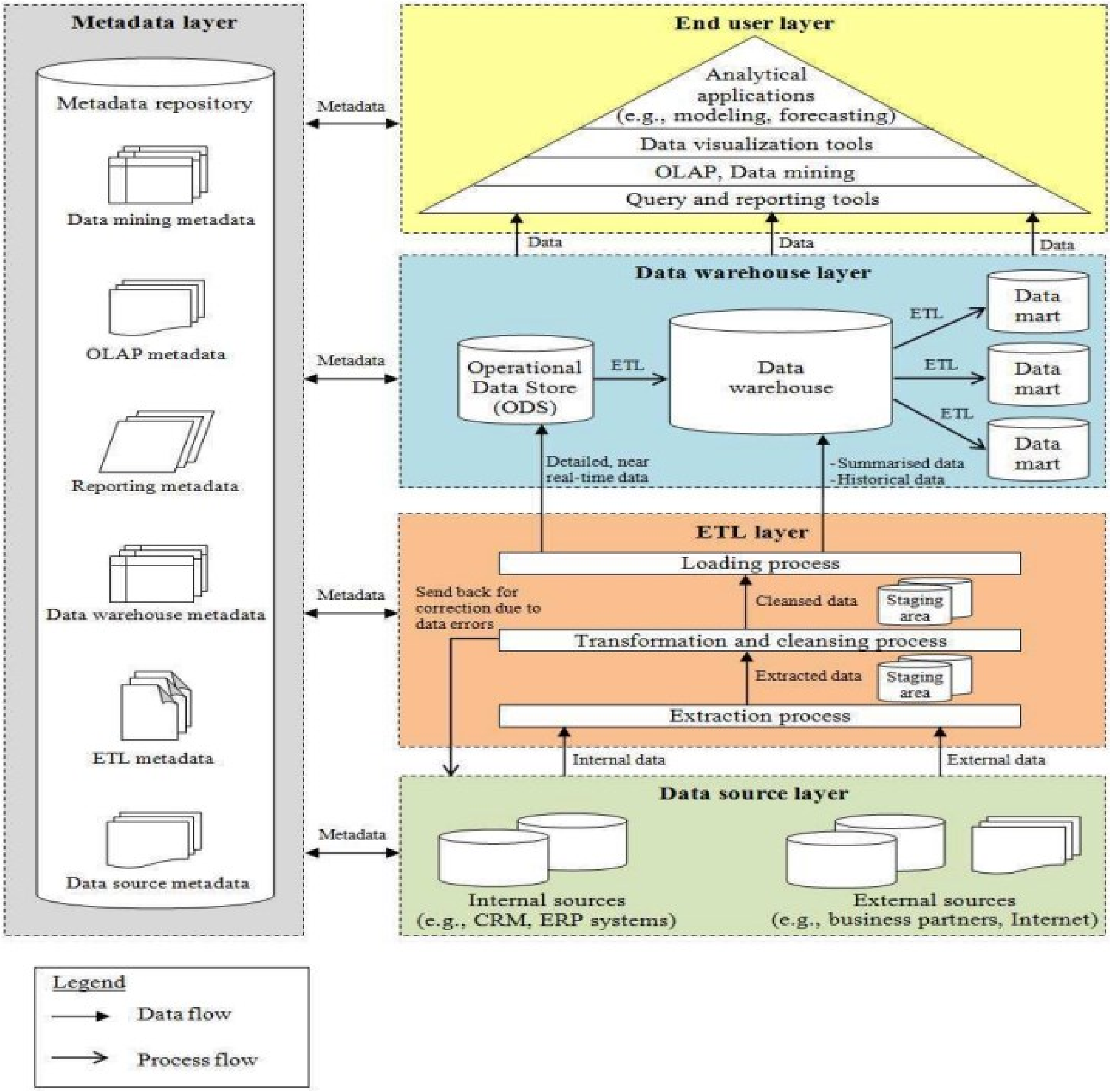
In the last years, a noticeable and important effort was put to solve 2 big issues of business intelligence architecture, caused by certain designing choices. The first one is due to the unidirectional flow of data. If the data cannot flow from the data warehouse to the data sources, there is more difficult, or even impossible, to perform adjustments, increasing the risk of the phenomenon of “garbage in-garbage out” and increases the time needed to identify these kind of problems, since data (and information) has to pass through the entire process. Not only, but without a bi-directional flow, and so without the ability to quickly perform the adjustments to the source, the “filtering” and the “cleansing” of data becomes more and more difficult [35]. The second issue was the lack of support in terms of architecture, procedures and software, of metadata.

Metadata is a category of data that describes a certain property of another data and covers different key functions. First of all research, identification or identify the existence and availability of a document. Then localization, so tracking certain aspects or the entire document itself, and selection (through analysis, filtering and evaluations). They are useful to manage resources and organize databases and catalogs, and, finally, semantic interoperability: the ability to exploit equivalence relationships between descriptors to operate research in different fields and scenarios. This property indicates the ability to recognize the meaning of a piece of data and be able to trace it back to the object or phenomenon it describes, irrespective of its source. In other words "*[...]they are used for the identification and retrieval of digital objects; they consist of descriptions of source documents, or of documents born in digital format, they generally reside in the databases of Information Retrieval systems outside the digital repository, and are linked to the latter by special links*" [59]. Having a metadata layer is very important for the BI functioning and performance, because can guarantee consistency and clearer definitions of data flow and description, avoiding misinterpretation or misunderstanding of data, all this while contributing to standardization and interoperability between many different systems [35]. The system proposed by In Lih Ong , Pei Hwa Siew and Siew Fan Wong consist in five different integrated layers. This is not the only scheme found in literature, but it presents all the common cardinal points which are always present in every representation. These elements are represented in the following picture and discussed more in detail in the following sub-sections.

Metadata Layer:

This layer is transversal to the other four, which means that it is collateral to the main data processing workflow. It's a repository o technical and business data regarding rules and data definitions that carry information relatively to the stored data. The data structure is instructed by the metadata layer, which has to be maintained and updated over time. Being able to correctly manage and use this section means that development and analyzing time can be reduced, data maintenance can be simplified and users can never lose track of data sources, processes, rules and procedures for each of the other layers.

Figure 2: BI application's proposed architecture



Source: *Arinto Hadi Wiharyo. "Extraction and Transformation of General Ledger Data from SAP ERP to Microsoft Power Pivot". 2014. https://api.semanticscholar.org*

Data Source Layer:

In this level arrives and is stored the data that comes from the business sources, that can be categorized in two groups: internal and external. The data coming from both types of sources can be structured (e.g. customers profiles), semi-structured (e.g. e-mails or XML files) or unstructured (e.g. texts or multimedia files). The internal data comes from the organization’s operational systems, such as ERP, CRM or MES. These applications are known as OLTP (Online-Transaction-Processing) systems, which means that there is no significant delay in data transaction, that means that data processing does not occur in batch, but continuously [60]. This type of data refers to specific business operations, and so bring information regarding, for example, sales, customers or production. Companies also collect data from external sources, such as business partners, market research organizations or data suppliers. It's important to identify and keep track of data sources, since it can be useful because makes it possible to quickly trace back to the root of the problem in the event of unreliable or incorrect data, and to improve and speed up the extraction, transformation and cleaning process in the next layer.

OLTP (On-Line Transaction Processing):

OLTP is a database system's functioning logic that deals, most of the times, with business transactional data, at the highest level of detail available and required by operational activities. This type of system is designed privileging 3 aspects: offer a suitable transaction security (for parallel queries and data manipulation), have a quick response time and, finally, to achieve the highest throughput, to be intended as the number of transactions per period. With these features, first and foremost the near real-time response and updating of data, they are an excellent candidate in operational and daily decision-making support [60]. An example of these systems are ERP's.

ETL Layer:

ETL is an acronym that refers to the three main steps that take place at this level, namely Extract, Transform (and "cleansing") and Load. These three phases are decoupled and asynchronous, and between each process, data is temporarily stored in a dedicated space called "data staging area", and this allows, in case of problems, to recover data without the necessity to repeat the entire process if not strictly needed. It's important not to forget the feedback channel, that allows to send back corrections to the previous layer, as already explained in the chapter. In the first process, "Extraction" data has the purpose of ensure that the data coming from the different sources is properly integrated, not incomplete or duplicated, so data has to be selected to be significant. Then data is transformed, according to business rules and procedures, and converted into predetermined formats for reporting or to be further analyzed. The rules and procedures are determined to guarantee consistency in the entire organization. In the same time, data is "cleansed", so mistakes are properly identified and corrected applying pre-specified rules and protocols (and the correction has to enter the feedback mechanism and be implemented upstream to the source). At this point, data is stored in another staging area, waiting for the last process of this layer, which is the loading phase to a targeted repository.

Data Warehouse Layer:

This layer can be structured differently in each company, but it is always characterized by 3 fundamental elements: "Operational data store", "Data warehouse" and "Data marts". Data flows following this order. Firstly, the Operational Data store (ODS) is a database that stores subject-oriented and detailed data, providing an almost real-time integrated view. This means that that this element does not store historical data, on the contrary, the data contained in this database can be over-written or updated by other data loaded in this stage very frequently (usually in a span of hours, or even minutes), and the storage time can be around 60-90 days. It's useful to run specific business applications that aim to support the management for short term decision making. Then the data warehouse is a fundamental element of BI architecture, defined by Immon (2005) as a " *a subject-oriented, integrated, time-variant, and non-volatile collection of data in support of management's decision making process*". More in detail, that definition means that the data coming from the different sources is consistent in terms of formats, naming conventions and other characteristics (integrated), it is organized in groups based on the subject, so the phenomenon of interest (e.g. products or customers) that the data itself represents (subject-oriented), it has the possibility to keep track of historical changes and evolutions (time-variant) and, in the data warehouse the data is "read only", so new data can be added but no data can be deleted or over-written (not-volatile). These are the fundamental characteristics of this element, which is the central storage unit of data in a multidimensional structure, in order to support queries, reporting, analysis and supporting OLAP (Online Analytical Processing) applications. Data inside a Data warehouse is updated on weekly or, usually, daily basis, with a storage horizon of 5 to 10 years. Differently from the ODS, the purpose of this database is to support strategic decisions, which means decisions that have impact on the long term future of the enterprise, that require deep analysis involving huge amounts of data regarding many different aspects of the business. Lastly, the Data marts is a subset of the data warehouse, or sometimes (if required by certain circumstances) a smaller dedicated warehouse, that has the purpose of responding to the specific needs of a department, business unit, function or process. It contains historical data with a multi-dimensional data model, as data warehouses, but usually with a reduced storage time horizon (typically from 60 to 90 days).

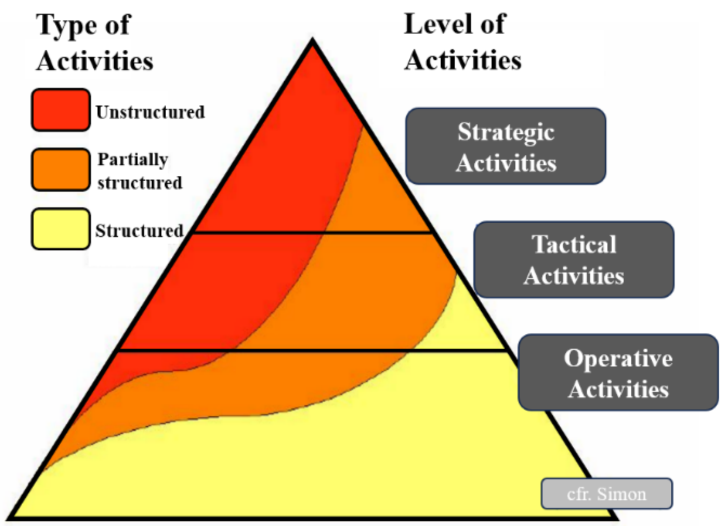
End User Layer:

This is the level in which are located the applications that interact with the users within the organization. In the representation, the pyramid scheme represents the tools mirroring the organizational hierarchy. From the bottom to the apex, the complexity of the decisions increases, same with the time span impacted by the decisions themselves. At the base there are tools such as queries and reporting, characterized by quick access to data, they are useful for operational decisions. Moving upwards there are OLAP tools and Data mining, then visualization tools, so Dashboards and Scorecards, and finally analytical applications. The latter provide functionalities that allow managers to conduct activities like modelling, forecasting or developing what-if scenarios analysis. As far as Dashboards, Scorecards and indicators, nowadays the solutions on the market allow to design specific solutions for each user, sometimes giving them even the possibility to interact and personalize it themselves. This is important for two reasons. The first one is to ensure that security and privacy are always under control, but it is also fundamental for data accessibility: in this way every user have direct access only to the data that is relevant to his role and responsibility. Usually, on the main screen of each user, one can find simple summary tables or indicators. Visual signals will draw attention to any anomaly or phenomenon of interest. The system is interactive and allows filtering, comparing or drill-down to the necessary level of detail, and once the problem has been determined, the necessary action can be taken promptly. This is, at least in theory, the philosophy behind the representative part (the most 'external', front-end layer) of a business intelligence system, i.e. the management dashboard.

The reason behind this pyramid representation can be explained through the Anthony-Simon model. Anthony's model is represented, indeed, with a pyramid, in which the organization's activities are classified in three groups, which are "operational", "tactical" and "strategic". The first one refers to operations that have impact in the short term or that are conducted on a daily basis, while tactical activities are related with mid-term decisions and results. Finally, there are the strategic activities, which have a long term impact on the company. Usually, the cadence and frequency of the activities has an inverse relationship with the length of the time span (short/mid/long) relative to the activity itself. Simon, on the other hand, defines the different types of organization's activities based on how much the activities are structured. Structured activities and decisions are characterized by a high degree of repetitiveness, fairly determined data, and the tasks are unambiguous, in other words a higher level of standardization.

Then there are partially or unstructured activities and decisions, characterized by non-repetitiveness and occasionality, operate in a context of higher uncertainty and with more indeterminate objectives. The combination of Simon's and Anthony's models results in the image shown. By moving from short to long term activities, the degree of structuring of the activities themselves, progressively decreases. It is important to emphasize, to avoid misinterpretations, that the hierarchy shown by this model does not refer to personnel but only to decisions and operations.

Figure 3: The "Anthony-Simon's pyramid"



Source: *own elaboration starting from Bolisani, Ettore. "Gestione dell'informazione aziendale", IN02103638. Handouts, slides and notes from the lessons. 2021.*

In fact, a single person can be responsible for many different activities, each of them falling in a different combination of characteristics [56]. Confronting the Anthony-Simon model to the hierarchical classification of the different tools, it is possible to appreciate the how the different tools respond to specific needs depending on the characteristics of the activities that aim to support and the objectives that help to achieve.

OLAP (On-Line Analytical Processing):

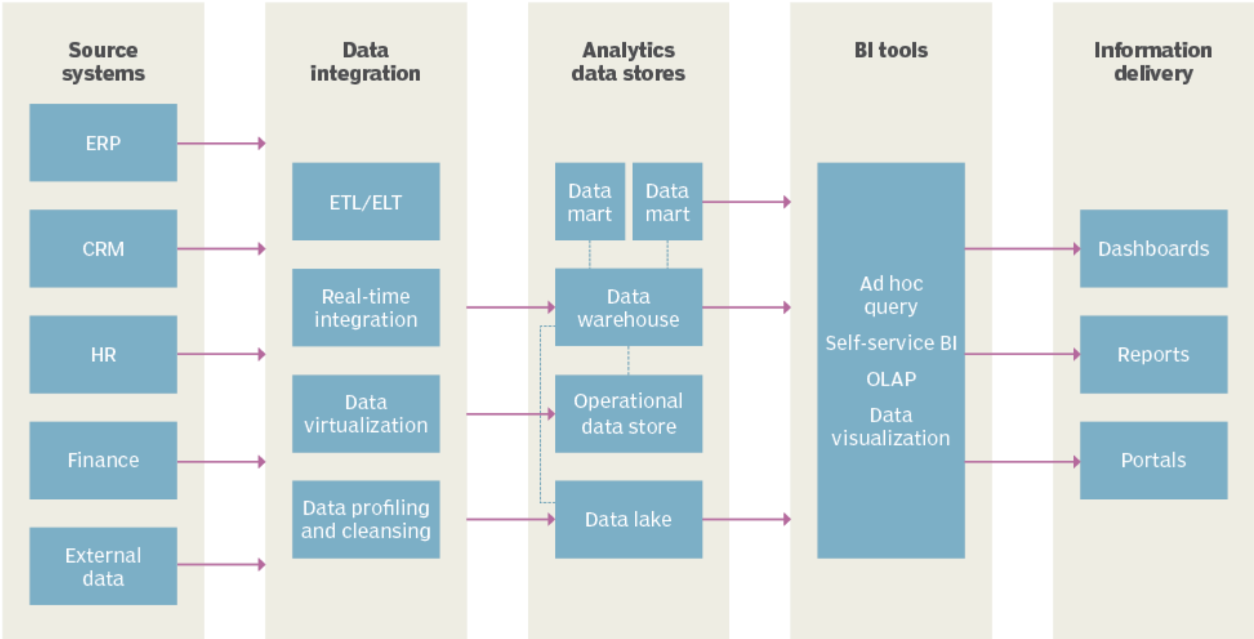
The primary purpose of Online Analytical Processing is to perform complex analysis (e.g. trend identification) and elaborations over a huge amount of aggregated data to generate reports and insights in a relatively short time. This type of techniques aim to achieve a high level of articulation and depth when querying the database, for this reason their typical application is within Business intelligence tools. OLAP is based on the concept of relational database and hypercube data structure. There are different types of OLAP, depending on the specific type of database on which it has been optimized. Regardless of the type and concept of OLAP considered, they rely on specific operators. They act on the data, manipulating it in an appropriate way to extract information from it, so that it is possible for the user, based on it, to interpret and make decisions. The operators are [61]:

- **Pivoting:** useful to realize transversal aggregations of data or analyzing the distribution of totals in relation to different dimensions.
- **Drill-down:** consist in an "explosion" of a datum in its determinants, following a hierarchical path (e.g. from "Country" to "Region"/"City"), or an analytical relation (e.g. from "marginality" to "revenue" and "costs").
- **Drill-across:** it's an operation that allow to move across the same hierarchical level of a dimension (e.g. moving from one "City" to another).
- **Drill-through:** the idea of this operation is to move to the level of detail belonging to the normalized dataset starting by an aggregate level. It's less used compared to the other two "drill" operation, as well as it could generate some security and performance issues.
- **Dicing:** is also referred to a subset extraction, resulting in a subset that has the same number of dimensions of the original dataset.
- **Slicing:** extract a subset of data from the total, fixing a specific value for one of the dimensions (in this way the subset will resemble a slice of the total). This operations results in a subset that has "n – 1" dimensions, starting from the "n" dimensions of the original dataset.

These are the typical fundamental operations on data performed by a traditional BI system or Decision-Supporting-System. However, especially in recent times and in the face of new needs, these types of methodologies have shown significant criticalities. In fact, they are not at all well suited to dealing with "big data", which means large quantities of data, mostly semi-structured or unstructured. As their operation is conceived, the amount of intermediate data required for their operation increases exponentially with the amount of data processed. In addition they require data with a certain format as input and producing, when performing operations, very complex queries that can be very demanding in terms of computing power. This makes it particularly complicated to apply these methodologies to the modern need to handle "big data" efficiently and in a short time, resulting in a bottleneck. This means that a different solution has to be found to overcome this limitation [62].

Another representation of a BI architecture scheme is the following (Figure 4). Despite the differences, it is important to note that the logic and fundamentals are virtually unchanged. In fact, even in this case, data undergoes the process of collection from multiple sources, is then extracted, cleaned, filtered and aggregated, before being sent to a Data Warehouse or ODS.

Figure 4: Alternative representation of a BI architecture



Source: *https://www.techtarget.com/searchbusinessanalytics/definition/business-intelligence-architecture*

Here again, the presence of dedicated data marts is highlighted where it is necessary. This is then followed by the analysis phase using queries or other procedures. Finally, the data must be communicated and, therefore, appropriately visualized in reports, insights, or in dashboards with tables or various indicators. However, this representation highlights some fundamental aspects, on which it is good to dwell: the first aspect is technological, in fact the providers of BI applications progressively moved towards a "platform" based strategy, by proposing Cloud solutions to their customers. This choice was primarily dictated by market logic. It is in fact convenient for large companies, and all the more so for small and medium-sized ones, to rely on a provider, since it can take advantage of the economy of scale from which cloud systems benefit, it relieves customers of the problems of operation, available capacity, compatibility, maintenance, security and robustness of the systems, and finally it offers an environment in which, although less technical and specialized knowledge is required, customization of solutions is possible, the spectrum of which depends on the characteristics of the offer (and will be clarified in another section of the chapter).

Then, the second motivation can be identified with performance necessity: Cloud systems are more suitable for dealing with “big data” processing and analyzing, activity which, otherwise, it would be too much costly (in terms of effort, i.e. hardware, software and professional investments and operating costs) or too much time consuming (latency and processing time too high) if resorting to a traditional system. This means that the implementation of cloud computing ab “big data” processing techniques is quickly became an essential element, not only for big companies, but even for smaller organizations, since the ability to collect and produce data exponentially and rapidly grew in every possible sector. These aspects are treated separately in this chapter.

In conclusion, this scheme of a BI architecture workflow shows the importance of having properly designed layers, each of which covers a key role in the process of collecting, processing and distributing data and information within the organization. It’s important to deploy a systematic network of links between the different parts, ensuring a bi-directional flow of data since “*A multi-directional flow can enhance query performance and improve accuracy because data error at one layer can be returned to the previous layer for clarification if error occurs*” [35].

2.3) Technology Implementations in "State of the Art" BI Platforms:

2.3.1) Cloud Computing:

To overcome the limitations of classical systems, many scholars over the years have looked for possible solutions. A good number of them have pointed to "Cloud computing" systems as a possible way forward [62]. And indeed, many vendors have recently started to offer solutions that include this very technology. The theoretical idea at the base of this technology is to virtualize equipment and services to exploit a network of nodes in a platform that can realize a superposition and a coupling of the available resources [63]. In other words, computational and storage resources do not reside locally but in a superstructure, at least virtually, centralized (though often also at the hardware level), accessible locally via the internet. This section will briefly discuss this topic. The goal is not to be exhaustive, but to convey the idea that, behind the term "cloud computing" there is not a monolithic concept or a single technology, but a broad, dynamic field of research with many different solutions, approaches, methodologies, and tools, each of which is best suited according to the specific situation.

Brief Introduction to Cloud Computing Technology:

"Big data" characteristics are the following: massive volume, rapid in change, a low ratio value/volume, high variety and mainly semi-structured or unstructured [62] [63]. The usual configuration is centralized, to benefit the massive "scale economy" effect. A very important facilitator role is played by the spread and evolution of broadband internet and high-performance optic fibers in the industry, which allow a rapid transmission of incredible amounts of data per time unit, covering the time gap required by data transfer. In this situation, the traditional data processing techniques became soon the bottleneck: companies could collect and communicate data much faster than they were able to manage and process. Since the value of data is strictly dependent on the ability to extract information by processing and analyzing them, it is this very aspect the fundamental value driver for the company in this context of "data driven" decision making. And these systems are precisely designed to ensure high computational and storage power, so that they do not constitute a bottleneck, as well as to avoid duplication, nonconformity and errors at the information level. The idea at the base of Cloud computing mechanics is "parallel computing", which a very simple concept. The main "mission" assigned is divided into a certain amount of elemental sub-tasks, which are processed separately with a parallel scheme. The results are aggregated in the end, obtaining the desired output of the mission. Progress has been, and currently is, extremely rapid in terms of both hardware and software. Hardware improvements include technologies such as multi-core CPUs and GPUs, the increased clock speed of microprocessors (that reduces the time to execute sequential instructions), and, finally, high speed networks and data storages, while in the software field, an important extent has been brought, with libraries and frameworks to support parallel programming and algorithms, and with a strong academical interest in new research, but above all in revision, so as to bring order and clarity, so that an established and reliable best practice could be developed and adopted [63].

What Is Cloud Computing:

Cloud computing has been defined by the US National Institute of Standards and Technology (NIST) as "*as a model that can achieve convenience for obtaining the required resources (including networks, servers, storage, applications, and services) through network access on demand, and the required resources can be quickly provided or released, with little management effort or little interaction with service providers interaction*" [64] [65]. This technology is generally characterized by the following set of concepts:

- **Virtualization:** this a core technology that allow the integration of heterogeneous computing resources from a pool at users' disposal. Notice that this is the most important point, the one on which all the others are based on.
- **Elasticity:** the scale of the Cloud system can quickly adapt to the users' needs, without affecting the existing processes and services in use.
- **Scale effect:** this technology is greatly affected by the phenomenon of the economy of scale. This means that the computing power over price ratio is favorable, therefore it is neither cost-effective (for hardware, management and maintenance) nor performance-wise for a company to build its own system or platform instead of taking advantage of the cloud. This because a large number of idle ordinary computers can be integrated into the resource pool through virtualization.

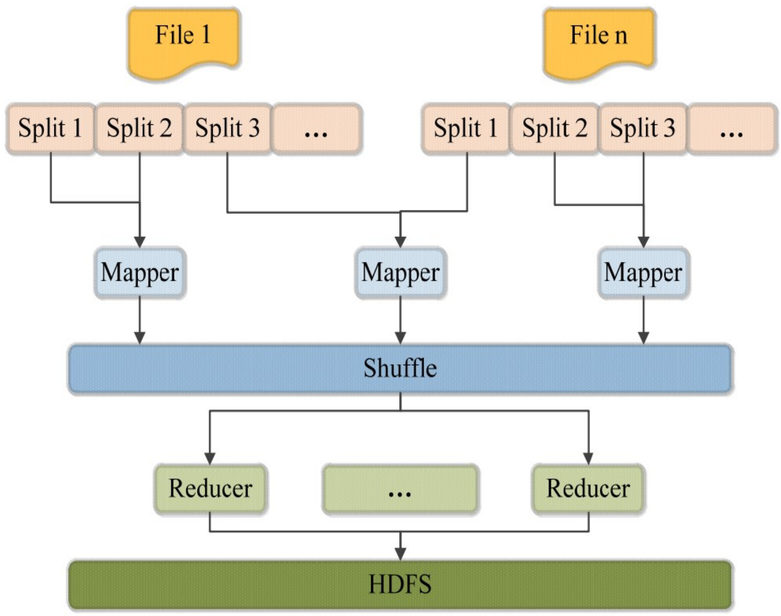
- **Reliability:** these systems proved a high fault-tolerance of their mechanisms and a high reliability, both in terms of functionalities (a local failure doesn't compromise the overall functioning, thanks to virtualization) and storage (extremely difficult to lose data since there are multiple copies in different storing sites).
- **Service oriented:** there are three possibilities which are: Infrastructure as a Service (IAAS), Platform as a Service (PAAS) and Software as a Service (SAAS). The first one guarantees the highest level of freedom of development to the users but requires specific capabilities, while the last one allows low or almost no freedom of development but offers easy to use applications that don't require specific knowledge from the users.

The need of processing big data with a cloud computing technology led to the emerging of different computing and programming models, suitable for a parallel computing environment.

Hadoop Technology:

The Apache Software Foundation brought into the market the Hadoop, an open-source data processing system. Operation takes place in parallel: the computation operation is divided into subgroups of tasks, which are easier and quicker to be solved, that are assigned evenly (balancing the workload) to the various nodes, which will go on to determine and execute the core tasks. The outputs of the various nodes are collected and "assembled" into the final output sought. To have a more detailed idea it is possible to observe the presented picture (Figure 5).

Figure 5: Hadoop fundamental programming logic



Source: *Al-Jumaili, A. H. A. et al. (2023) [63]*

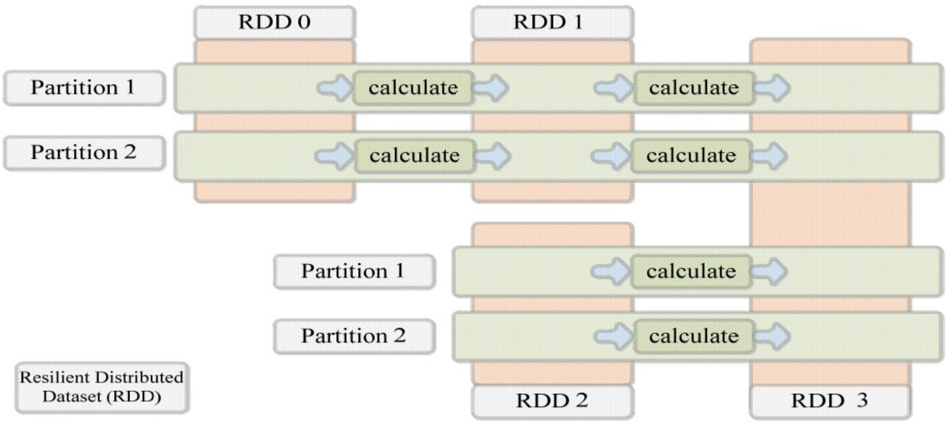
The system has two main functions, map and reduce, which automatically perform more basic sub-operations, such as [66] "Task division and assignment", "Task scheduling", "Workload balancing" and "Failure recovery". The files received as inputs, are get split into several subsets and then converted into a specific format (key-value), before being took as inputs from the "Mapper", that will then proceed with the calculation. The intermediate results, so the outputs of the "Mapper" calculations, are still in the "key-value" format, and, after a the "shuffle" phase, they're aggregated by the "Reducers" producing the final and overall output, which is saved in the memory storage. A limit of this system is the fact that is mostly batch oriented, and therefore tends to perform better on static and historical data, while lacking performance with real-time data.

Spark Technology:

The Spark system [67], appeared for the first time in 2012, is similar to the Hadoop as conception, but, unlike the latter, perform a considerable number of calculations in memory, avoiding a large amount of disk I/O (reading and writing time). This feature makes Spark more suitable and efficient for interactive and iterative procedures [68].

The in-memory computing is based on RDD (Resilient-Distributed-Dataset) [69], which, in brief, allows the system to partition the main operation into subgroups of tasks that are gradually more basic to solve, while keeping track of dependency relationships between subdivisions (this "father-son" relationship of dependency is called "lineage"). This aspect is very useful because, in case of errors, it quickly allows the source to be traced and the computation to be repeated. That is what makes this system so failure-resistant. A visual representation is given in the following picture (Figure 6).

Figure 6: Resilient-Distributed-Dataset base of the Spark model



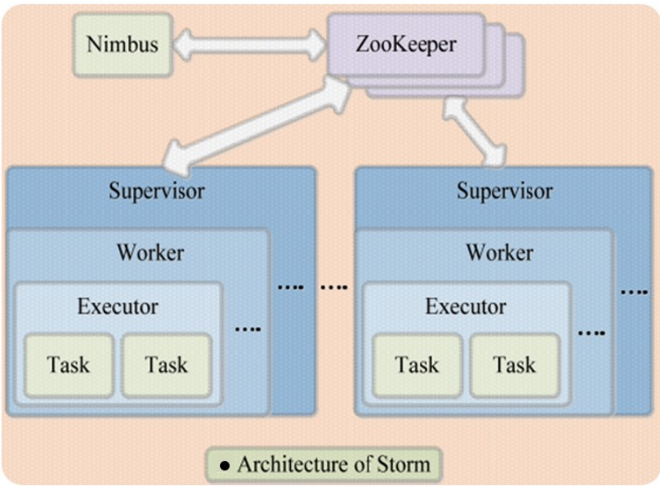
Source: *Al-Jumaili, A. H. A. et al. (2023) [63]*

This model proved to be more flexible and efficient than the Hadoop system, from which was inspired. Spark has been already applied successfully in big internet companies such as Amazon or Yahoo, and currently is facing an experimental phase for smart grids and power production industry's applications, since it seems to struggle in calculation speed and latency when dealing with complex signal processing algorithms [63] [70].

Storm Technology:

The architecture of the system is clustered (managed by a node custodian of the specific topological rules to be followed by the actual system as needed) and a coordinating node. In the case shown in the picture (Figure 7), from which a visual representation of the architectural scheme can be obtained, "Nimbus" and "ZooKeeper," two ASF software, are used, as is often the case, respectively. A cluster comprises a number of supervisors, each of whom monitors a number of workers, who in turn have a number of executors. The latter are responsible for carrying out the elementary tasks.

Figure 7: Storm architecture concept



Source: *Al-Jumaili, A. H. A. et al. (2023) [63]*

Differently from the previous two systems that are based on a batch logic, the Storm technology was developed to support real-time analytics on large scale. A necessary clarification must be made: The systems showed here are not the only one, and similar ones are available on the market. The decision to take these specific examples was due to the documentation availability in regard.

The growing demand and need for "Big data" processing by companies in more and more sectors, and the development of cloud computing platforms have required the development of new computational, programming and technical models to cope with the new needs. This resulted in different concrete solutions:

- **Public Cloud:** the most typical, especially for smaller companies. As suggested by the name, it is a service open to public, so it is not exclusive for a single organization. It is characterized by a large overall scale and low-cost, especially if it is a SAAS (Software as a Service) Cloud, since it's the provider's role to ensure the technical functionality of the system and its maintenance. A famous example is AWS.
- **Private Cloud:** a system that is meant to be exclusive for a group or even an organization. Typically, a solution that only big companies (or groups) are able to afford and to justify the investment in terms of performance that needs to be achieved.
- **Hybrid Cloud:** in this situation there is a combination of the two previous solutions. It could be a valuable option since it can provide the performance and level of control of a private cloud, but without the need for an over-engineered system, since the peak-performance, when needed, can be achieved by can be obtained by recurring to the public Cloud. In this case, due to the overall system structure, particular attention has to be given to the security, encryption and transfer aspects.

In more recent years, the concept of "Distributed Cloud Computing" has developed, which means a geographically distributed network of resources, dispersed among different users that share the hardware and the infrastructure to create a system able to respond to the users' needs themselves. The decision to mention it, although not going into detail, is justified by the fact that, for the sake of completeness, it was necessary to take into account the fact that cloud computing, like many other technologies, is not limited to a single implementation paradigm, but that it is possible to find several alternatives while retaining its original philosophy, logic and objectives. Namely, the ability to execute several tasks, jobs and processes simultaneously, reduce CPUs consumptions, reducing processing times, and improve speed and effectiveness of communication (since every user, accordingly to his authorizations, can almost instantly have access to the resources stored in the Cloud) [63].

2.3.2) Data Lake:

As stated earlier in the chapter, traditional solutions, based on centralized databases and "data silos", while still accounting for the majority of market share especially in the case of small and medium-sized enterprises, are not adequate to meet the new needs of organizations and providers of business intelligence systems. Without any doubt "big data" are the most important challenge to face in terms of database management and research. Data lakes have been proposed as a technical application that can bring the expected performance in terms of data analysis capabilities, latency and processing time in many different use cases such as Internet-of-Things management, manufacturing, medicine, biology, mobility and logistics, smart grids, up to smart factories and smart cities [48]. Since, in this chapter, we want to go and identify the main features of the state of the art of business intelligence platforms, it was deemed appropriate to briefly mention this feature, which seems to be adopted and promoted by several vendors of these systems.

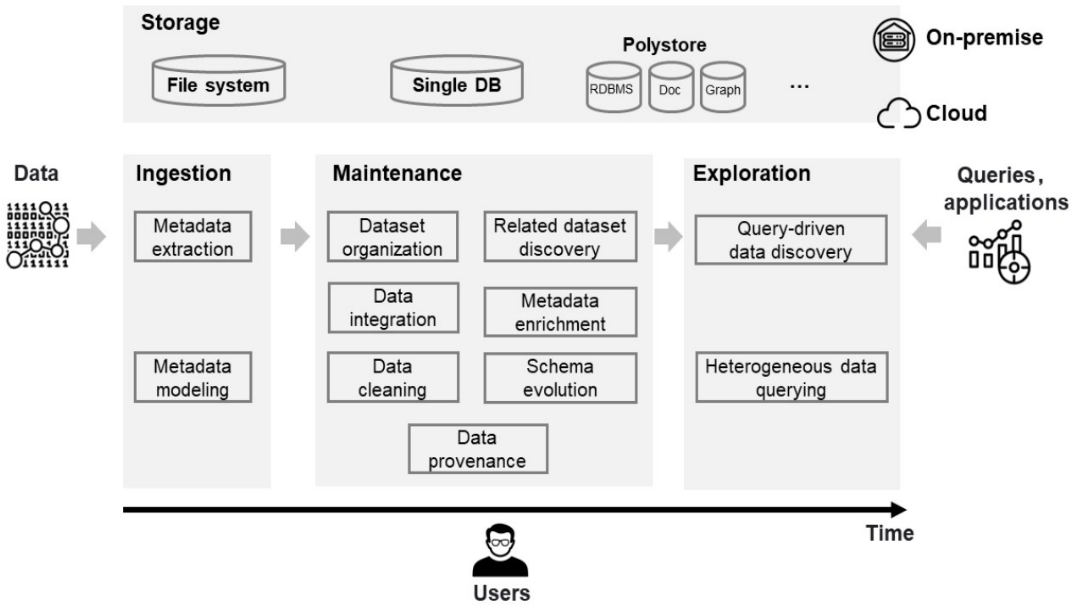
Origins:

The term appeared the first time in 2010, proposed by Pentaho CTO James Dixon, as a solution to directly handle raw data from one single source, in opposition to the more traditional systems (e.g. Data warehouse). In 2013, *Pivot* proposed an evolution of this idea, oriented to business application, that was able to handle raw data from different sources, that was running on a Hadoop system. The development continued until nowadays, in particular, around 2016, an important growth of the interest in industry and research has been registered, and many IT companies (e.g. "GOODS" from Google, "Azure Data Lake" from Microsoft, "AWS Lake2" from AMAZON, "Vora" from SAP, IBM and Cloudera, Oracle, and Snowflake. "Delta Lake" from Databricks) are starting to develop tool to realize data lakes. This technology can be very useful for "big data" analysis, improving the time responsiveness of analytics (and potentially achieving a real-time monitoring of the operation). This is realized by exploiting bigger amounts of data in the same time span in comparison to more traditional systems, and this enforces the reliability and accuracy of information. Not only, but many researchers believe that Data Lakes can be an important facilitator for the implementation of Artificial Intelligence in data analysis, with all the benefits related to the potential and capabilities that the latter technology would be able to bring [71]. Of course, this concept is by no means an exhaustive solution, nor is it without its criticalities. As pointed out by some, including Gardner (2014), this technology runs the risk, in the event of mismanagement of the technology itself, without proper "metadata management" and without conscious "data governance", of resulting in a "data swamp", which is a term coined by Gardner to indicate a useless and unusable set of data, from which it would be practically impossible to extract any kind of information [72] [73].

Data Lake Architecture:

The original idea has been developed by different researchers and companies. A Data Lake is a system in which data is reposited from different sources in its own raw (or natural) format [74]. PwC's definition is: "*a repository of structured, semi-structured, and unstructured data in heterogeneous formats, originating from the business transactions, sensors, or mobile/cloud-based applications*" [75]. In the figure below (Figure 8), it is possible to get an idea of the structure of a generic Data Lake system, in which it is possible to see its architecture and the typical sub-phases of each section that go to make it up. We will not go into technical detail here, as this would be off topic.

Figure 8: Proposed architecture for data lake solution categorization



Source: *Hai R. et al. (2023) [72]*

However, we can see that a data lake consists of four elements, which therefore also determine its four main phases (it is important to underline the fact that different developers may use different names, but usually the fundamental concepts are pretty similar to the ones presented here):

- **Ingestion:** Data from the various sources must be loaded into the system, and metadata must be identified, extracted and modelled. In such a system, the presence and good management of metadata is even more important than in others. Since its organization is fundamental to ensure that the content of the Data Lake respects the FAIR principles (Findable, Accessible, Interoperable and Reusable) [76], and metadata is fundamental for this objective.
- **Maintenance:** in this phase the main objective is to unify all data coming from many different sources into a single database. A key aspect is the ability to determine relations between data, but mostly, between metadata, since that can be used to enrich the data comprehension and interpretation. Nevertheless, in this situation the data has to be prepared for further analysis, so data has to be filtered and cleaned. Lastly, the concept of "lineage": keeping metadata able to give information that can specify sources, operations and elaborations (maybe even tracking the time of them) used to obtain certain data is fundamental, in case of failures or errors, for the "trace back" operations, allowing to operate corrections and recoveries.
- **Exploration:** it answers to the necessities of identifying datasets that are related in terms of source and to provide a unified query interface that can work on data from heterogeneous sources.
- **Storage:** after processing, data and information must be stored in such a way as to be readily available and accessible to users. The solutions can be many, for example maintained on a cloud or with "poly-store" systems (storage space consists of several different methods) [77].

It can be said that the Data Lake concept can be seen as an evolution of the more traditional methods of data storage and processing, usually by adopting cloud solutions and a philosophy more oriented towards real-time response and updating (to use a manufacturing metaphor, moving from batch production to a mixed-model line production).

In conclusion, in the first decade since their existence, Data Lakes attracted lots of interests and attention both from industry and academics. Many believe in the potential of this technology, especially because of the potential synergies between Data Lakes, Artificial Intelligence and “Advanced Analytics”. As much as concerns Artificial Intelligence, Data Lakes can offer a favorable environment to implement and optimize this technology. The important presence of metadata, which usually lacks in the more traditional forms of databases and data warehouses, is believed that can be an important resource for achieving the expected effectiveness and efficiency necessary for the reliability of AI models, especially after the recent leaps forward made by AI in terms of capabilities and reliability in dealing with semi-structured and unstructured data. The other important aspect, which is arousing great interest, is the contribution that Data Lakes can bring to business analytics, but, even if there are some proposals on the market that are trying to combine Data Lakes and Data Warehouses, lot of work has still to be done in terms of optimization and in terms of comprehension by the companies: these concepts are relatively new, very fast in their evolution, with a lot of marketing contaminations and still unstructured academic works. This situation means that there is still only a superficial understanding of these technologies, and it is therefore difficult to get a clear idea of the potential they can have and how it can, in practice, be realized. Many questions are still open and matter of research [48]. However, there is reason to believe that, in the near future, the synergy between these four technologies (Data Lakes, Artificial Intelligence, Cloud computing and business Analytics) could be the basis of the innovative drive for businesses.

Chapter 3) AI in Supply Chain Management and Logistics: Where and How it Enables Competitive Advantage and New Opportunities

In this chapter will be treated more in detail the artificial intelligence topic, especially in relation to Supply Chain and logistics and how this technology can help the improvement in this field. First, it is necessary to clarify the concepts of artificial intelligence and machine learning, as they are very often the subject of misunderstandings. This is not only due to the fact that the subject has, until recently, been the focus of interest almost exclusively in the academic world, but is also due to the fact that, especially in recent times, the subject has been involved in massive marketing and coverage by the mainstream media, as a result of a growing interest in regard even by "general audience", given the recent major breakthroughs. Finally, the subject is indeed covered in the literature, but only recently it has been emphasized that there is a need to "put things in order" and to structure the great amount of works that have been done in a largely unstructured manner, as is normal in any new field of research. It should be emphasized that, until now, most of the work has been done from an IT point of view, focusing mainly on the development of algorithms and programming, while the management and business side has been neglected. Although understandable, this may end up limiting this technology, as a lack of understanding, and thus of trust and desire for experimentation in the field (beyond the IT and tech sectors), may limit the virtuous circle of development. The first part will introduce the topic in a more general way, with an overview of the subject. Later in the chapter, the topic will be analyzed more specifically from a more applicative perspective in the field of Supply Chain and logistics.

It is necessary to point out that topics related to generative AI will not be dealt with in this thesis (there will be references and citations, but no in-depth focus whatsoever). There are several reasons for this, first and foremost the need for brevity. The field of AI is extremely vast, complex and rapidly evolving, so it would be difficult to develop the topic exhaustively even in case of a completely dedicated and focused paper. To deal with this topic in a non-superficial way would require an excessive deviation from the aims of the work. Furthermore, at the time this work was carried out, no concrete and substantial contributions from this field of artificial intelligence were found within the existing literature in the specific case of the BI field and from a supply chain management perspective. However, these technologies, in particular generative AI, are apparently evolving at such a fast pace that it is by no means possible to rule out possible applications and developments for BI in the near future, also considering the interest of the public and the investments made by numerous companies in these tools. In any case, it is not the goal here to put order in a so dynamic and rapidly-evolving field such as AI, but only to collect the most important concepts that are functional to the main objective of the thesis. It is a brief analysis of the topic to gather the tools for a better understanding and comprehension of the terminologies, the logics, the features, the technologies and the implications necessary for to analyze the applications and the case studies.

3.1) What is AI

The this section will focus on clarifying the meaning behind the term "AI", this by bringing a brief categorization of the different technologies that compose this field and trying to point out the main concepts at the base of this subject.

3.1.1) Definitions:

"Artificial Intelligence" (AI) is a term that John McCarthy, emeritus Stanford Professor, coined in 1955 to indicate "*the science and engineering of making intelligent machines*" [78]. Another Definition can be provided by Gardner Glossary, as: "*Artificial intelligence (AI) applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions*" [79]. Otherwise, some other definitions can be [80]: "*Artificial intelligence is a computerized system that exhibits behavior that is commonly thought of as requiring intelligence*" [81], or as: "*Artificial Intelligence is the science of making machines do things that would require intelligence if done by man*" [82]. In alternative, there definition of Alan Turing, considered the father of AI, said about this discipline: "*AI is the science and engineering of making intelligent machines, especially intelligent computer programs*" [80] [83]. In other words, the concept behind Artificial Intelligence is to combine the efficiency, effectiveness and reliability of computers in managing big amounts of data in a short period of time, with the capabilities of the human brain, especially, but not limited to, patterns, analogies and similarities recognition, learning over time through experience, recognize relationships of dependence and causality and, finally, the ability to adapt to new situations. The combination between the two aims to merge the strength points and to contain the respective weaknesses.

Over the course of time, feelings towards this topic have been quite changeable, alternating between periods of optimism and periods of skepticism. But nowadays the situation seems near to an actual splitting point since certain evolutions in the environment or technology can bring a significant overall impact in terms of diffusion and development. First, compared to the past, libraries with specific algorithms are now becoming more widespread, which facilitates the access to this technology. This aspect is crucial since, from one side, enables possibilities of application even to users that don't have the deep knowledge and the skills to build these kinds of applications from scratch, from the other, the availability of "off-the-shelf" algorithms and applications, can heavily reduce time and issues required to come up with a functioning project. Today, on the other hand, it is not strictly necessary to have a team able to deal with complex math, statistics and large programming code capabilities at disposal, since it is possible to implement an algorithm that can be found by means of special libraries, perhaps even with documentation to guide the choice appropriately, and by resorting to programming languages, such as Python, that have the capability of reducing by a lot the amount and the complexity of the code to be produced. Another important aspect is the availability of "Big Data" (large amount of fast-moving heterogeneous data) [84] and the related development and spread of Cloud Computing solutions, even for smaller companies, reducing or even eliminating the limitations in terms of computational and storage power and capacity. This acted as a catalyst, creating the ideal environment for the development of AI and led to leveling the field for technological competition and development [85]. In fact, we are witnessing a steady growth and companies recognized the importance of this technology in terms of business opportunities that can be enabled, starting a transformation and e re-engineering of products, services and business models [84].

3.1.2) Main Types of Artificial Intelligence: “Weak” vs “Strong” AI

Before going into more detail, it has to be clarified that all the AI applications in enterprise and business consist in “weak” (or “narrow”) AI, that means an artificial intelligence that focuses on performing a specific tasks, being able to mimic human behavior. For example a chatbot is able to emulate a human conversation, or AlphaZero, a chess playing program developed by Google. This term is meant to oppose another conception, much more fascinating and portrayed by cinema and fiction but far from the actual present day research field, which is “strong” AI: it doesn’t simply emulate a human-like behavior, but it is also self-conscious. Another classification distinguishes three types of artificial intelligence: “weak”, when it is able to perform a single specific task, “strong”, when it is able to perform different tasks in a certain field with the ability to train itself and improve autonomously over time, and “super”, when can achieves self-consciousness [86]. However, self-aware artificial intelligences remain, for the time being, only a theoretical concept and of purely academic interest, far removed from the current needs of industry and business.

3.1.3) Pre-Requisite: The “Bias-Variance Trade-Off”

Every type of Artificial Intelligence is based on a model. A model is a stylized representation of a specific aspect of reality. It is therefore a convenient analogy, which does not have to be identical in every respect to reality itself, but useful for a specific purpose. When developing a model, the following concepts must be taken into consideration.

Bias:

This type of error occurs when the analytical model chosen it is too simple to describe the behavior of the object taken into exam, which means that the analytical model takes into account too few parameters, i.e. variables, than necessary to represent the phenomenon of interest accurately. This situation must be avoided, because are left out some important and relevant relations between input and output characteristics (under-fitting).

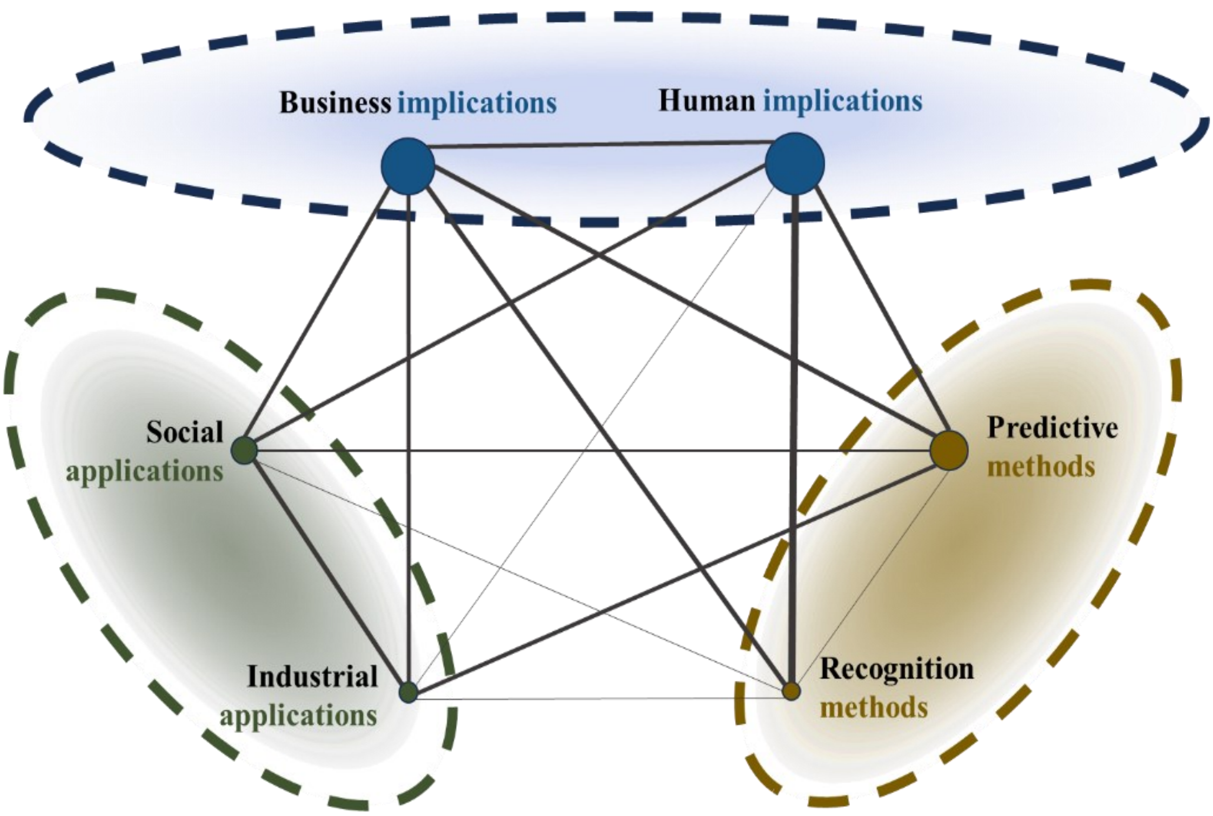
Variance/Error:

Variance, or the squared difference between the desired and the obtained output. The objective, when developing a model, is to find the value of the parameters that can guarantee the "best fit" in relation to the available data (parametrization), and so, in other words, to minimize the error (the overall difference) between the model output and the behavior of the actual phenomenon. For this purpose, it is necessary to have data on the latter, so that parameterization can be carried out using them. The measurable error in this way is the "In-Sample Variance", which is the model error with reference to the sample of data/observations used to parameterize the model itself. Generally speaking, it is not possible to reduce the error to zero, however, usually the greater is the complexity of a model (i.e. the number of parameters it takes into account) the smaller will be the error obtained. However, the real objective is not to minimize the "In-Sample Variance", but the "Out-of-Sample Variance", which is the error between the model, parameterized based on the available sample, and the external phenomenon. In other words, the objective of the model is not to show a perfect fit of the data used for its parametrization, but to perform with a sufficient accuracy when dealing with "new" or "unseen" data, proving itself capable of describing the "general" phenomenon (within the limits of the model's assumptions). Now that the meaning of these concepts are clarified it's possible to analyze the "Bias-Variance trade-off", which means that the model has to show enough complexity, otherwise it won't be able to show acceptable performance outside of the "training sample", but, at the same time, it can't be too complex, because it will show an "unstable" behavior (due to the fact that the instability of a function, especially if polynomial, vastly used in this applications, grow quickly with the increasing of the complexity of the function itself) and will, once again, perform poorly in describing the phenomenon of interest when not dealing with the parametrization sample's data.

3.2) Implications, Applications and Methods: Research Themes Until Today

Data Analytics techniques are normally classified as descriptive, predictive and prescriptive, offering a growing level of business potential. Descriptive analytics is the most traditional application of data analytics and it is historically linked with the concept of Business Intelligence (BI), as introduced by Luhn (1958). The more advanced applications of Data Analytics make use of AI in the attempt to anticipate scenarios by promptly implementing useful business strategies. Exploring and analyzing data, might support the construction of AI, facilitating predictive analysis and automation tools. Predictive analysis solutions are largely powered by ML and AI tools and are profitably leveraged for managerial or marketing purposes aimed such as designing new business strategies or investigating consumer behavior [87].

Figure 9: Network visualization of the studies grouped by topics



Source: *Sestino A. et al. [84]*

Among the various attempts to bring order to this subject, it is worth mentioning the research by Andrea Sestino and Andrea De Mauro, who attempted to identify the main themes/keywords and determine their mutual relationships. To this end, they used artificial intelligence algorithms, in this specific case text recognition algorithms, on a large portion of papers (which they had collected and appropriately prepared). The result, as can be appreciated from the image taken from their work, indicates that there are essentially three areas of interest, or "themes" in the research, each consisting of two main sub-areas. The size of the circles indicates the recurrence of the treated theme, while the thickness of the lines indicates how often the two themes are treated within the same paper [84].

3.2.1) Implications:

As the previous image (Figure 9) shows, the theme that has attracted the most interest from researchers is that of human and business implications. Understandably, it is very important, as well as very much felt, to analyze the possible consequences of the spread of AI, so as to be able to try to identify, and consequently be able to try to seize, possible opportunities, and at the same time, to determine in advance possible risks in order to prevent them, or to take them into account and elaborate a strategy to face or to avoid them. In terms of business applications, emerged the importance of the impact that AI can have on Data driven decision making, process mining and automation. Reporting Davenport (2018), the AI can have a positive impact on automating many administrative and bureaucratic activities, with important outcomes in terms of speed and costs of execution. Another important contribution can be brought to data analysis and mining, helping to manage effectively bigger amounts of data and finding patterns, relationships and correlations that that can be hidden within the data, which users could not be able to imagine themselves. Another aspect of interest is the possibility to support customers or employees through interactive systems powered by an artificial intelligence, such as chat-boxes for example.

Obviously, when talking about artificial intelligence, it is also important to consider the possible impacts on the human component. Indeed, not only will it have a strong impact on the digitization of human resources management, allowing it to act on the environment, behavior and methods in order to put employees in the best possible conditions to perform at their best in terms of efficiency and effectiveness, but it will also have very important effects on the structure and composition of personnel. Since it may allow the automation of many tasks, especially "desk-tasks" [84], not only will this have an impact on the skills that will be sought in personnel, but also on how the workflow and the organizational structure of the company itself will be organized. As AI gains importance as an "enabling factor", and results in increased staff productivity, thus reducing the costs of various projects or processes [84], it will force companies to rethink their organizational structure, roles, responsibilities and the skills to be acquired and developed [84]. Of course, all this comes with difficult challenges in terms of availability "on the market" of people with the necessary skills and knowledge, not to mention the issues related to the privacy and ethics.

3.2.2) Methods:

As far as the "methods" theme is concerned, most of the attention was brought to predictive methods, mostly due to the industrial interest in relation to them. And yet, recognition algorithms are in fact extremely useful, especially in responding to a growing need in the business sphere, namely knowing how to deal effectively with unstructured data. An important development in this direction has recently been observed: Siri or ChatGPT are just two of the many examples of artificial intelligence based (at least in part) on recognition algorithms.

Especially in industry and manufacturing, understandably, "predictive methods" attract lots of interests from enterprises. When dealing with predictive methods is meant the ability to anticipate the future behavior of a certain phenomenon by the analysis of data form the past. According to Hair: "*confirmed relationships between explanatory and criterion variables from past occurrences to predict future outcomes*" [84]. There are different types of algorithms and techniques that are able to achieve this result, and nowadays are available solutions whose application can be reasonably fast and cheap, proving their ability to cover a key role in determining a competitive advantage for organizations that are able to exploit their potential. In their research Andrea Sestino and Andrea De Mauro [84], found a major disproportion towards the application of supervised machine learning (clarified in another section of the chapter) techniques if compared to all the other possible alternatives. It also emerged that the most common fields of application include, even if not limited to, sales forecasting, maintenance, sentiment analysis, financial distress and risk evaluation analysis. "Recognition methods" are techniques that aim to identify significant patterns, schemes, correlations or relationships hidden within data. As already mentioned, this field has been more neglected, at least in the past, if compared to predictive methods, yet their potential is not to underestimate.

From literature, it is possible to find successful and interesting applications in some fields, such as customer segmentation, anomalies detection, which can be very important both from a financial point of view, improving the ability to detect frauds or critical situations (so reducing credit issuance) (Ryman-Tub et al., 2018) [84], and from a manufacturing perspective, since it can be applied to automatically detect issues in business processes and allowing a quicker response, improving the reliability of the processes themselves [84].

3.2.3) Applications:

Finally, the last field is, at least for now, the most neglected one among the three: applications. This could be justified by the fact that a real jump forward in this direction has been done only in recent years, and the role and potential of this technology is still to be fully comprehended [84]. Another aspect could be the fact that companies are still lagging behind in terms of the enablers of AI [84]. In fact, in order to successfully apply it to the business, it must be supported by an appropriate organization and process structure, there must be a solid foundation in terms of information management and systems, not to mention specific skills and cultural inclination. To be effective it must play defined and coherent roles within the company's business model. The sectors in which a lot of effort has been put to implement artificial intelligence is the healthcare, medical science, and pharmacy [84]. Meanwhile, the manufacturing sector seems to be more lacking in this respect, but many believe that many of its aspect could gain important benefits. For example, from this perspective, AI may unlock possibilities and opportunities for an evolution of purchasing processes, supply chain management [84], definition of price and relative policies, supporting finance and accounting, optimizing the scheduling process, marketing analysis, service management and many more. Regarding "social applications", researchers believe that AI can bring a huge advantage in understanding consumers' purchasing and social behaviors. Not only that, but there are certain algorithms, such as Artificial Neural Networks or Fuzzy Logic Techniques, that seem to perform quite well in supporting the management in situation and events characterized by uncertainty. Moreover, AI could be able to bring more accurate inference models for consumers' purchasing propensity and for developing personalized offers to maximize the sales (mass-customization concept) [84].

3.2.4) Machine Learning (ML)

The term "Machine Learning", coined by Arthur Samuel in 1959 [88], is often the subject of much confusion, mainly due to its use in the marketing sphere. Furthermore, there is no univocity in the scientific literature on the subject, in fact it is used in some cases as a synonym for artificial intelligence, in other cases as a subset of it, or even the term is used to refer to ANNs or DNNs. In general, the deepest objective of machine learning as research field is to understand how to improve perception, knowledge, thinking, and actions of computer agents, based on experience or data, according to the definition of Professor Christopher Manning. To achieve this result, this discipline combines knowledge and techniques from many different disciplines, not only limited to computer science and statistics, but even also from psychology and neuroscience [78]. It is possible to say that, in a more general conception, the "Machine Learning" field concentrates on the "learning" aspects and mechanisms, which are a fundamental feature and characteristic of Artificial Intelligence. According to Tom M. Mitchell "learning" means: "A program is said to learn from experience E with reference to some class of task T and with performance measurement P, if its performance in task T, as measured by P, improves with experience E" [89]. It is therefore possible to identify different fields of interest of Machine Learning as an approach and research topic, and among the main ones it is possible to find:

- **Concept learning:** originated, as idea, in psychology, it refers to the human ability to learn categories for objects or situations and the ability to recognize, and so to be able to classify, new instances of those when they are presented to the subject.
- **Decision tree learning:** it is a supervised learning approach, used as a predictive and hierarchical model able to derive conclusions from a set of (finite) observations. It is a technique capable of resorting to both regression and classification. (It is treated more in detail in another section of this chapter).
- **Perceptron learning:** which is the logic behind "Artificial Neural Networks" and "Deep Neural Networks" (Already treated in the chapter). The original idea was to develop a "supervised learning" algorithm for binary classifiers, but the concept, as it was originally, proved to be too limited in its application possibilities. However, the underlying logic have been used for Artificial Neural Networks, which essentially are, from an architectural and

logic point of view, a network of "perceptrons", whose great capabilities and potential have now been demonstrated in several practical cases.

- **Bayesian learning:** this term is referred to a computational methodology for "unsupervised learning" based on Bayes' probability theorem of causes, which formalizes analytically the probability that one cause (among many) is associated with, and therefore responsible for, a given event. This is particularly useful when dealing with situations characterized by uncertainty, and it is considered one of the most powerful predictive modeling techniques [90].
- **Supervised, unsupervised and reinforced learning:** (Already mentioned within the chapter).

Regardless of the nature and characteristics of the techniques applied, the ultimate goal of machine learning as a field of research is to be able to model parts of human behavior in order to be able to replicate it by means of software, automating part of the information processing procedures, just as, in the past, automation has more or less partially replaced humans in the logistical-productive sphere in a whole series of operations. The advantage of machine learning lies in the fact that, by automating the analysis of information in a manner akin to human beings in order to extract information, it allows a much larger amount of data to be taken into account more quickly and reliably, instantaneously, as well as to keep track of a larger amount of past data without distortions or forgetting typical of human memory. In fact, if the greater the amount of (exact) data and thus experience available, the greater the likelihood of making correct decisions, then the benefit of this technology appears immediately clear.

3.3) Classification Based On Training Approach: Supervised, Unsupervised and Reinforced

As already mentioned, artificial intelligence is an extremely broad and varied field of study, but in any case, the basic philosophy is the same: it adopts an approach based on identification, which is opposed to the mechanistic and analytic method traditionally adopted in science, mathematics and physics. This is to overcome two disadvantages: the analysis of complex situations is either not feasible in a closed form or requires the introduction of simplifications, and it is computationally expensive. The identification approach consists of having available inputs and (sometimes, not always) outputs, linked by an unknown function: if sufficient data is available, it is possible to identify a relationship that links inputs and outputs, and it can be easily applied [91]. To try to outline this in more detail, an initial subdivision can be made according to the approach adopted, i.e. AI with "supervised", "unsupervised" or "reinforced" learning.

3.3.1) Supervised Learning:

This subset of artificial intelligence techniques requires the use of labelled datasets as input and output, which allow the model to measure its performances, and consequently improve its accuracy over time. These algorithms are mostly used for:

- **Classification:** the algorithm's objective is to learn how to assign the data received as input into a specific category (e.g. decision trees, random forest).
- **Regression:** (or predictive models). In this case, the objective is to identify a function (or a system of them) capable of providing a good approximation/representation of a given phenomenon, which means to provide the behavior of the variable of interest to monitor from input values of one or more observed independent variables.

3.3.2) Unsupervised Learning:

This part regroups all the algorithms and techniques that analyze the unlabeled datasets they receive as input. It is possible to identify three main themes:

- **Clustering:** it is a data mining technique that aims to create groups of records based on similarities or differences identified/founded within the data itself. An example is K-means algorithm, useful for market segmentation (in marketing analysis).

- **Association:** there algorithms rely on a set of rules that are used as a starting point for learning to identify relationships between variables in each dataset.
- **Dimensionality reduction:** the objective is, starting from a given dataset took as input, to obtain an output dataset lower in terms of dimensions or number of features (sometimes can be both). This, for example, proved to be extremely useful in noise removal (from images, videos or sounds).

3.3.3) Reinforced Learning:

Reinforcement learning may appear, at first sight, to be an intermediate situation between supervised and unsupervised learning. It differs from the former in that it does not require a labelled input/output pair, while it differs from the latter in that it receives feedback at each iteration cycle. The process follows the following pattern: the agent performs an action in the environment, which will be influenced by it. This is interpreted positively or negatively, depending on the effect obtained, and the reinforcement (whether positive or negative) is communicated, as feedback, to the agent [92]. The main objective is to maximize the "cumulative reward" by finding the optimal (or near optimal) solution. This approach has been proved to perform particularly well in problems characterized by short-term vs long-term trade-offs. The two most obvious strengths of this approach are the use of samples in performance optimization combined with the use of approximation functions in the interaction with large environments. This allows this technique not to limit itself to sub-optimal actions, but to weigh both short-term and long-term effects in order to optimize the solution globally. A few examples of the techniques based on this approach are multi-agent systems and swarm intelligence [92].

The two approaches are distinguished by several key features. Firstly, the type of data they receive as input is decisive. Supervised systems receive "labelled data" as input, i.e. structured data. These systems tend to be more accurate, as they have both input and output datasets available for learning purposes. This results in the possibility of proceeding with a trial-and-error approach until the model has reached a sufficient level of accuracy, usually proving to be more accurate than their counterpart. In contrast, in unsupervised systems, there is no need for output datasets, and in some cases not even structured input data. Clearly, this means that learning will be less efficient than in the other case, and the resulting accuracy is often lower. It also requires human intervention, of data scientists (or whoever), in order to validate the proposed results by ensuring that they make sense. The second point of divergence lies in the

different objectives at which the two different methodologies are aimed, and consequently, the applications to which it is designated. The second point of divergence lies in the different objectives at which the two different methodologies are aimed, and consequently, the applications to which it is designated. The aspect of complexity is also very relevant: with supervised learning, one is faced with systems that tend to be much simpler to implement than its counterpart, which requires much larger training datasets as well as greater computational capacities. Finally, as far as the flaws that may afflict these two different types of systems are concerned, we have on the one hand models that may be very time-consuming before being able to offer an acceptable result (supervised), while on the other hand (unsupervised) models may be very inaccurate and require much more human intervention to validate their results [93].
At this point, it is clear that artificial intelligence is by no means a single tool, but is, in fact, a very vast and varied field, and it is necessary to understand what tool is the best for the specific the needs.

3.4) Classification Based on Distinctive Features

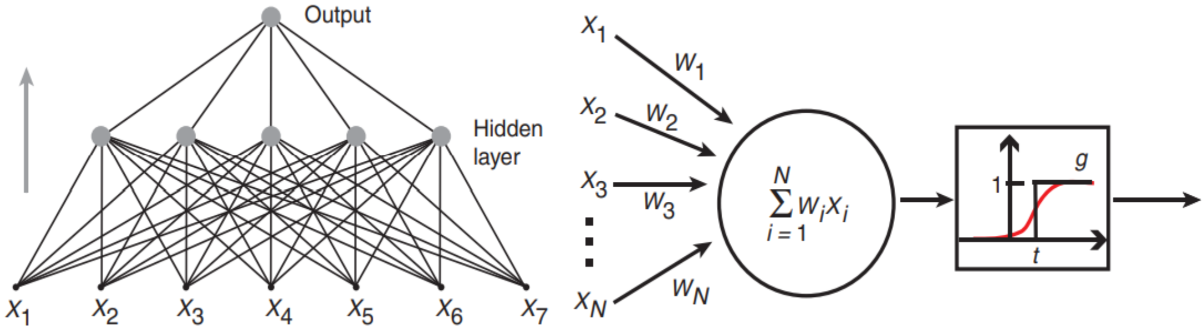
In this section we will look at an alternative classification to the previous one, which focuses on a different aspect, namely the distinctive features. According to Russel and Norvig [94] definition, AI "*is known for its ability to think like humans, act like humans, think rationally, and act rationally*" , and so it is possible to classify the different techniques in sub-fields, according to the aspect on which the most of the focus is put. For each sub-field will be brought a few examples of AI tool that fits with the corresponding distinctive feature.

3.4.1) "Thinking Humanly": Artificial Neural Networks, Decision Trees and Rough Set Theory

Artificial Neural Network (ANN):

The theoretical concept behind the Artificial Neural Network is to replicate the mechanism on which is based the human brain, mimicking the biological neurons interactions. For this reason, these types of systems inherit some of the strengths of biological brains, given precisely by their logic of operation. First and foremost, robustness, in fact, the overall functioning is not impaired by the failure of a few individual nodes. Another important feature is flexibility. It has been proved that these systems can be, with a few specific adjustments, adapted to operate in very different contexts and for very different purposes, from predictions to relationship recognition.

Figure 10: Basic scheme of an ANN



Source: *own elaboration*

The basic elements that characterize an ANN are the nodes and links. The former represent the "neurons", where occurs the elaboration, while the latter represent the "synapsis", so how the connections between the nodes to transfer the signals. Usually, the Artificial Neural Networks are organized in three layers, which are the input layer (which acquires the data from "outside" the system), the hidden layer (responsible for the elaboration), and the output layer (usually consisting in a single node, responsible to determine the final response). When an ANN has more than one hidden layer, usually it is called Deep Neural Network (DNN).

Operation and training: In the operating phase, ANN (and also DNN) receive signals/data as input. Each node computes a "weighted sum": the weighs, each of them assigned to a specific link (i.e. a "synapsis" link) during the training phase, multiply the signals, which are the output of the other nodes. The weight represents the strength of a synapsis and can be positive (excitatory) or negative (inhibitory) [95]. The weighted amount is given as input to an "activation function" which determines the node's output. This mechanism is replicated by each node in each layer until the final output. As already mentioned, the training phase consists in a "trial-and-error" learning phase, in which the system receives data as input with the objective to determine the combination of weights to use in the computation for each node that allows the "best fitting" output. This phase, in case of ANN and DNN, can be performed with supervised, unsupervised and reinforced approach, depending on which is going to be the application field and goal [94]. There are many different methods that can be applied for minimizing the error through the iterations. Three of the most common, or at least noteworthy, will be presented here:

- **Maximum descending gradient:** to reach the optimum this method proceeds with successive steps following the maximum slope of a function. It is possible to apply this method only in context of differentiable functions (or at least sub-differentiable). It is very useful in simpler contexts and in situations such as "cost minimization" or "revenue/margin maximization" [96].
- **Stochastic gradient descending:** it works identically to the previous method, but the gradient is not calculated on the whole training dataset, but on a random sample extracted from it. It is used mostly for DNN, and in general when there are big amounts of data to process that would require too much time in relation to the needs. This consists in a trade-off between accuracy and computational load, to achieve similar results with less time given a certain problem [97].

- **Branch and Bound:** this method calculates the optimum with successive subdivisions of the problem to sub-problems, each of them representing a “branch”, and then, by using a “bounding” function, it eliminates the branches that, according to it, cannot contain the optimal solution. The good choice of bounds is crucial to the efficiency and effectiveness of the system, since if they are too stringent, the risk is to exclude a branch “too soon” and ending up to accepting excessive sub-optimization; if they are not stringent enough, the system lapses into an exhaustive search (or “brute force approach”) [98].
- **Simulated Annealing:** this is a probabilistic, more precisely a metaheuristic, technique that aims to approximate the global optimum point in a very large space of possible solutions, mimicking the mechanism that occurs in the similarly named metallurgical process. Although it is not an exact algorithm for precisely determining the formally optimal solution, it allows a good approximation to be found in virtually every case. It is particularly useful in the case of extremely complex problems, where "exact" algorithms either fail to arrive at a solution or would require excessive time or computational resources not compatible with available time and means. decrease the algorithm selects a random solution close to the current one, measures its "quality," and will decide whether to move to it based on the probability that the choice will lead to a better or worse solution than the current one, a probability that slowly decreases toward zero [99].

One important necessity in deciding the best approach for the problem to treat is the time required for achieving acceptable (or even optimal) results in the lowest possible time span, especially if the goal is the application of ANNs (that perhaps they exploit one of the mechanisms just discussed above) into feed-forward systems [95]. In conclusion, a note must be made. This type of system increases its performance as the complexity, so the number of nodes, the number of links and the number of hidden layers, increases. However, it must be remembered that the demand in terms of computational effort and memory grows just as rapidly, since the number of weights that must be parameterized and then stored grows exponentially as the aforementioned complexity increases. This, moreover, exposes the model to the risk of over-fitting. For example, a simple system with only 10 hidden units, would end with 221 parameters to be determined: 20 weights and one threshold for each hidden node, and 10 weights and one threshold for the output unit [95].

Decision Trees and Random Forest:

Decision trees is a technique that relies on the supervised learning approach that works as a predictive model with a hierarchical structure. It can perform both as a regression or classification model and allow the system to determine a conclusion based on a set of data/observations. Decision trees are called “Regression trees” are when the observed variable is continuous, while “Classification trees” deal with discrete variables. Each tree composed by “leaves”, which are the classes’ labels, and the “branches”, that represent the conjunctions of features that lead to the various classes within the model [100].

Operation and training: Every tree starts from a single point, the so called “root”, and then it splits into the son” leaves, and so on. Each splitting point means a decision, so the application of a criteria to the analyzed element. In data mining the tree can be described as a combination of mathematical and computational criteria that aim to describe and categorize data, through generalization, form a set of data received as input. During operation, the system receives data as input and, starting from the root, conditions are applied successively following the branches until the input is assigned to one of the “leaves” of the tree. The tree structure and the conditions of the branches, are determined in the training phase. The algorithms to construct decision trees work with “top-down” logic, and decide, for each subdivision, which variable is “best” able to discriminate the data it receives as input. To determine the concrete meaning of the “best” variable, there are different metrics that it is possible to adopt [101]. Five relevant examples are given here, but it is worth noting that these are not the only possibilities:

- **Estimate of positive correctness:** this metric resorts to the use of Confusion Matrix and hit-rate calculation. The "goodness" of the discriminating ability of the variable is measured by the ratio of records correctly classified by the algorithm to the total headcount belonging to that class (or "leaf"). The higher the ratio, the better the discriminant variable [102].
- **Gini impurity:** also known as “Gini-Simpson Index” or “Gini diversity index” and used by CART algorithm (“Classification-And-Regression-Tree). This index measures how often an element, randomly selected from a certain set, would be miscategorized if it was labelled randomly and independently according to the set labels’ distribution. From a theoretical point of view, it could be said that this index is nothing more than an adaptation to the decision tree method of the concept of entropy [103].

- **Information gain:** the decision of the most consistent variable for input discrimination is chosen based on the maximum mutual information gain which "represents the expected amount of information that would be needed to specify whether a new instance should be classified yes or no, given that the example reached that node" [104]. The method proceeds to determine whether split can bring the bigger amount of information, and that is taken as first, and then it continues with the same logic, until the information gain reaches zero (or, alternatively, a certain limit chosen according to convenience criteria).
- **Variance reduction:** this concept is particularly useful and used when dealing with continuous target variables, and so in the case of "regression trees". This method choose the variable that can allow the bigger total variance reduction after the splitting that would occur by using it as a discriminator (subtracting to the variance amount before splitting the variance amount calculated afterwards) [105].
- **Measure of "Goodness":** the variable choice aims to optimize the candidate's balance in relation to their ability to create, at the same time, "pure" and "equally sized" (in other words, proportioned) children. This technique can lead to a bigger number of splits if compared to other methods, but, in exchange, it can lead to the creation of a more balanced tree, which can lead to more consistent decisions [106].

Decision trees, like all technologies underlying artificial intelligence, are not perfect and can be affected by problems. In addition to carrying with them all the merits and flaws of supervised learning algorithms (since they are part of them), they have a predisposition to bias and over-fitting errors [107].

Random Forest:

In an attempt to guard against these critical issues and to improve the accuracy and reliability of this technology, Leo Breiman and Adele Cutler developed the "random forest" algorithm, which uses decision trees as its basic building block but, instead of using a single one, the algorithm plans to construct many (hence the name "forest") that can interact with each other [107]. The two underlying mechanisms are the concept of "bagging algorithm", which means that the records to create the random samples (samples with replacement, or bootstrap samples) of data from the dataset that are extracted for training, can be chosen more than once, and feature randomness, which are fused together into the "random subspace method": its objective is to generate a subset of random features with low correlation among the trees. The difference between "Random forests" and "Decision trees" is that the latter considers every possible alternative, while the former considers only a subset of them. There are three parameters that have to be chosen before the training phase, which are the "node size", "number of trees" and "number of features sampled". The values of these parameters can have big influence on the results, and so on the final accuracy and reliability of the entire model itself, so they have to be chosen wisely and taking into account the specific needs of the application context.

The "Random forest" method can bring important benefits. First, it reduces the risks of overfitting in comparison to a single decision tree solution, due to the more robust logical architecture of the random forest and a training technique that is less focused to be precise on the training sample. Then it provides more flexibility, since it can maintain the accuracy even when a portion of the data to be analyzed is missing, while keeping the capability of decision trees to deal with both regression and classification contexts. Lastly it makes easy to determine and evaluate the features' importance and contribution to the model, and this is fundamental for the comprehension of the phenomenon of interest. However, it is not a perfect method, as it tends to be costly both in terms of time and resources used. Moreover, understanding a decision is easier and more transparent to the user in the case of individual trees than in the case of the forest [107].

Rough Set Theory (RST):

To fully understand the significance of RST, one must consider both its logical/philosophical and practical aspects. From a logical/philosophical point of view, Rough Set Theory concentrates on the concept of "vagueness". In fact, one among the most relevant differences remained between humans and machines it is the ability of the first ones to deal and comprehend vague situations and concepts. One of the pioneers of the modern logic, Gottlob Frege, developed the "boundary-line approach to vagueness", whose basic idea is that a vague concept is not defined sharply, but is characterized by a "boundary region" composed by a set of elements that cannot be classified by remaining "inside" the actual concept itself, nor "outside".

Other ideas at the base of RST are:

- **Reasoning Methods (from George Boole):** also known as "Boolean algebra". It can be considered a formalization of the classical logic, and it is the fundamental concept for software programming. However, Boolean logic has some limitations, and, for this reason, the rough set theory can be considered as an extension of the basic Boolean logic to being able to deal and solve problems characterized by "uncertainty".
- **Indiscernibility (from Gottfried Leibniz):** the "Identity of the "indiscernibles", sometimes known as "Leibnitz's Law", is considered as one of the three basic metaphysical principles among with the "non-contradiction" and "sufficient reason" principles. It states that "there cannot be separate objects or entities that have all their properties in common. That is, entities x and y are identical if every predicate possessed by x is also possessed by y and vice versa".
- **Multivalued logics (from Jan Lukasiewicz):** This is a field of philosophy, logic and mathematics that goes beyond the concept of classical bivalent logic (originating with Aristotle and identifiable, in its most modern form, in Boolean logic). Which means that the field is no more limited to two possible outcomes ("true" or "false"), but there can be a set of multiple values that variables can assume.
- **Inductive reasoning (from Thomas Bayes):** consist in the application of the probability theory to inductive (principle of finding a universal law by generalizing the results of a finite number of observations) and abductive ("inference to the best explanation") reasoning. This approach considers probability as expression intrinsic uncertainty at the base of the world, and considers that inductive reasoning, when performed correctly and accordingly to certain rules and boundaries that depend on the context of application, is a generalization of deductive reasoning (examples of the latter are mathematics and classical logic). In this generalization, truth and falsity concepts of logic are associated to, respectively, the extreme probabilities "1" (100%) and "0" (0%). Among the various advantages proposed by this interpretation, the one worthy of emphasis here (for the sake of brevity) is the fact that it allows for several rational levels (a fundamental element in order to be able to convey a concept to an AI) of confidence in relation to a wide set of propositions, even to the ones that are uncertain/unknown, though settled.

This makes the logic derived from Rough Set Theory capable of emulating the ability to recognize and classify objects, typical of human beings, and thus enables the development of decision rules for AI applications in the areas of classification and recognition. Possible fields of application in Supply Chain Management and logistics can be, for example, monitoring and "critical event management" within a the supply chain, or "suppliers' selection" applying a multi-criteria evaluation [94]. It can also play an important role, thanks to its new mathematical approach, into improving DSSs (Decision Support Systems) and data mining processes [108].

3.4.2) "Acting Humanly": Expert Systems and Genetic Algorithms

Expert Systems:

In the Artificial Intelligence field, an "Expert system" is a computer system that aim to reproduce the decision making abilities of human beings experts, making it able to solve complex problems based on acquired knowledge, rather than through conventional procedural code. A few examples of this kind of technology has been successfully applied to medical diagnosis support. It is evident that, here, appear the three aspects of artificial intelligence: the "learning" aspect (the system is able to use the data progressively collected to improve its accuracy), the "recognition" (the system is able to detect and recognize patterns, relationships and similarities and to distinguish them within specific, more general categories from particular cues) and the "decision", which is the higher possible level for artificial intelligence: this requires the ability to identify relationships and patterns not only within the data but also from the information that if derived (knowledge), as well as to be able to analyze the effects on the analyzed events of possible actions taken and to be able to evaluate them in relation to each other in perspective to an established main goal, and to be able to determine in view of the latter the optimal solution to be implemented. There are 4 main elements that contribute to the overall "expert system". The first one is the "inference engine" (that can be considered, by analogy, as "the brain"), which is a cluster of programs and algorithms responsible for the application of the set of rules over the known facts to deduce new ones and get to the result (in some cases, especially in the more modern projects, it can include even the explanation and debugging abilities), while the second element is the "knowledge base", which includes the facts, the rules to apply for analyzing, recognizing and performing decisions, and the datasets to which the rules are applied and that allow the system's learning process to take place. Another important element is the "scheduler/justifier", which plays the role of explaining how the "expert system" arrived to a certain result (justifier) while controlling and coordinating the sequencing and the application of the rules (scheduler). Finally there is the "user interface", since these systems are meant to support the decision-making process of a human being [94] since, by now, for responsibility reasons, every decision has to be validated by a human operator, so an interface with the user is needed to guarantee the interaction and the possibility, for the user, to apprehend the system's result and to analyze the motivations that led it to the proposed solution. "Expert systems" can differ in terms of algorithms and rules that are applied within the "inference engine". For example, it can use Artificial Neural Networks, Deep Neural Networks, Genetic Algorithms, decision trees, or a combination of several techniques, either among those just mentioned or others. In terms of practical applications, this technique proved to per particularly effective in many fields, from the medical support to Supply Chain Management and Logistics, and regarding the latter topic it's possible to cite a few honorable examples [94]:

- **Inventory control:** Allen (1986) proposed an application for the US Air Force Logistics Center, that has been successful in improving the accuracy of the inventory management [109].
- **Logistics scheduling, monitoring and control:** a real time-transaction based expert system for IBM semiconductor's facility could improve the overall output of 35% (approximately $10 million of capital expenditure's savings), by Sullivan and Fordyce (1990) [110].
- **Traffic control, (airline) yield management, spatial mapping vehicle repair and maintenance scheduling:** as proved by the studies of Findler (1987) [111] and Jefferies and Yeap (2008) [112].
- **Demand forecasting:** DeLurgio (1998) studied the improvements brought by expert systems in relation to accuracy, computational speed, user understanding and cost effectiveness to the demand forecasting processes [113].
- **Product design and planning:** as shown in the work of Zha et al. (1999) [114].
- **Gas pipeline operations:** (Uraikul et al. 2000) in which an expert system could minimize the inefficiencies of the dispatcher (who operates and runs the pipeline system), by supporting operative decisions and scheduling the activities [115].

- **Supplier evaluation:** the supplier evaluation is a complex problem and, especially in this day and age and with current supply chain management and partnership policies, one whose consequences are difficult to reverse in the short term. Decisions in this area are, therefore, critical, and the support of expert systems can certainly lead to improvements in business performance, as shown by Kwong et al. (2002) [116].
- **Evaluation of 3PL (third-party logistics) providers:** it can be considered a sub-problem related to the previous field indicated in this list. An example of application to this specific situation is the research of Yan et al (2003) [117].
- **Formulation of a logistics strategy:** Chow et al. (2005) successfully applied and expert system, or as they called it "knowledge-based logistics strategy system (KLSS), to logistics development strategy at Eastern Worldwide Company (EWW), achieving an improvement in terms of resource utilization and work efficiency, by supporting the selection and the timing of the actions to take for developing the company's logistics system [118].
- **Production planning and control:** Lawrynowicz's paper (2007) proposed a new approach for production planning and control, with the support of an expert system powered by a second phase genetic algorithm, helping to improve short-term decision making. The system was even able to consider alternative process plans for obtaining each workpiece and even facing "make or by" decisions (i.e. evaluate the convenience between producing or outsourcing a product's production). In the research has been also proved that, in the scheduling performances, genetic algorithms can lead to a better yield than "dispatching rules" based methods [119].

Based on the evidence, it is reasonable to expect that expert systems will replace the older generation of DSS, as they are not only able to provide useful information for making data-driven decisions but may be able to suggest solutions and guide choice by making the reasons for proposals known. This aspect is also extremely important in terms of the resilience of business know-how, which would no longer depend solely on the human expert, whose absence (for whatever reason) would no longer be an impediment to the smooth operation of the processes he or she oversees.

Genetic Algorithms (GA):

As the name suggests, “Genetic algorithms” replicate the evolutionary mechanisms of living species in order to identify, at least in theory, an optimal solution following successive attempts in which the solutions evolve until a single one, or possibly a set of them, presenting the best possible "fitness" according to the context of application is determined. it should be emphasized that, the way the procedure is structured at the theoretical level, the starting base for the algorithm, the population, cannot be infinite, so, from a logical-mathematical point of view, it cannot be said with 100% confidence that the best result obtained from the application of this type of techniques is the theoretically sought-after condition of global optimum. Nevertheless, the solutions proposed are a quite satisfactory response to the optimization problems. Generally speaking, with GA is meant a field of artificial intelligence that aims to solve optimization problems, based on stochastic techniques that mimic the concept at the base of the Darwinian evolution idea. Genetic algorithms can usually be divided in 5 basic components [94]:

- **Individual representations:** it has to be set the individual representation of every member of the population, in other words the “chromosomes”, that will allow evolution and selection to take place and to determine the identity and the characteristics of the final solution (or solutions).
- **Initial population:** it is a group of randomly selected individuals, which represent the initial set of possible solutions. As already mentioned, the number cannot be infinite, but it must be finite.
- **Operators:** decisions have to be made about which operators will be able to go to work on individuals in the population. Usually, the ones that are never missing are “reproduction” (the “most fit” individuals are copied through the selection process), “crossover” (in which two individuals’ chromosomes are combined to form 2 new similar individuals) and “mutation” (a random alteration in one individual's features).
- **Selection:** to determine the fitness of the possible solution, it has to be determined a set of criteria on which the selection is based. The rules determine, by successive confrontations and cycles the fittest solutions, and the algorithm proceeds until a termination condition is reached.

- **Parameters:** the parameters determine the algorithm functioning. People has to settle and assign values to the various aspects, for example the number of bits per dimension in the individual (a measure of the individuals genetic legacy's dimensions), the population size, crossover, reproduction and mutation probability rates, and many more (depending on how much the specific algorithm is complex).

As already mentioned, Genetic Algorithms proved to show good performances in optimization problem in many different real life situations, even in industrial, and in particular in "Supply Chain Management & Logistics" field, such as (but not limited to) the optimization of vehicle routing and scheduling, "delivery and pick-up", pallet or container loading/unloading, inventory control and location-allocation problems. Nevertheless, these types of algorithms are not only suitable for solving day-to-day optimization problems, but turned out to be helpful even in supporting even more "long term/strategic" decisions, for example facility layout design and optimization, facilities distribution and localization decisions and supplier selection problems [94].

3.4.3) "Thinking Rationally": Fuzzy Logic

Fuzzy Logic:

Fuzzy logic is a multipurpose logic model that surpasses and extends basic Boolean logic by allowing a proposition to take on "truth" values other than just 0 and 1. It is a model, in some respects, similar to "rough set theory", since both aim to build a foundation that allows formal systems such as AIs to handle the concept of vagueness. However, the two models differ in that in RST the indiscernibility between objects is considered through, typically, equivalence relations, whereas in fuzzy logic this concept is not used. In fact, in the latter, the Aristotelian concepts of "non-contradiction" and the "excluded-third", foundations of classical logic, decay, but it bases the classification of predicates with a probability (of truth) that varies continuously between 0 and 1 and, in practice, the value is determined based on "expert opinions". This allows some paradoxes of classical logic (such as the liar paradox) to be overcome and resolved. It possible to consider the rough set theory and the fuzzy logic as distinct, but related and complementary, since each of them deals with the "uncertainty" concept but differ in the way they treat it. From a logical point of view, neural networks are based on this very concept. In fact, they receive as input a set of data, which will be evaluated. Then the data will be evaluated and weights will be assigned. Finally, a decision is reached, typically characterized by a value

[120]. Furthermore, by applying these principles, it is possible to go on to determine “fuzzy relationships” based on which it is possible to go on to structure datasets and, subsequently, relational databases. Query techniques have also been developed that adopt precisely fuzzy logic. This approach has been particularly successful, particularly in industrial settings with a "Supply Chain Management" perspective, in applications where it is necessary to use stepwise variation for mathematical expressions formalizing state changes in the phenomenon of interest, and in cases where performance must be monitored with subjective, or otherwise non-rigid, performance criteria. A few examples that are worth to cite here are location problems (these kinds of decisions rarely rely only on minimum distance or minimum cost, but many other factors that are difficult to quantify objectively count, such as proximity to important partners), the traveling salesman problem, (once again) suppliers evaluation or selection and forecasting and measurement of the “Forrester effect” [94].

Support Vector Machines:

This is a supervised learning model able to perform in classification and regression contexts of analysis.

Operation and training: The training algorithm of this type of model is based on the vector concept: it maps the records used as training in a multi-dimensional space. After that, by applying a set of established criteria, we go on to train the function, so that it can best determine the membership of records in the various classes. Then, in operation, it will go on to determine the membership of the input records based on the spatial placement of the records [121]. Among these systems, operating with this underlying logic, it is possible to identify systems of varying degrees of complexity, ranging from linear systems to systems based on nonlinear and “soft edge” logic (i.e., admitting a separation zone instead of a sharp line).

Applications of SVM proved to be suitable to solve various real-world problems. For instance in the fields of hypertext categorization and shallow semantic recognition [122], or in the area of image classification and segmentation, proving, even after few rounds of relevance feedbacks (sometimes just 4-6), a higher accuracy in comparison to more traditional methods [123]. This included even technical situations such as satellite data classification or even handwriting recognition [124]. Finally, important successes have also been noted in the fields of chemistry and biology, particularly in the recognition and classification of proteins and other complex chemicals and even in the medical field [125]. Recently these techniques are also being applied in industrial and supply chain management contexts.

3.4.4) "Acting Rationally": Agent-Based Systems

Agent-Based Systems:

The "Agent-Based Systems" or "Multi-Agent Systems" (MAS), are computerized systems that are composed of multiple different intelligent elements, called "agents", that interact with each other and sometimes compete, sometimes cooperate to solve a problem [126]. This structure allows them to be able to successfully solve much more complex problems than individual agent (also called "monolithic") systems. With the term "intelligent", referred to the "agents", is referred to their ability to learn (supervised, unsupervised and reinforced learning) and to the methodic, functional, procedural and algorithmic approaches applied. It is important to clarify that there is a difference, despite a strong relationship and partial overlap, between "Agent-Based Model" (ABM) and "Multi-Agent Systems" (MAS). The difference is that ABM focuses on the modeling aspect, of explaining its structure and determining the nature of the relationships it establishes between different agents, not necessarily intelligent ones. On the other hand, MAS is focused precisely on constituting a technology based precisely on the interaction of intelligent agents. Thus, we can consider the latter as a subset oriented to the technical-application domain of the former concept.

The best fitting description of the modeling process at the base of MAS is "inductive": starting from the assumptions that are considered the most relevant for a certain situation, the main problem is divided into sub-problems, and each agent solves sub-problems by resorting to techniques, methodologies, and knowledge they have at their disposal. The solution emerges from the agents' interactions with each other, sometimes cooperating, sometimes competing, and it can be identified, depending on the specific context, as an equilibrium point or a pattern. The strength points of these systems are their ability to exploit different methodologies and the amount of domain knowledge, the possibility to actuate abstractions and overcoming eventual error in the inputs, learn from the decision environment, and, finally, the capability of operating real time and to sustain communications in natural language (Newell 1989). Their capabilities proved their proficiency even for shop-floor management support, especially, but not limited to, in the field of scheduling/traffic control, in supporting activities such as procurement or customer relationship management, bidding evaluations, Supply chains and operations performances assessment [94].

A derivative, if one can call it that, of multi-agent systems is a methodology based on meta-heuristic algorithms called “Ant Colony Optimization”, which is worth mentioning since it has been shown to result in extremely satisfactory results close to optimal conditions in incredibly short times. The basic idea is to mimic the social behavior of ants, which, within their colonies, identify the shortest paths to what they need by following appropriate pheromone trails (which represents the “collective memory” of the entire colony itself). Their success is due to their aptitude for information exchange, which enables them to solve even very complex combinatorial problems quickly and efficiently. Thus, one goes about imitating the behavior of the ants, making the different agents in the system act accordingly through a positive feedback mechanism. This type of methodology is extremely effective and efficient in solving routing, sequential ordering and process plan selection related problems, whether in a broader context as in the Supply Chain framework perspective [94], or with a narrower horizon as within a function, department, cell, or even a single workstation.

3.5) AI in Supply Chain Management and Logistics

Having gone into more detail on AI in the previous sections, it is now important to go on to understand the effects and implications in the more practical field that this technology can bring, namely in a supply chain management and logistics context. This section will briefly look at the contribution and importance that the application of artificial intelligence can bring to various business functions at the process level, particularly focusing on aspects relevant to activities related to Supply Chain Management and logistics. The aim is not to be exhaustive, but to put the focus on some very concrete aspects, and briefly citing at least one real case study of concrete application for each topic, demonstrating the actual improving impact of these technologies in the application field.

3.5.1) Procurement

In SCM, procurement and purchasing activities are extremely important. In fact, they are not only responsible for minimizing resource acquisition costs, but for minimizing the total cost of ownership, ensuring continuity of supply, securing the quality of incoming raw materials, and, more recently, also for managing "procurement marketing," that is, applying the same reserved logics in selecting, managing and developing customer relationships so as to maximize the value stream in the case of suppliers as well. The concept is intuitive: if it is well true that the "garbage-in garbage-out" rule applies, it is reasonable to assume that by improving the quality of inputs, it is possible to improve (provided one has sufficient value-enhancing capabilities) the quality of outputs as well.

Supplier Evaluation:

The first publications regarding the application of techniques for supplier evaluation date back to the 1960s. The evolution has never stopped over time, and with the advent of AI, experimentation has taken place in this area as well [127].

Fuzzy ART for supplier selection [127]:

In this paper, a method based on an ART (Adaptive Resonance Theory) system, similar to a neural network but without a hidden layer, is used. Fuzzy logic was applied to this, developing an unsupervised learning algorithm capable of working not only with binary but also continuous variables. In the case discussed, other methods were also considered as a yardstick, such as total cost-based methods, statistical methods or mathematical programming methods. The results show that the "fuzzy ART" system is able to perform better, i.e., lead to more advantageous decisions, because it is able to handle situations of uncertainty better than statistical-mathematical methods, both, at the same time, because it is more consistent and "rational" in the evaluation of possible trade-offs than traditional methods that are more dependent on human judgment. The interesting aspect of this method is precisely that it can fill many of the gaps in traditional methods. Noteworthy in this regard is its ability to cluster suppliers by degree of similarity among them. In fact, it overcomes the limitation given by traditional aggregate score rankings, which could end up considering suppliers with even very different behaviors and performance as similar, not replicating this error. Finally, the proposed algorithm proves to be flexible and easily adaptable in different contexts (suppliers for different sectors/companies) while maintaining its ability to foster correct decisions about suppliers.

3.5.2) Production

"Production", in the extended sense, can be regarded as the business function involved in carrying out the activities that transform inputs into the outputs aimed at satisfying customer demand. Therefore, in this section, we consider this term to refer to the set of core activities, those that determine the main purpose of an organization. For this reason, it is more than reasonable to assume that these activities are particularly felt at the enterprise level. Having a state-of-the-art production function is critical to securing the highest possible quality of output, thus competitive advantage, and maximizing efficiency, thus profitability. The three main typical activities of this function are planning and control of output production activities, quality control and ensuring safety. Therefore, technology can impact this function along three main directives: on how the activities are performed (process support), how they are organized (management and planning support) and for risk evaluation and assessment.

Risk Assessment and Evaluation:

Mitigation of drilling risks [128]:

The aim in this study is to find a method that can assess the riskiness in the field of hydrocarbon and gas extraction in cold environments, such as areas near the Arctic Circle. In this area, temperature and pressure conditions may lead the drilling operations to cause destabilizations that could result in large gas releases, which could put operators, structures, and machinery at risk (in order of priority). For this reason, is required a "Process Knowledge Management System" able to perform reliable evaluations and assessments in an environment characterized by high uncertainty. This is accomplished through a dual system based on fuzzy logic. One part deals with providing an answer about the drilling parameters that should be adopted in a certain specific scenario, while the other part enables dynamic simulations of the borehole construction. The benefits that such a system can bring are an increased capacity for risk reduction, coupled with reduced costs resulting from better data-driven decisions (a concrete example may be that delays or suspensions of work can be contained by avoiding plant shutdowns caused by safety issues, or by avoiding damage).

Process Quality Improvement:

AI in radiology workflow [129]:

In the paper published by Dikici et al. (2020), they showed how a system based on a DNN (deep neural network) improved the radiological process of diagnosing brain tumors and metastases. The accuracy of diagnoses improved along with the ability to detect problems earlier, which can make a huge difference in this context. The study deals not so much with the tool itself but proposes a real work frame that considers all aspects (from research, to algorithm training, to data management, and in general all the activities required not only for the diagnosis process per se, but also involving all the necessary support activities). However, although an objective improvement has been demonstrated with the application of this model, it is only feasible if one has a sufficient amount of data, sufficiently modern machinery and, in general, an adequate technological, organizational and information substructure to properly support the operation of such a model.

3.5.3) Maintenance

Predictive Maintenance:

Artificial intelligence applications in maintenance are not a recent novelty; in fact, there has always been a lot of interest in this area, as being able to reliably predict failures becomes essential to implement optimization of maintenance processes, minimizing interventions and only going to implement them when necessary, avoiding unplanned downtime. The obvious result of this is minimized costs and increased productivity. The success of these predictive techniques in maintenance has already been demonstrated, however, many, if not almost all, of the most used systems tended to work as black boxes, i.e., not providing explanations. And that, precisely, is the next step, to develop systems that are not only productive, but are able to provide as much detailed and accurate information about them as possible.

Explainable artificial intelligence application to an industrial tool machine [130]:

In the case study, a concise yet realistic application of predictive artificial intelligence algorithms is presented in the context of machine tool machining that can explain details of impending failures to operators. Two different approaches, one based on a decision tree and the other using an SVM, are compared in the paper. The ability to be able to explain the possible causes of an impending failure have the advantage of allowing for understanding, and possibly verifying, the soundness of the prediction, improving the effectiveness of decision making and ensuring greater rationality. Going to look at the reported results, one realizes that each of the two methods has strengths and limitations. In the case of the decision tree method, it can give more detailed and higher quality information, however, there are a not inconsiderable number of cases in which it is unable to provide any explanation. Conversely, in the case of the SVM, it is indeed true that the quality of the explanations provided is less high, but it is far more consistent in being able to answer about the causes of the expected failure.

3.5.4) Warehousing and Inventory Management

For manufacturing and production companies, inventories and their management pose a major challenge to their competitiveness and profitability. Inventories, which are made up of raw materials, semi-finished and finished products, are undesirable, as they constitute fixed capital (and therefore not usable), exposed to risk (obsolescence, damage, depreciation and, in the case of semi-finished and finished products, that it is not sold) and generating costs in terms of management (warehouse space, handling, opportunity costs, and so on). And yet their presence is indispensable, especially in uncertain contexts, as it is essential to be able to respond quickly to demand, when operating in markets where it is uncertain, and ensure operations by avoiding production stoppages, in case of problems in supply. And yet their presence is indispensable, especially in uncertain contexts, as it is essential to be able to respond quickly to demand, when operating in markets where it is uncertain, and ensure operations by avoiding production stoppages, in case of problems in supply. Depending on the case, it is possible that the amount of these items can average from 15% up to 35% of the asset value under consideration, as shown by the study of Timme and Williams [94]. In many cases this is necessary in order to ensure that high levels of service are maintained with customers, especially if the company works with a global network, has to deal with particularly fluctuating and unpredictable demand, deals with high added-value or “expirable” goods, for example fashion and tech products or, in general, services, for which is imperative to not lose any potential customer), or a combination of these conditions together. Traditional methods and solutions (such as the "economic order quantity", for example) are not only insufficient, but not suitable to the actual competitive situation of the market, especially for companies dealing with a B2C market, especially because many of them are NP-hard problems, which means that are impossible to solve in a polynomial time (at least with the actual knowledge of the mathematical field) [131]. For these reasons AI and the possible solution that could derive from their application captured the attention of the researchers.

Inventory management Assistant [109]:

Cases of practical applications capable of bringing concrete benefits in this kind of context date back to 1986, when Allen developed an expert system called IMA (Inventory Management Assistant) for the "U.S. Airforce Logistics Command", which was able to improve effectiveness in inventory management by about 8-18 percent, depending on the case, while drastically reducing errors.

DRL for healthcare IM optimization [132]:

In the study conducted by Zwaida et. al. (2021), a "Deep Reinforced Learning" method has been applied to a case of inventory management in the healthcare sector. The main objective was to optimize the management of drug stockpiles, since avoiding a shortage is critical for the sake of patients in a complex and unpredictable hospital setting. This problem is real and all too common, so vital and to be taken very seriously that it has attracted the attention of major bodies such as the FDA (Food and Drug Administration), which has introduced the necessity to counter this issue in the "Innovation Act and Strategic Plan", and the WHO (World Health Organization), which has officially recognized resolution of this situation as a priority. Therefore, a supply chain and inventory management optimization is a fundamental achievement to reach in the near future. The solution proposed in this study has the double aim to provide optimization for the storage capacity and replenishment policy and conditions, while minimizing the overall costs in the same time. To achieve this, it was developed a proper objective function for cost minimization and it was developed a "Deep Reinforced Learning" method (i.e. a DNN with a reinforced learning approach) that was able to determine, depending on the situation to find the optimal solution in terms of coverage that allowed the cost minimization (determined by the objective function). After the training and the application this method proved to be more cost effective (the second best method showed an increment of costs of 11,8%) with a significant reduction of shortages and stock-outs if compared to other methods.

3.5.5) Research & Development

Research and development is the fundamental driver for a sustainable long-term competitivity of any company. Technological and market needs evolution force manufacturers and service providers to continuously re-invent themselves and their offer. The interest, even from an economical point of view is proved by a study conducted by UNESCO (June 2018) showed approximately 1.7 trillion US dollars' worth of investment in research and development among all the organizations around the world, in an increasing trend over time. The traditional R&D process is long and complex, characterized by low success rates (not all projects are successful, but still required resources), long time-to-market and long and repeated cycles of iterations, and considerable criticality and complexity of management. For this reason, over the years many techniques have been developed to improve R&D activities (such as methods based on "Technology roadmap & Product portfolio Plan", "Stage-gate" methods, "Agile/Scrum", "Lean startup", "Design thinking" and many more), and recently even AI-driven methods have been experimented in this field, bringing some important benefits. First, AI can help the company better understand customer needs through application in market, needs and competitive analysis contexts. This improves the acquisition of information by enabling better targeting of efforts [133]. In addition, it is also possible to refine and expand the ability to identify, and possibly exploit, relevant market trends, which can be very important, especially if one is able to intercept them in the early stages, or even predict them (Deep learning and DNN algorithms have been shown to perform very well for this purpose). Next, AI can help improve efficiency in development by optimizing and speeding up the design, material/feature/process selection and testing and simulation phases (the latter can also be very expensive, so being able to achieve savings at this stage can greatly increase profitability), all while making sure that the process is rational and data-driven. In addition, the use of AI has been shown to provide higher levels of security, both during testing and launch. Finally, it can also bring an ameliorative contribution in terms of improving the knowledge produced and facilitating its communication between various actors and also to customers [134].

AI-Based autonomous technology scouting [135]:

This project involved developing and testing the effectiveness and feasibility of a tool that can do automatic scouting of new technologies, which is one of the typical activities of the R&D function. The idea is to facilitate the identification of new technologies and the comparison between them, supporting decisions. The system is structured on three levels. The first deals with "data gathering" and uses API queries combined with a system very similar to a crawler used in web browsers. The collected data is first collected in a database to be later analyzed by NPL. The processed information is stored on a database in high-dimensional vector form, while the original source data collected is, after a certain time limit, deleted to make room for the new ones. The methodology works by deriving generic elements that are progressively assembled into a reference model, that allows the automated scouting process. Finally, there is the user interface, where, just as in a browser, one can go and search for keywords and the system will respond with the results it considers most relevant in this regard. In the system, it is possible to go and create multiple "user-stories", or person archetypes, so that based on the role of the user interfacing with the system itself, it can go and present results accordingly, since a user's role and purpose go to influence the concept of what is relevant. This allows the value-in-use of the system to be maximized. In addition, this system can be the starting point to which additional modules can be connected, such as, for example, a system, perhaps also based on artificial intelligence algorithms, that can support the selection process itself (as already seen in the previous section, regarding suppliers' selection and evaluation process).

3.5.6) Human resources

The HR function can also benefit in various ways from the contribution that digital support offered by AI. First and foremost, consider recruitment: in the selection phase, especially in cases where there are many applications or in cases of urgency, one could, ideally, achieve faster screening of participants and a more rational and objective first assessment. This would greatly ease the paperwork in terms of time and resources, and avoid having to outsource to third parties for selection, thus ensuring higher quality. Other benefits can also occur in terms of managing existing resources, monitoring the situation, morale and conditions, as well as analyzing the situation with a view to the future, taking action in good time so that human resources, both in terms of quality (skills for example) and quantity, are sufficient for the company's future smooth operation enabling it to effectively achieve its goals. This would make it possible to plan in time for recruitment, replacement and possible upgrading and training of staff [136] [137]. In fact, IBM has experimented with the application of AI techniques in its selection of candidates, observing an increase in hiring in both quantitative (more hires for the same amount of time spent) and qualitative terms (greater fitness between required skills and skills possessed by hires), leading to an overall savings that IBM claims reached $107 million in 2017 alone [137].

3.5.7) Finance

Finance Risk Assessment:

A company's profitability does not derive solely from its production capabilities, and the financial component is no less important an aspect than other functions such as "Marketing", "Purchasing" or "Sales", since it is responsible for finding the financial resources with which to fuel operations. Over the last two decades or so, a change in the condition of financial markets has been observed: crises, or at any rate situations of uncertainty and risk, are much more frequent and likely, in an environment where volatility has reached very high levels. Therefore, successful companies, if unable to manage their financial resources properly, can find themselves in serious difficulty even if perfectly healthy from an economic-productive point of view. However, risk, in the financial sphere, is something that cannot be eliminated and inherent, but can certainly be minimized. To this end, there has been much experimentation, including in the AI sphere, trying to develop algorithms that are able to improve the assessment of risks to be able to minimize them, or, at the very least, be able to develop a relatively solid base from which to develop assessments of them.

Business failure prediction model extended to textual website content [138]:

In this case study, the aim was to test whether it was possible to improve the effectiveness of a risk assessment process, i.e. to assess a company's exposure to financial and insolvency risk, by analyzing data, especially textual data, from the respective sites. The process was based on applying an NLP model to extract and pre-process the data. The study tested 3 different methods: logistic regression (LR), XGBoost (XGB, which is possible to affirm that is a "random forest" type of ML algorithm) and a Multi-layered perceptron (MLP, a technique that can be classified as DNN method). The examined study reported two important conclusions: Firstly, it was able to show that the implementation of methods that also consider unstructured data, such as information from websites and other documentation produced and published by the companies themselves, improves predictive ability in the context of risk assessment. It also showed that (subject to the use of an effective and efficient technique in the area of data extraction and pre-processing) the use of MLP was far more accurate in forecasting. Therefore, this recent work helps to validate the effectiveness of AI techniques in improving forecasts even in complex and uncertain contexts. It also demonstrates the ability of these techniques to operate with a share of objective success even when working with unstructured data.

3.5.8) Marketing

Customer Relationship Management:

Change in various markets and marketing (in terms of principles, approaches, and techniques) are intertwined. The complexification of buying behavior, stratification of consumers and great competitiveness make marketing operations complex, therefore expensive. But the cost aspect is not the only relevant one; it is also and above all the fact of intercepting smaller but selected niches to maximize the effectiveness of the actions taken in terms of response and result. This is in the B2C sphere, while in B2B there are important trends or oriented to very strong collaborations and partnerships, in the case of aspects considered strategic, or flexible relationships, seeking comprehensive solutions to business problems or needs ("Servitization"). For example, one of the major changes in the business-to-consumer market is the use of the smartphone and mobile access to various apps and sites (opening up great possibilities for customizing ads and offers). In this situation the CRM paradigm is fundamental for achieving and maintaining a durable and profitable relationship with the customers. In fact, indiscriminate approaches targeting the entire market prove, with a few exceptions for a narrow set of goods (mostly necessities), to be no longer successful. If a company wants to be successful, it must be able to identify, know, select and manage its customers continuously and systematically.

Customer churn prediction model [139]:

In this study, De Caigny et al. (2020) wanted to prove that is feasible and convenient for companies to aim at the implementation of CCM (Customer churn models), due to the financial incentives derived from a high-fidelity base of customers. In this situation, the paper propose the implementation of unstructured data, in particular textual information, to improve the accuracy and the reliability of this type of analysis. More in detail the aim was to improve the ability to forecast if a customer is going to abandon the company in the future, by implementing to the usual structured data of the CRMs processes (judged insufficient by this paper's authors) information coming from unstructured data (i.e. texts) that are able to describe individual features and the personality of the customers analyzed. The proposed method provides a framework for extracting, integrating and generally pre-processing the data that will be given as input to the prediction algorithm. In this case, several algorithms were tested for this purpose, in particular logistic regression and a random forest algorithm (typically a good performer in this type of situations) and a CNN (Convolutional Neural Network). The paper was able to show not only that implementing unstructured data improves prediction accuracy, but it suggests that using a CNN may be one of the best methods for this purpose, since in the case at hand it was shown to bring a significantly greater improvement in predictions than the other methods tested (although all of them lead to an improvement over using no method at all). Augmenting the data for CNN analysis with unstructured data has been proved to be effective in improving the company profitability. (Note: the authors underline, as a limit of this technique, the fact that dataset with paired the data, structured and unstructured paired, are very difficult to find in public, and so it has to be evaluated the economical convenience to invest resources in building them).

3.5.9) Sales

Demand Forecasting:

Demand forecasting has, since time immemorial and for obvious reasons, been one of the most important aspects of interest to any business. Knowing in advance and reliably the output that will be demanded from the company at any point in the future would at the same time allow the company to respond perfectly to demand, avoiding waste and maintaining overcapacity, and to avoid overutilization without running the risk of not meeting customer demands. Of course, many techniques have been developed over time, and they have become more and more articulated. Obviously, the problem of accurately predicting demand becomes more complex the further down one goes from an aggregate level to a level of detail and the shorter the time horizon examined. The numerous theoretical and practical efforts to realize forms of inter-firm collaboration along supply chains are by no means new to the market, and yet they have not achieved the success and spread that had been optimistically hoped for. This is not because the value of information sharing is not recognized by companies. They, indeed, understand its potential beneficial effect in terms of demand distortions in the supply network [140], yet a certain gap between the ideal and theorized condition of integration and the actual situation has been demonstrated [141], identifying the main causes [142] [143]:

- Issues in the alignment of the different companies' business interests
- Difficulties and criticalities in long-term relationship management (e.g. lack of flexibility)
- Reluctance to actually share information
- Complexity of large-scale supply network
- Competence of the staff responsible for the SCM
- Performance measurement and incentive policy

In addition, another important aspect is the presence of more or less local regimes of (bargaining) power on the part of certain companies, which act as deterrents to a supply chain optimization, even if technically feasible [143]. Furthermore, outside the theoretical situations, there have been evidences in which a complete SC integration caused an intensification of the Forrester, instead of bringing a decrease [143]. Nevertheless, it has to be emphasized that the advantages and benefits are accessible only if assuming that the shared informations are correct, otherwise they contribute to increase the distortions. A notable example is the case of Telecom, where some partners developed inflated forecasts, even doubled forecasts, despite the presence of means to incentivize correct behavior in the system [143]. In conclusion, especially with the development of e-business and e-commerce, the trend has been moving more in the direction of "dynamic" and "agile" approaches, making it convenient to focus on flexibility and disfavoring investment in strong, long-term partnerships, which are typically rigid, restrictive and difficult to reverse in the medium to short term [143] [144]. To try to circumvent these problems, apparently not solvable by more "traditional" ways, answers have been sought by applying AI.

Load demand forecasting for a smart grid and buildings [145]:

This study focuses on a very important problem, especially considering the present day and near future situation. In fact, if renewable energy sources are going to play a major role in power supply, an effective and efficient management of the smart grid will not be prescindable, even if that consists in a series of particularly harsh challenges, due to the intrinsic variability in terms of intensity and continuity of renewable sources. In fact, this is the main cause of problems for the grid's balancing operations in day-to-day forecasting and management, the very central topic of this case study. In particular it has been developed and applied a model based on ANN, trained on a dataset composed by records of a four years timespan (2005-2008) and validated on a dataset consisting in a 1-year timespan (2009). The model took as input a variety of different data (e.g. weather conditions and temperature, week, day, previous day's load,…) to generate the output, consisting on the forecasted load demanded by the grid (specifying week, day and hour). The ANN based method performed better than the more "traditional" statistical-mathematical methods chosen for the comparison, providing more accurate data more quicky and without the need of excessive sophistication. Furthermore, it proved to be more robust and reliable in terms of results even if compared to another AI based system (an "expert system"), causing a reduction of the forecasting error and, consequently, a reduction of energy wastage.

Spare parts demand forecasting in aircraft business [146]:

The demand for spare parts in the aviation industry is very fluctuating and unpredictable. This is also a result of the most modern approaches in inventory management, in which minimal levels of inventory are sought but high levels of service and short lead times. This situation is particularly extreme in the sector of aircraft spare parts, characterized by harsh competition and an extremely high number of SKUs (in the order of hundreds of thousands of different components), which exponentially increases the computational complexity of the issues to be handled. Under these circumstances, classical predictive models do not perform at all and do not meet the required needs. In the case dealt with by Amirkolaii et al. (2017), we set out to identify the best system for developing the most accurate demand forecasts possible, including using artificial intelligence. Different methods were tested in order to determine the best, i.e., most accurate, prediction method. In the case under consideration, records were available for 23,646 SKUs from 22 locations and 48 time periods (2012-2015). In the study emerged that traditional methods for forecasting perform poorly in such a complex and unpredictable environment, while methods based on ANNs (tested in the study), even though not able to provide a very high level of accuracy, proved to be very promising and leading to better reliability that the other solutions tried in the case.

3.5.10) Logistics

In today's context of supply chains and global markets, knowing how to organize transportation optimally is critical not only to prevent its enormous costs from eroding profit margins and thus generally worsening the efficiency and effectiveness of resource use, but above all to ensure better service levels and faster response times to one's customers, qualities that are very important for building a competitive advantage. Transportation-related problems have always attracted great interest, mainly because they have always proved to be particularly complex to solve and optimize, especially in "real time". Tools that can support optimization processes for these types of problems are of particular interest not only to companies, which may find themselves solving problems about the organization of customer deliveries or the scheduling of customer visits by the sales force, but also to public and government agencies, for example, for the optimization of public transportation (as shown in fact in the following example). AI applications have proven their effectiveness in meeting these needs.

Transportation Routing and Scheduling:

Travelling salesman problem [147]:

The TSP can be formulated in the following question: "*Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?*". It is a problem of combinatorial optimization in the fields of theoretical computer science and operations research. In general The interest relatively to this problem, from an SCM perspective, lies in its implications for logistics and warehousing. Typical examples are necessities such as vehicle fleet planning, and static or dynamic routing scheduling of vehicles, both outside (e.g. trucks) and inside (e.g. AGV/LGV or picking activities) the industrial plants. One interesting way to solve this problem and achieve an optimized solution has been proposed by Teodorovic et al. (2002), by applying an agent-based system, in particular with a "Bee system". This method was developed mimicking the behavior of the bees in nature, in which each decision-making agent is a "bee", which, through successive attempts and interacting with each other, is assumes as able to solve combinatory problems and, in this particular case, determine the optimal combination that minimizes the overall minimum paths to link a given amount of nodes in the space. In the cases scouted by Teodorovic et al. (2002), this algorithm could provide the optimal solution in a very small amount of time if compared to other more traditional algorithms.

Schedule synchronization in public transit [147]:

Another important application is the one proposed by Teodorovic et al. (2002), by using the "Fuzzy logic" in a system called "Fuzzy ant system" (FAS). This technique is inspired by ants' behavior, which allows them to always find the shortest path that link a location to another, by exploiting pheromone traces. As a whole, ants as a colony behave as a single system with shared and adaptive memory. And it is precisely this aspect, formalized in a logical-mathematical way, that underlies the operation of the method. This was complemented by fuzzy logic, combining the two concepts together. The result is a multi-agent system in which individuals operate not in a binary way, but rather in a way that handles uncertainty (typical of fuzzy logic). In their proposal Teodorovic et al. (2002) In their proposal T they took as their goal to minimize the required waiting time (in a public transportation system), successfully achieving excellent results in many schedule synchronization tests. In addition, attempts have been made to integrate fuzzy logic to the “Bee system” as well, succeeding in proposing optimized solutions for vehicle routing problems (such as in the case of deliveries) even when characterized by uncertainty in the nodes (the actual value of the node's demand is not known with certainty a priori, but only after it is reached). In general, these methods have been able to respond to and optimize situations that are difficult to handle by canonical methods, improving the overall performance achievable [94].

The demonstrated ability of technologies such as “expert systems” to detect patterns, recognize and adapt to unforeseen events, and successfully forecast demand makes it possible to overcome the old trade-off between high service level or low inventory level, while providing safety from the “Forrester” or “bullwhip” effect.

3.6) Final Conclusions

In conclusion, it seems from the studies that have emerged that it is now only a matter of time before AI sees a major expansion in the world of industry. The benefits are numerous and demonstrable, enabling increased productivity, reduced errors and decision support. Yet in many cases these are technologies and methods that have been known for many years and it might be surprising that they have not caught on sooner. From all the studies read and considered so far for this text, it is possible to draw hypotheses to try to explain this paradox. First of all, as indicated earlier (e.g. in Chapter 1) in order for AI to function properly in a concrete and applied context, a solid organizational and information base is needed. Furthermore, there must be sufficient understanding and appropriate skills in the companies, both at management and user level, to be able to exploit the usefulness of such tools. There is also another aspect: the productivity paradox, which underlines some issues in terms of technology-productivity correlations measurements [148]. As has already been pointed out, in order to fully exploit AI and its benefits, not only an evolution of means and processes is required, but also of organization, professionalism, and business models. Including this is the productivity paradox, which is that technology investments especially in IT (thus including AI and Business Intelligence), do not seem to have improved profitability, when measured by more traditional performance indices (such as ROI: it is difficult to quantify in the case of IT investments). This would seem counterintuitive, since the adoption of IT or AI systems has repeatedly been shown to have beneficial effects in terms of productivity, both quantitatively and qualitatively and yet it is complex to trace and quantify these results to traditional performance indices [149]. This could be explained, at least in part, by the fact that, in the presence of such a radical transformation, traditional performance indices are no longer adequate in terms of representativeness and reliability to be able to make rationally reasonable assessments of them. New ones would therefore need to be developed.

Chapter 4) Review of the Case Studies for Applications of Artificial Intelligence in Business Intelligence

This last chapter will briefly report on case studies of real applications of artificial intelligence in the field of business intelligence. This is in order to bring tangible proof that it is not only a feasible and tangible way forward, which some companies are already seriously considering and experimenting with, but that it can actually bring positive results and lead to improved performance. For this reason, the following case studies will all follow the same outline. First of all, the scope and purpose of the application will be introduced. Attention will then turn to the type of algorithm, without going into too much detail, just enough to broadly understand its operating logic and the approach used. Finally, we will emphasize the benefits that this application was able to bring and that could not have been achieved without the cooperation and the integration of AI and business intelligence. After the presentation of the cases, the final conclusions of all the work will follow.

4.1) Case 1: "Automotive Repair Equipment OEM uses AI to Monetize Repair Service Data"

The first case examined consists of the analysis of a case resulting from a collaboration between Predii (www.predii.com), a company specializing in AI software, and Snap-on Incorporated (www.snapon.com), a tool manufacturer [150].

4.1.1) Business Process

The objective of the study was to develop a diagnostic platform to facilitate the work of operators who must deal with the repair of motor vehicles, specifically by acting on three fronts:

- **Information seeking:** each model of motor vehicle has its own manual (Original-Equipment-Manufacturers) containing information about specific procedures, parameters to be met, compatible spare parts, and more. This amounts to thousands of pages for each one. A system able to perform queries and keywords' searching can speed up the consulting process significantly.

- **Problem diagnostics:** modern automobiles have many of sensors that can also collect data in real time. This data can be used in diagnostics to facilitate problem detection by relying on data while reducing variability induced by subjective judgment of technicians (which is not replaced but supported by software). Not only that but the system can use the sensor data, both historical and real-time, to detect possible future maintenance activities to be done.
- **Enhanced maintenance:** third-party vendors are a commonplace in this sector, which means that many different technicians work and create invoices on the same vehicle independently. By gathering and processing data from millions of different repair orders it is virtually possible to determine maintenance patterns (if existent) or the most common reparations and issues associated with each specific vehicle model, enabling a data-driven predictive maintenance.

Predii wanted to provide for the development of a single platform that could achieve all three of the above goals while properly supporting technicians in the vehicle repair phase. The added value lies precisely in the modularity of their pre-purposed solution, as it would allow, at least virtually, to possibly add additional modules in the future. We want to emphasize this aspect as it responds to an issue that has already been stressed several times in this work: the problem of scalability of investments in the AI field. Having potential for future developments and implementations that are compatible with existing elements is helpful in encouraging the approach to these technologies and their progressive development. The final output (consisting even in a dedicated hardware) of the project is represented in the following picture (Figure 11).

Figure 11: Final project's output

Source: *Aditya Shastry, K et al. [150]*

4.1.2) Kind of AI

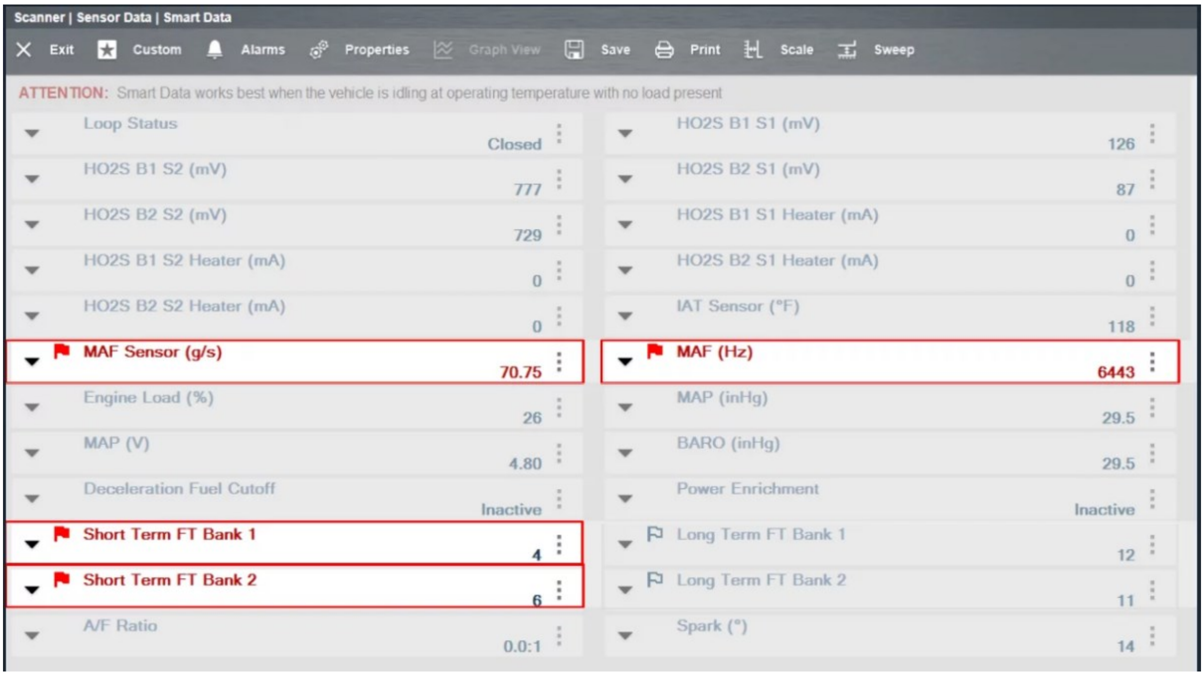
Having known the goals that Predii and Snap-on have set for themselves, it is good to go into detail to understand how, on a more concrete and application level, they have planned to achieve them:

- **Information seeking:** Regarding this aspect, i.e., searching OEM manuals, Predii has utilized NLP to constitute a database on which searches and queries can be made, which automatically goes about collecting and categorizing key concepts from the manuals as they are loaded into the system. Unfortunately, the companies don't provide information regarding the specific algorithm used for the purpose, even though they used an unsupervised learning method to solve this classification problem. Probably one among the most suitable solution would be a SVM (which is a technique known to perform very well in these contexts), a classification method based on an ANN technique.
- **Problem diagnostics:** Predii has built software that can use sensor data (including historical data) to develop insights into problems and possible causes. It also allows, by identifying anomalies, possible future maintenance work to be identified. All of this is shown via a dashboard, first with visual warning signs, and later with the ability to drill down and deepen the information. As in the previous case, there is a lack of detailed information about the algorithm used, but it seems reasonable to imagine a system either based on a random forest (and in general on the concept of decision trees) or an ANN or DNN algorithm, since the latter have proven to be particularly performing in developing predictions starting even from many inputs as in this case (each sensor is an input source).
- **Enhanced maintenance:** with this purpose, the software assembles and interprets service order data originating from the various repair shops and technicians that worked on a vehicle during its history. Combining the invoicing information with warranty data can provide valuable insights. allowing us to go in for more accurate preventive maintenance. No details are given for this aspect either, or yet it turns out to be the part of the software that is certainly the most articulated. It is assumed that first one must have a system that can, automatically, process all repair invoicing over time and be able to automatically go and categorize it by intervention and vehicle, uploading the data to a database while also keeping track over time. For this purpose, a recognition algorithm is needed (the same argument as in point 1 of this case study applies, so one can imagine, for example, a Support Vector

Machine). Second, an algorithm is needed that can analyze this huge amount of data and detect meaningful patterns, especially along the temporal dimension, and in this case it is possible to assume that a reasonable adoption could be an ANN or similars. The system then proceeds to determine the recurring maintenance patterns for a certain vehicle (or category, brand, etc.) and, by comparing the results with the history of the specific vehicle goes on to determine what work should be done and within what time horizon to do it. It is not known how many variables the software considers, but it is reasonable to imagine that it is well true that the greater the number of them, the greater the computational and storage difficulty required, but it is also true that it opens up greater possibilities for identifying patterns across features, improving the accuracy of predictions. By assembling together these two sub-systems, ensuring that there's coherence in terms of complexity and data characteristics between them, it is possible to achieve the overall solution for the last point.

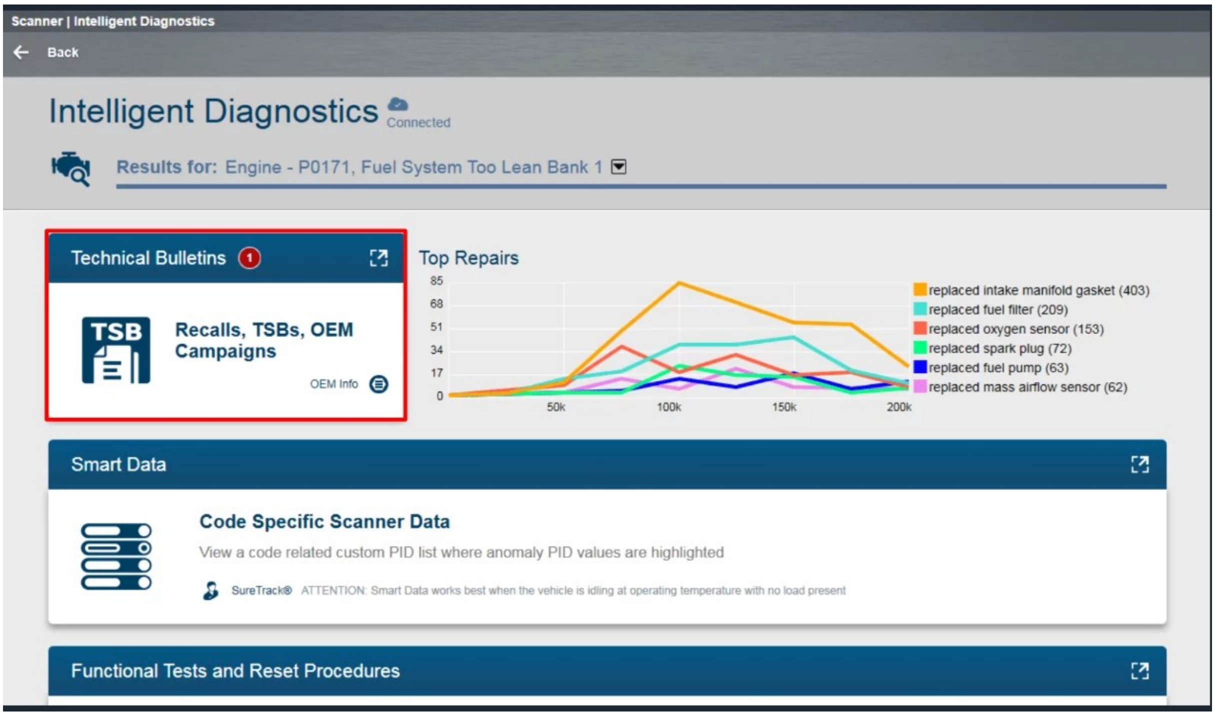
In the pictures below it is possible to have a visual example of, following this order, of the dashboard with the alerts and regarding the dashboard (Figure 12) with the overall analytics for a certain code/element in the database (Figure 13).

Figure 12: Example of the alert's dashboard



Source: *Aditya Shastry, K et al. [150]*

Figure 13: Example of the diagnostic dashboard



Source: Aditya Shastry, K et al. [150]

4.1.3) Benefits

Although the company does not want to share detailed data about the operation and results obtained from the system (most likely for commercial reasons), they are satisfied with the result obtained, which seems to have brought about a real improvement in the working conditions of the technicians who got to try the system. Quoting the words expressed by Sierra Stanton, as the company's technology provider: "*One of the Snap-on products powered by Predii Repair Intelligence is a diagnostics tool, called Zeus. Technicians using Zeus reported average savings of 30 minutes per job in diagnostic time*". It is possible to see a picture of "Zeus" below. So, it seems that the technology developed by the collaboration between the two companies has been successful in bringing concrete and measurable results. In addition, having such a system in place allows for easier access to information and knowledge, which has the dual effect of facilitating the work of more experienced practitioners, as well as facilitating the induction of new, less experienced members. It is also a source of increased learning opportunities. This is justified by the fact that it makes it possible, through automatic recognition of a large number of repair invoicings, to broaden the base of "experience" to which an operator can turn with regard to the most frequent problems related to a specific vehicle, without having had to experience them firsthand. Decisions will therefore be more accurate, as they will be based on a greater amount of data. Still quoting Sierra Stanton: "*Reading one summary of a service order is easy. Reading and learning from millions of service orders in a few hours is an entirely different problem, and if you can solve it, you're really winning*".

4.2) Case 2: "Machine Learning for Customer Support"

The next paper consists in a review of a project commissioned by a company in the retail of furniture items [151].

4.2.1) Business Process

A company (whose name is disguised) engaged in the retail sale of furniture items found itself with the need to upgrade its customer support service, and was faced with two possible paths: increase the number of employees or increase the productivity of existing ones. The organization decided to opt for the latter, developing an automated live chat that could carry out conversations with customers and understand their problems and classify them automatically.

4.2.2) Kind of AI

The company DigitalGenius developed the software for the above company, using a DNN (Deep-Neural-Network) model as a pillar, devised to extract end to end conversations, along with meta-data about the tickets and using this data as input to operate a classification based on the meaning of the requests, so that we can respond according to the actual need of the customer. Training of the system occurred in two stages. First in a supervised manner, using historical data from past tickets of requests that had already been fulfilled. Next came the validation stage with a reinforced approach: the customer service team was responsible for checking whether the algorithm's responses were correct in the case of new requests. At the end of the testing period, the system was applied and sent to full operation, making it available to all customer agents.

4.2.3) Benefits

The company does not provide very detailed data about the results obtained; it also offers no perspective in terms of economics. However, the system seems to have met the company's expectations, since, following implementation, 70% of requests are successfully processed by the system. In addition, it is able to provide operators, should their intervention be necessary, with information about the classification of the problem and a range of possible solutions, allowing problem resolution to be sped up markedly. It has been registered a reduction of the overall waiting time for the customers, even though the company does not provide any measurement on this topic.

4.3) Case 3: "Data Mining of Environmental Data and Bio-Signals"

This case study is not referred to a manufacturing process or a business activity, but it is an application in a medical field. The reason it was decided to bring it anyway is that it is a real-time monitoring system, so it is more important to bring this example as evidence of the feasibility of these systems even if not in a purely industrial context than the nature of the actual operational situation [152].

4.3.1) Business Process of the Application

The system could be classified, if it were in industry, under production planning and control, imagining applying such a system to products delivered as part of a service offered, or to machinery or robots used in manufacturing, handling or assembly. The goal of the project, called "ActOnAir" is to develop a personal guidance system able to help people who suffer from asthma to reduce their exposure to pollutants and, consequently, their health's risks. The final pre-posed goal was to develop a functioning system capable of fulfilling the pre-posed purpose, and then make it available to the public via smartphone app, which acts as a conduit and allows the user to access all data at all times, as well as making it possible to alert by notification in case the system predicts a risky situation The project was supported by the "German Federal Ministry for Economic Affairs and Energy "and the "HPI Future SOC Laboratory".

4.3.2) What Kind of AI

With this purpose, the developed tool has to measure continuously the environmental data and bio-signals, analyze them and applying a classification model, based on AI techniques in order offer a solution able to apprehend and tailor the solution to the specific individual's situation, to predict the health- risk in real time. The real time analysis procedure was carried out using SAP's HANA platform, which allows data mining techniques to be used on a continuous stream of data. The operation of the system is based on a decision tree. The approach used for learning is not specified; however, it occurred following a segmentation of individuals so that, based on the user profile, the algorithm would be more accurate in its predictions. The system takes into account both a number of individual bio-signals related to the individual's health, as well as atmospheric elements (dust, pollen, ozone, temperature,...). The system assesses on the basis of all these inputs the level of risk, whether high or low, and communicates this to the individual in real time.

4.3.3) Benefits

From the text of the paper (dated 2016) the system was found to work properly and bring very promising results, announcing a second stage of testing on a larger scale than the first attempt. It should be noted, however, that no certified papers can be found at a more recent date that can elaborate on subsequent developments. What can be said is that the system, although still in the experimental stage, was found to be working. This means that it is possible to realize a system that allows real-time monitoring of individual elements, each with its own subjective characteristics. In this case, it has been possible to reduce the incidence of asthma attacks in people, although there are no precise and detailed results on the extent of this benefit.

4.4) Case 4: "AI-Based Edge Acquisition, Processing and Analytics for Industrial Food Production"

The next case will treat the subject of predictive maintenance in a high automation context [153].

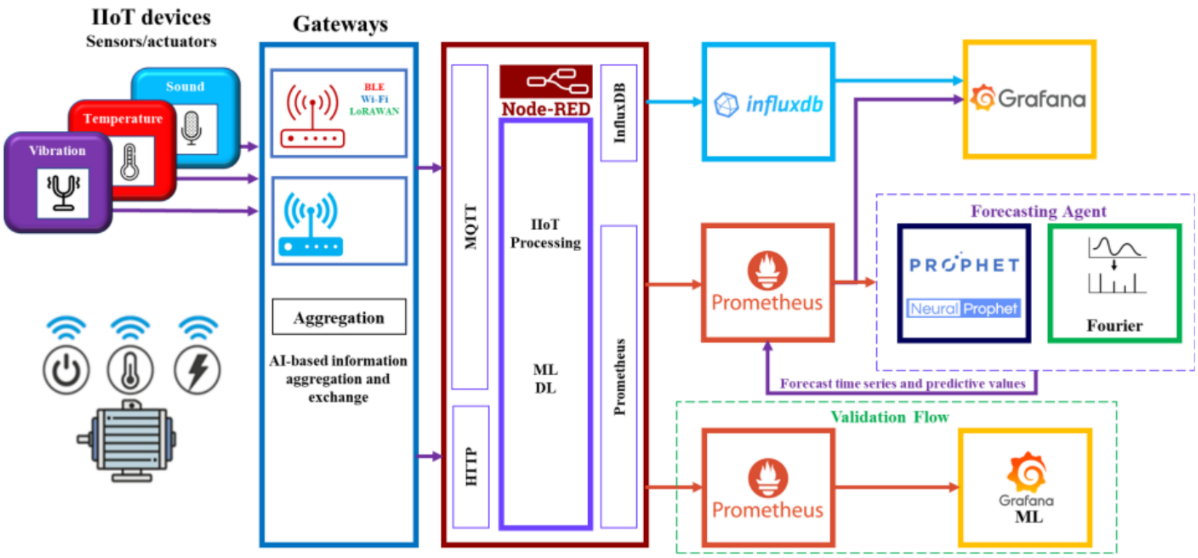
4.4.1) Business Process

This is a case of application to preventive maintenance in the food industry. The company under consideration developed a framework capable of exploiting the sensors and data produced by the machinery itself, so-called "IoT data", collecting them appropriately and using them within a system with a dual objective. On the one hand, it wanted to go, by monitoring the values coming from the sensors (in the specific case, among the various parameters, those considered of primary interest are those related to vibrations, temperature and electricity consumptions' profiles), to feed an artificial intelligence algorithm capable of predicting the optimal date of future maintenance in order to optimize productivity and minimize costs, as well as to indicate on which elements to go and focus the work. Secondly, the system must be able to handle unexpected events appropriately, such as recognizing whether an anomalous data item constitutes an outlier or sensor reading error (which must therefore be filtered out), or whether it is a failure or unforeseen problem on which to intervene (of which the probable cause must therefore be indicated).

4.4.2) Kind of AI

For this study, the data used as input, both for the training and operation phases, came from industrial machinery. The company in question has developed a special framework (visible in the image below in its parts) for this purpose. We will not go into the detailed operation of either the system as a whole or its components here, for the sake of brevity and not losing focus. What is important to emphasize is its operating logic.

Figure 14: Framework proposed in the case study



Source: *Vermesan et al. (2022) [153]*

As can be seen from the figure above, the infrastructure put in place consists of a first layer that takes care of aggregating data from the sensors and actuators. The aggregated data is processed and prepared for use. A portion of the data is used as input for the operation of the algorithms, while a subset of it is kept aside for re-training the algorithms (as this is unavoidable and must be taken into account). The predictions are sent, along with current and actual operating data, to a dashboard that allows the data to be viewed in real time (picture below, Figure 15). In addition, there is the possibility of setting alerts, which will be triggered if one or more parameters approach or exceed a certain threshold value, or are even capable of self-adjusting over time, so that there is no need for periodic interventions by operators.

Figure 15: Example of dashboard

Source: *Vermesan et al. (2022) [153]*

For the company, it was important to process IoT data in real time, so that artificial intelligence algorithms could be applied both for phenomena of long-term interest such as trends, which are necessary for forecasting and planning maintenance activities, and for seasonal and/or short-term phenomena, such as recognition and management of measurement noise or detection of anomalies in the process. For trend prediction (vibration, temperature, and electricity consumption) they relied on an algorithm based on ANN. For the detection of outliers and measurement errors, they made use of Node-RED ML, i.e. a particular classification algorithm of the "decision tree" type, and finally, for the detection of anomalies, they made use of methods such as "Random forest", "K-nearest-neighbor", "Support Vector Machines", and "decision trees", although no more precise details are given as to which type of algorithm has been chosen nor the specific tasks that have been assigned to them. The approach applies a decentralized ML solution for industrial applications, reducing bandwidth consumption and end-to-end latency. This was achieved by exploiting the possibilities offered by the company's IoT machines, and centralizing the data only at the dashboard level. This makes it possible to implement a different type of algorithm for each piece of machinery, depending on requirements, thus explaining the variety mentioned, but not specified, with regard to the algorithms that have to determine anomalies.

4.4.3) Benefits

The application of this framework that integrates BI tools with artificial intelligence techniques allows the overall downtime of machinery and equipment to be reduced, acting on two different aspects: firstly, it allows forecasts to be improved, since they are not based on estimates but on data relating to the actual operating conditions of the machinery, and consequently scheduling interventions by reducing the amount of unexpected failures. Secondly, it optimizes interventions, as this framework makes it possible to know which elements need to be replaced and which do not, without the need for inspections (which would require more time to disassemble, check and reassemble), while in the case of unforeseen problems, it makes it possible to circumscribe eventualities from the outset, facilitating the identification of the actual cause and, consequently, reducing the time needed for repair. Finally, compared to a periodic or purely probabilistic approach to maintenance, it allows costs to be reduced, since interventions take place only if and when necessary, improving the utilization of components and reducing downtime for maintenance. These benefits translate into greater overall plant efficiency, which reduces the time to market (higher productivity) for the same production capacity, and thus allows for a better utilization of invested capital. Unfortunately, the company in the case study under review does not provide numerical, or even qualitative, details about the performance improvements or savings brought about by the adoption of this framework. The only thing known is the fact that they actually decided to adopt it within their processes, and therefore it is reasonable to assume that it had a sufficiently positive impact to consider the use of this system beneficial.

4.5) Case 5: "AI Enhanced Failure Mode Effect Analysis"

This case, that can be considered as related to the process and quality control, although not particularly in-depth regarding the BI aspect and more focused on the AI aspect, was chosen and deemed important as it brings attention to certain aspects (clarified later) that are usually overlooked by other cases [154].

4.5.1) Business Process

In this case, a semiconductor company wants to go and develop an automated system that improves the FMEA (Failure Mode Effect Analysis) process. Risk assessment and root cause analysis are two practices performed in the industry that capture and document causal domain knowledge. Although fundamental, these activities are prone to undesired errors, usually consisting on missing informations or cases of conflicts in the causal chains (i.e. the direction of the causal effect relation is reversed). On one hand, the company wants to improve the consistency, and thus reduce errors or undefined records, while at the same time facilitating the work of the experts involved in this process, as the writing, correction and analysis of reports is slow and inefficient, as well as time-consuming and brings little added value. In addition, errors are often caused by the manual writing of reports by experts, so the paper proposes a classification scheme to provide an improved understanding of the of the consistency impairments in relation with respect to the causal relations expressed in FMEA documents, consisting in metadata annotations to the tabular data. Due to the dataset size and the fact that the operation should be performed in a production environment, it is impossible to manually label all the available datasets: for this reason the paper proposes to leverage artificial intelligence to develop an automatic (or at least semi-automatic) classification method.

4.5.2) Kind of AI

First, the study proposes to review some fundamental aspects of the process in order to improve it by resolving some critical issues. In particular, the proposed change concerns the classes used for expert evaluations, which had to follow three rules: be completely separable (i.e. no overlaps), more aligned with the perspective of the experts performing the analyses, and such that consistent causal relationships could be established. To determine the new classes and their respective causal chains, the experts in question were interviewed and consulted. This brought two benefits: improving the effectiveness of the text recognition algorithm (based on

NPL) and allowing domain experts to being ablet to map defined concept classes to the corresponding measurement data types (monitored during the process). It is essential to emphasize the importance of the correspondence between the concept classes chosen (that logically should be represented by the data) and the concept used by experts for their interpretation.

The system developed for the case study examined consists of two stages. First, the data is processed via NPL in order to extract data from the texts that can be processed by an artificial intelligence algorithm, which in this case was based on a Deep Neural Network (specifically 4 different DNN architectures with different technical specifications). The approach adopted is that of supervised learning. The input data consisted of handwritten reports by specialists, and the application in question had to be able, by analyzing the content, to recognize and communicate inconsistencies in the report, indicating their nature (“missing information”, “reverse causality”, “same concept”, etc.). The data was therefore divided into 3 datasets (training, validation and operation), and they conducted the process for each proposed solution, in order to determine, an so then to apply, the best performing one.

4.5.3) Benefits

The study emphasized that data inconsistency detection in a complex environment, as highly automated production lines are, tends to fail in conducted exclusively in a data driven approach, and so it is fundamental to support it with domain-specific knowledge to achieve good results. The application of a causal model as the one developed in this case study proved to helpful in the detection of those inconsistencies. The system based on the best performing algorithm was able to recognize and communicate up to 91% of the inconsistencies in the reports to the experts. It should, for the sake of transparency, be emphasized that, however, not all types of inconsistencies are equally frequent, and in the case of the less frequent ones, during the test performed and reported in the paper, the accuracy in those cases fell into a range of 56-63%. This is still a satisfactory result, yet still far from perfect. And yet, as a whole, this application proved capable of achieving, although not 100%, the desired result, improving the consistency of FMEA reports. Although it is not specified in the paper, it is reasonable to think that, associated with the improved quality of the reports, it was also possible to reduce the time spent by experts on this activity, thanks to the support of the model. Moreover, it allows for future developments, extensions and adaptations to other contexts, guaranteeing scalability (an aspect much appreciated by business managers).

4.6) Limitations of the empirical information reported

The analyzed cases can be considered with the purpose to examine potential and future developments of AI in BI, and particularly the possible benefits that the integration of artificial intelligence technologies can bring to Supply Chain Management and to BI seen in a broader way (i.e. not only reporting systems for the organization's executives). However, for the sake of transparency, it should be emphasized that the literature currently lacks case studies that can help us to respond fully and exhaustively to the posed questions. First, studies lack concreteness; in fact, it would be necessary to find a description of real projects that were actually implemented and not mere proposals of frameworks or experiments created "ad hoc". The second missing point is reliability, which means that there are few cases that are fou:nd in trustable sources (e.g. academic papers). Finally, there is the issue of completeness: it is not easy to find case studies that are complete and provide significant results and sufficient detail regarding techniques and methodologies applied in a company or project. Here, the effort was to find case studies which fit the mentioned aspects, rather than just proposing cases that can be "impactful" only apparently, but instead fail to be useful for understanding the actual state of the technology and its related potential. In any case, the amount of papers that focus on the various characteristics of artificial intelligence and specifically on application cases is growing going fast. For this reason, it is reasonable to expect that it will not take long before these gaps in the literature are filled. In any case, we argue that the information presented here is sufficient to get a clearer picture of the topic treated in this thesis.

Chapter 5) Final Conclusions

The following are the conclusions regarding the work done so far. In the first part, a brief analysis will be made of the current situation, from what we have been able to learn from the work done here, as well as analyzing the main difficulties encountered. The second part, on the other hand, will focus on outlining the main benefits and criticalities related to the topic that have been learnt from the work done so far, trying to go a bit into more detail for each of them. The idea is to try to offer a perspective in terms of the main strengths, weaknesses, opportunities and threats that it is reasonable to expect in the near future. The paper concludes with personal and more general final considerations that developed over time as a result of individual meditations on the topic.

5.1) Current Situation, Difficulties and Critical Issues

In drawing conclusions regarding what has been learnt, a good starting point may be a brief analysis of the current situation in the light of what has been learnt from the work carried out in the research and writing of the previous chapters. This is followed by a section dedicated to the critical issues that have been encountered, as they are extremely important in order to better and more fully contextualize the work carried out up to this point.

5.1.1) Considerations Over the Actual Situation

From what we have learnt during the production of this paper, everything seems to suggest that the industry is approaching a turning point, as confirmed by the growing attention shown both by large companies and numerous institutions that are beginning to take an interest in the subject. Among the most recent news, one of great relevance comes from SAP itself, whose CEO announced a few days ago a turning point in the company's strategy, not only by increasing efforts and investments in the development of AI supports and tools for the services they aim to offer their customers, but also for internal use, presenting their generative AI assistant, "Joule". Certainly they are not the first to propose similar solutions, in fact many providers of business intelligence services and platforms (Qlik or PowerBI to mention two of the most famous names, though not the only ones) have already enriched the options offered to their customers in this direction, but it contributes to a whole series of indicative signs that a turning point may be around the corner. However, there is reason to believe that this moment is less close than expected, at least for an important number of players on the market. The benefits of the spread and application of AI to various processes is a certain fact (examples can be found in Chapter 4), and it is indeed true that they can also be very significant, but succeeding in achieving them, especially meanwhile constructing and securing an economic, financial and competitive advantage, is not entirely taken for granted and depends heavily on the presence and accomplishment of certain prerequisites (discussed in more detail below). In particular, the situation seems to be quite critical for the European companies, in relation to the situation in other areas, such as North America or China. This could be exposing them to the risk of not being able to seize the opportunity, seemingly, about to present itself and finding themselves chasing the vanguard instead being part of it. Companies, with a focus on SMEs, in the area that adopt IT technologies at least at a basic level are 55% [156]. It is estimated that until 2020 the global BI adoption rate across all organizations was 26%. In more detail, it is noted that this figure is not homogeneous neither geographically, nor in terms of company size, nor by business sector. At a more granular level, based on the company size, survey results showed that the adoption incidence was concentrated mostly in organizations with more than 5,000 employees and geographically located in European and North American countries, Finally, the sectors that see the highest rate of adoption are healthcare, IT services and manufacturing companies [155]. All metrics shows that the trend is clearly growing, but this situation can, at least partly, explain the criticalities found during the work on this topic, especially when it comes to find information regarding AI in BI applications: in order to successfully integrate these two fields it is fundamental the presence of a robust base of structured processes and efficient and integrated ICT systems. In fact, without an adequate base of information infrastructure, especially if the various modules and layers (ERP, CRM, MES, etc.) are not integrated of not present at all, the use of advanced tools and business intelligence platforms is not only useless, but also not even possible (See the next sections for more detailed information). This situation explains what emerged from the analysis reported in the Chapter 1, which underlined the great importance that companies seemed to attribute to aspects such as “Data Quality Management”, “Data Culture”, “Data Governance” and “Modernization of Existing Systems”. On the one hand, this shows that a not inconsiderable, indeed almost certainly a majority, part of the market is not yet ready for a massive implementation of AI in its processes and that, on the contrary, companies are still working to “preparing the ground” for this purpose. In any case it is reasonable to think that the efforts in this direction are widespread and concrete.

5.1.2) Difficulties and Critical Aspects

We will now go on to list and analyze the main difficulties encountered during the thesis work, as these too can be a useful contribution to outlining the current situation, as well as contextualizing and explaining certain aspects also related to the thesis itself. The main critical points encountered can fall within three main areas:

- Difficulties in finding structured information on AI
- Lack of “management approach”
- Scarcity of comprehensive case studies on the subject of “AI in Business Intelligence”

Scarcity of Structured Information on AI

The field of studies relating to artificial intelligence is extremely vast and rapidly expanding, at least in terms of academic interest and study. This can be taken as a positive sign, as it indicates that interest in this discipline is alive and prolific, however, it is very difficult to navigate through the papers and literature productions on this topic, especially for individuals not specialized in this specific field. It is believed that this is also due partly to the lack of an unambiguous and standardized classification system of the various “AI tools” and techniques. This is fundamental to put order in such a vast set of notions. It has to be pointed out that some “de facto standards”, best practices and conventions seem to have emerged, more or less spontaneously. However, in the search for information for this work, was noted a lack of univocity at a global level in this field, and it is deemed important to emphasize this aspect because of the implications it may bring. Although this is more than understandable in a dynamic, fast-growing and evolving environment, such a situation could obstacle the future development and diffusion of AI technologies and their applications. A more systematized approach and a more ordered knowledge would avoid slowing down research (as it would avoid overlaps or redundancies in research and production) and would facilitate the access and understanding of information both for scholars, researchers and experts in the field themselves, but especially for those who have to approach this field from the “outside”. The in-depth study carried out in Chapter 3 did not pretend to achieve this, for which an “ad hoc” work it is considerate necessary and appropriate, but it did at least attempt to align some of the main concepts regarding the very vast field of artificial intelligence with the aims of this paper.

Lack of Managerial Approach and Perspectives

The following aspect is related to the point discussed above, and yet deserves to be dealt with separately. During the research of information useful for the writing of this text, it was noted that the literature relating to artificial intelligence technologies is, for the vast majority, produced by and for "technical" figures, and for this reason mainly focused on algorithmic-mathematical and programming aspects. Based on the assumption that it is not possible for a person or an organization to successfully apply in real contexts techniques and technologies that are not fully understood, it is important to place more emphasis on involving in the field also managerial figures, so those who have decision-making power at organizational and corporate level and that could benefit from the application of AI, even including the Supply Chain Management and Business Intelligence. There are some examples in the literature, among which there are the ones that have been reported in the previous chapters, that show that the application of AI techniques has been able to bring benefits and advantages that could not otherwise be achieved, and yet, the most successful cases, seem to be those in which the process itself took into account the application of these technologies as an integral and integrated part of the process itself, rather than cases in which AI is seen as a heterogeneous body added aside an existing process. But to be able to realize such a situation, it is essential that the application of AI takes place with full knowledge of its potential and limitations within the process. Hence the need to deepen and structure the issues also from a "managerial" perspective, focusing on the logical, technological and economic aspects that have been neglected so far, yet are fundamental to improve and enrich the dialogue between the various professional figures that such a complex and eclectic field requires, leading to a development and diffusion of these technologies. It is very important to emphasize that it's not simply a matter of lack of training or notions on the subject, but about a lack of literature designed and targeted specifically for the needs of managerial figures, for example with regard to tools for measuring the operational and financial performance of these projects, since traditional metrics and performance indicators are deemed inadequate, given the complexity and, in many cases often impossibility, to determine a direct correlation between achievable benefits and cash flows generated. This leads to a conflictual situation within the organizations, since managers often find hard times to justify and quantify investments, performances and results, and this, even if it's not a technical or technological issue, it is clearly a relevant obstacle that slows down the adoption process, and so it would be important for new future studies to work in this direction.

Scarcity of Comprehensive and Specific Case Studies on the Subject

The last aspect concerns the difficulty of finding complete and exhaustive case studies, especially at the level of information on the type and characteristics of the AI models used, and at the level of the benefits and results obtained. This difficulty was particularly pronounced, although not limited to case studies of the type presented in chapter 4, which means those concerning the integration of artificial intelligence in business intelligence. This does not mean that there is no literature on the subject, however, the vast majority of papers that bring application examples or case studies are not real and actual applications in the business or operational sphere, but are either proposals of frameworks od application cases that have either not yet been concretely tested or are being tested but with no follow-up on the results, or are concrete situations but which, probably due to issues of secrecy and protection, are too vague or incomplete to provide enough concrete information on benefits, characteristics and performance, resulting on being unsuitable for the aim of this work. Therefore, at the moment it is possible to say that there are companies that are attempting applications, but it seems that the spread is less extensive than expected, and this is most probably caused on the one hand by the lack of the prerequisites necessary for the successful integration of AI in processes and, above all, in business intelligence, and on the other hand by a reduced understanding and awareness of this technology especially among non-specialists and especially outside the academic and research sphere (see the two points above).

5.2) Business Intelligence and Artificial Intelligence: Future Perspectives

In this section we are going to define, as far as we were able to learn during the work for this paper, what are the benefits that AI can bring in the field of supply chain management and Business Intelligence, and then move on to an overview of what are the most critical points related to these technologies and regarding the integration between the two fields that should be taken into account in a perspective of future development. The idea behind the drafting of this section is the SWOT analysis, i.e. firstly to emphasize the strengths and opportunities, i.e. the benefits, and then the weaknesses and threats that need to be contained.

5.2.1) Benefits of AI to BI and Supply Chain Management

From what has been learnt during the work on the development of the previous chapters, it is possible to state the possibility of exploiting a synergy that seems to appear between AI and integrated information systems in the company, including those dedicated to business intelligence. Before proceeding in detail on this aspect, it is important to clarify a few concepts. To begin with, it may be useful to identify the main benefits that artificial intelligence can bring to these areas, if, of course, it is applied in a correct and reasoned manner:

- Improved speed, accuracy and consistency of information and decisions
- Exclusive technical potentials enabled
- Better utilization of IT investment
- Better utilization of human resources
- Possibility of continuous improvement

This is followed by a more detailed examination of each of these benefits, justifying them in the light of the work carried out previously and analyzing the features required to obtain them.

Improved Speed, Accuracy and Consistency of Informations and Decisions

Undoubtedly, the most obvious, important and sought-after benefit for anyone wanting to implement an artificial intelligence application in an organization is to improve the speed, accuracy and consistency of the information gathered and, consequently, the decisions that are made based on them. As far as the speed aspect is concerned, it is made possible by the fact that once one has a properly trained and validated algorithm, the response of the model is extremely fast, often immediate, ideally allowing for a real-time update of the output expected from the model. The other important aspect is the consistency: an AI model is able to learn systematically from a very large database (and indeed, the larger the learning base, the better is the theoretical the performance that the model should offer), without the judgement being impaired by undesired circumstantial situations (as may be the case for a human being with, for example, the tiredness or the mood in a certain time). Now, no algorithm can be held responsible to the point of making decisions autonomously, it remains the prerogative of humans. However, numerous studies have shown the effectiveness of pairing an AI algorithm with a human operator in the decision-making phase, as shown, among the most obvious and striking cases, by the cases in the medical field: here the use of AI models allowed to reduce errors and the time taken to diagnose clinical cases.

Exclusive Technical Potentials Enabled

Artificial intelligence models are extremely varied and can be applied to a wide variety of different fields of use, enabling in many cases potentials that would otherwise be untapped or impossible to exploit. The main reasons can be:

- **Technical:** for example, AI models based on "Rough Set Theory" or "Fuzzy Logic" are able to manage the intrinsic uncertainty that characterize certain phenomena, making it possible to automate processes, otherwise impossible with a traditional systems

- **Procedural:** when the time required to obtain a piece of data or information by a human operator is too high or in any case exceeds the time available for a certain procedure to be concluded

- **Economic:** this is often a consequence of the previous point, which means a case where the cost (possibly also opportunity cost) of obtaining a given piece of information by a traditional method exceeds the economic benefit it is deemed capable of bringing

Enabling these capabilities can, if an organization is able to identify the opportunity and implement it, allow it to develop an important competitive advantage. One of the most striking examples in this regard is the use of “digital twins” as in the case of Rolls Royce's airliner engines. Thanks to the development and spread of IoT and sensor technologies, it has become possible for them to collect a large amount of accurate data about the operation of each engine. By developing an AI based model that is then applied to each engine, which can be trained using data from all similar engines, but each fed with data from a single, specific engine. This means that they have a virtual, faithful and precise copy, or “twin”, of each engine in circulation with information about the specific engine’s current state. This has allowed Rolls Royce to increase its earnings by no longer offering companies to sell the engines, but to rent them, allowing them to pay according to actual flight hours without having to take care of maintenance, which remains among the responsibilities of the supplier. The latter, having a model with detailed information for each of the engines, can customize and optimize maintenance by carrying out only the necessary interventions at the right time, minimizing costs and downtimes, therefore increasing their profits. Not only that, the information obtained also allows the supplier to gather detailed information of the in-use-performances themselves, that can be (and are, indeed) used to improve on one hand the engine’s overall efficiency and fuel consumption, even in critical and transitioning phases such as engine’s starting or take-off, and on the other hand to reduce stress and wear on the components (for example by modifying the power and torque delivery adjustment) [157]. This is just one example, but similar applications have also been made by other companies (e.g. General Electric with their steam and wind turbines or Siemens in their automotive production line offering [157]) and, as AI technologies become more and more accessible, it is reasonable to expect that similar applications will be implemented on more and more business-to-business and business-to-consumer applications.

Better Utilization of IT Investment

In working on the following paper, particularly for Chapters 2 and 3, some very interesting aspects related to improving the performance and potential of the IT systems themselves could be appreciated. Considering the logical-architectural structure of an integrated corporate information system, i.e. made up of several layers and modules integrated with each other, starting from the sensors and PLCs of the machinery (where present in the company) up to the business intelligence and management support systems, AI can make a significant contribution at each level either by improving the performance of the existing system, or by expanding its potential. At the level of individual machines, AI can be useful, for example, to monitor performance and optimize consumption, maintenance and operativity, or improve human-machine interaction and interface (for example, by providing detailed information about a fault or problem by recognizing it from certain input signals). At a higher level, it is possible to think about integrating groups of machines or even entire departments in order to optimize work planning, streamline various flows or manage warehouses and inventories. Ascending to higher levels in terms of software hierarchy, AI is no longer only able to provide performance improvements but also cross-functional benefits. For example, AI classification algorithms can be exploited to “clean” input data, so to detect errors and thus either automatically correct or remove a potentially problematic outlier. This has the dual effect of improving the quality of the input data to a certain system and at the same time optimizing its use of computing power (by avoiding the storage, processing and analysis of erroneous, thus non-valuable data). It is important to underline that, during the thesis work, many proposals for similar applications were found, but since it was impossible (at least at the time of the writing) to find an actual concrete applications, not to mention a case study complete with the relative detailed results, those cases were not reported here since that would’ve meant a divergence from the original spirit pf the work itself. Nevertheless, it is considered worthy to mention that similar applications are attracting interest and effort and so it’s reasonable to expect that relatively soon will start their diffusion. In addition, regression and pattern recognition algorithms can be useful in the “Data Discovery” phase, by identifying hidden relationships within the mass of collected data and quickly and reliably identifying causal elements underlying dynamics within the data, thus increasing the quantity and quality of available information and, therefore, the knowledge of decision-makers. All these potentials can be translated into a better utilization and exploitation of the investment in IT technologies.

Better Utilization of Human Resources

Another, perhaps less immediate, aspect is the benefits that the integration of these technologies may bring in terms of human resources. Concerns about the possible threats to human employees within companies and organizations that the adoption of AI may bring with itself, are many and legitimate, and will therefore be briefly addressed in the next section. However, it would be unfair to merely demonize a technology for problems and possible harms that are not intrinsic to it but caused by the effects of its modalities of application, without emphasizing the possible benefits it could bring. In detail, the most immediate and intuitive effect consists in the fact that AI can automate certain procedures, making it possible to reserve for the staff higher-value activities, or in any case activities that expressly require a human figure in order to be carried out correctly. In the context of BI, it would make it possible to reduce the time and difficulty for the operator to perform analyses on large quantities of data, and at the same time to perform more in-depth analyses, looking for transversal relationships that are difficult to identify in the traditional way. In fact, performing data analysis, per se, is not a valuable activity, but necessary in order to monitor processes and to be able to make the appropriate decisions in order to maximize value. But it is not limited to this, in fact, the application of artificial intelligence to support decision-making enables the possibility to speed-up the problem detection and identification activities and at the same time reduce errors in evaluation. A few important examples of this can be found in the case of applications for medical diagnosis and prevention processes. Consequently, AI is not necessarily a threat to a company's human resources or a substitute, but if it is used as a supplement or complement to staff skills, it allows cooperation and efficient "human-machine" interfacing, and it can be a valuable tool for simplifying work and enhancing workers' performances, thus increasing the company's competitivity.

Possibility of Continuous Improvement

The improvement process, to be effective, must be systematic, as the engineer William Edwards Deming theorized and demonstrated with his PDCA (Plan-Do-Check-Act) cycle. In order to function correctly, both as a whole and in the individual phases, the definition of a standard is essential, which is logical because, trivially, it is not possible to assess improvement without having a benchmark. The digitization of information systems, in itself, drives a standardization of processes, and AI in this context has the potential to fit-in very interestingly from the point of view of management in terms of process control. This is due to the fact that the ability to control a certain process or activity is considered a basic requirement for quality assurance of it. In addition to the above-mentioned points, it is important to cite the great development that has been achieved in recent times in the area of unstructured data and in conditions characterized by intrinsic uncertainty (as seen in Chapter 3 in the case of "Fuzzy Logic" and "Rough Set Theory"), enhancing the offer opportunities to broaden the scope of application of IT techniques, even in situations that would otherwise exclusive to human personnel alone, due to both technical and economic constraints. Among the benefits that the latter can bring is, more precisely, the standardization of the processes themselves, laying the foundations necessary to be able to carry out a process of continuous improvement exactly in the situations in which it would benefit most, i.e. complex or high-uncertainty situations, without having to resort to excessive complexification of the systems (making their use and maintenance unfeasible or anti-economic) or over-simplification of the phenomena. On the other hand, AI benefits from the standardization and systematic nature of the processes with which it has to interact and/or be integrated, from the fact that this can grant the quality data, continuous monitoring and training necessary to AI models in order to function properly. There is therefore a condition of synergy between the two technologies, which is undoubtedly a very positive factor for its development and diffusion.

5.2.2) Criticalities and Weaknesses

As a final aspect, it is good to analyze the most problematic aspects in the field and the critical points (Weaknesses-Threats), since no technology is exempt from them and their comprehension is fundamental in order to contain and, subsequently, reduce or even overcome them. The main problem points identified during this work are as follows, and will be discussed in more detail below:

- Need for a structured and integrated organizational architecture and IT systems
- Need for staff adaptation
- Need for process analysis and integration management

Need for a Structured and Integrated Organizational Architecture and IT Systems

First of all, attention must be drawn to the fact that AI is basically a model (or a set of models in the case of more complex applications). As a stylized representation of a real phenomenon aimed at fulfilling a specific purpose [91], each model is intrinsically limited. Therefore, in each of its uses and applications, specific assumptions and limitations must be taken into account when evaluating the results obtained, in order to avoid reaching wrong conclusions. Knowing how to interface and correctly interpret a model, its operativity and its results is fundamental for the users (this aspect is dealt with below in an appropriate section). Furthermore, for every model, no matter whether it is extremely simple or very complex, the “garbage in - garbage out” rule applies: in order to have good output results, it is necessary, though not sufficient, that the input data also be of good quality. To guarantee the latter, an adequate structure of processes and information systems is required, which must be designed and able to provide for the basic necessities to ensure the correct and effective functioning of AI algorithms. In fact, they require continuous monitoring, maintenance and training to ensure alignment between the model and expected performance, and so all of this needs to be provided for, including, perhaps most importantly, the need to collect and prepare a large amount of good-quality data for algorithm training. These three activities are as fundamental as they are time-consuming, complex and expensive. Having a set of well-structured and integrated information systems is a fundamental prerequisite for having a sufficiently solid base of data to allow satisfactory training of the algorithms (which benefit from large masses of differentiated data, allowing, in the case of integration with business intelligence platforms, a more precise image of the modelled elements to be realized and thus provide better decisions). Lastly, a final aspect worth emphasizing from an organizational point of view is the fact that, especially in the case of integration with BI platforms, users of AI systems must be able to have the authority and autonomy to make decisions, exploiting the potential offered, otherwise, if organizational procedures stand in the way of operational ones, the investment in this direction is practically useless and in vain.

Need for Process Analysis and Integration Management

AI, in some aspects, can be seen as a form of automation, and indeed the similarities on closer inspection, at least in many possible applications, are not lacking: it is a matter of developing systems capable of learning and then being able to operate with, at least, partial autonomy of human operators. This means that in this respect, this technology, especially when integrated with Business Intelligence or as support for Supply Chain Management, shares some of the advantages and limitations typical of automation systems. One of these is the fact that, in order to be able to apply it successfully, it is essential to first carry out a process analysis. Since many companies are still in the process of implementing their information systems, a smart move could be to use the effort put into this transition to study a set-up that already takes into account future development and implementation, not only from a process analysis point of view, but also from a strategy, business model and offer portfolio perspective (see the Rolls Royce case discussed above: it aligns with the trend of "Servitization of the offer" previously cited) so as to optimize the value that can be obtained and avoid getting stuck in a situation of sub-optimization. This aspect can also be appreciated from the case studies analyzed in the previous chapter (Chapter 4), where the most successful example of the application of AI occurred precisely in the situation in which one did not simply attempt to apply this technology to an "as-is" process, but first carried out an analysis and partial adaptation designed precisely in view of the characteristics, needs and purposes of the AI model one wanted to apply. Obviously, we do not pretend here to make definitive judgements, and indeed in-depth studies on the subject would be needed (should it be possible in the future to find a greater availability of sufficiently complete cases to guarantee a more reliable judgement), but we nevertheless consider this conclusion here to be reasonable, at least as far as we have been able to learn during the drafting of this work. For this reasons, it can be said that this aspect, which is easy to underestimate, is potentially one of the elements that can then make the difference between the success and failure of an application.

Need for Staff Adaptation

Any technology that is inserted into a work context, in order to function at its best, cannot just be an addition alongside processes, but must be an integral part of them, possibly re-thinking and readjusting the roles and processes themselves to achieve the greatest possible improvement. This case is no exception, and this aspect has already been analyzed in the previous section, but due attention must also be paid to the other half of the matter: the human personnel. The latter, in this perspective, will have to be adapted in terms of training, responsibilities and roles for the purpose of integration. Indeed, it has already been mentioned in one of the previous points that organizational structure and procedures must not nullify the advantages that the potential of AI models applied to business intelligence in supply chain management can bring. Not being able to exploit the advantages means incurring unnecessary costs and effort, which is why it is important that staff have at disposal the necessary tools to be able to interface correctly with these systems and being able to interpret their behaviors and results. Furthermore, their roles and tasks must allow them to act and make decisions independently, thus possessing both the professional tools and skills as well as authority and responsibility. This requires investment and effort at the human level as well and not only at the technological level, or else the latter may not pay off. In the immediately preceding section, we saw how artificial intelligence models have many aspects in common with the concept of automation. But the term "automation" does not mean necessarily "autonomy", and in fact usually this last aspect is deliberately excluded and the case of AI is, at least in the short-medium term, no exception, as the responsibility for decisions remains exclusively human. From this perspective it is possible to appreciate how the integration of AI, also and above all in the BI sphere, is indeed capable of bringing great benefits, but in order to achieve them, there are many precautions to be taken. In fact, like many “disruptive innovations” [159], it entails a radical and extensive change, which is not limited to a single aspect, in this case the technological one, but extends to all aspects of an organization and its functioning. And in fact it is not surprising that the aspects considered as priorities in the near future by companies are precisely those that concern organizational procedures and structural aspects, such as “Data Governance”, “Data quality Management” and “Data culture and literacy”, so aspects more focused and strictly related to the human resources’ field of interest.

5.3) Final Remarks

In conclusion, it can be said that the integration of artificial intelligence in the corporate environment, and in particular in business intelligence, is not only feasible but appears to be a natural evolution of these same systems. There are real possibilities of benefits that can improve its functioning, although, from a business and application point of view, it seems that the current situation is only still at an early stage, since most organizations, especially outside the "Tech" sector and those working in the information sector (such as Google, Meta or Microsoft), large companies with large high-value projects (see for instance General Electric, mentioned earlier in the text) and IT system and platform providers (e.g. Amazon or SAP), are still having to focus their efforts on fundamental prerequisites such as the digitization of their processes. The situation is particularly backward in the case of smaller companies. And yet the efforts and interest in the matter is growing, so it can be said that the world is moving in that direction. It is important to emphasize that no claim is made here to be exhaustive or to make definitive judgments. On the contrary, it is always good to bear in mind the fact that, since the development of these technologies takes place in a rapid and turbulent manner, one can expect that new potentials and benefits, but also threats, may arise in the near future.

At the moment, the major concerns, even among the general public, are mainly directed in two directions. The first concerns the social implications, and in particular the effect they may have on employment. In fact, the case of SAP was mentioned earlier, where the CEO announced that the adoption of AI systems integrated with internal processes is expected to reduce the need for employees by about 8,000 units. Another recent example is the protests triggered in Hollywood by artists, writers and professionals employed in the film industry who saw themselves threatened by the advent of AI, which could greatly reduce the need for human resources required for (mainly, but not limited to) script writing, development of special effects, images, animated films, music and soundtracks, and much more. The risk of a social crisis is therefore real and concrete, and many world institutions are currently working to develop countermeasures and regulations to limitate the damages that a free-of-control approach could almost certainly lead to.

A second important social aspect that should be explored is the aspect of information. Generative artificial intelligences are rapidly improving on the one hand in creating from scratch videos of real people in which they make videos or actions that never happened in reality but are extremely verisimilar, and on the other hand in generating fictitious information that is credible enough to deceive the public (the phenomenon of “fake news”) or the use of “bot accounts” or “bots”, which are accounts in social media that don’t respond each to an actual real user but programmed to act autonomously. With a reasoned and planned approach, this technique is capable of altering, favorably or unfavorably, the perceptions of the real audience on a given topic by acting on the content of comments generated, posts published and other interaction that can be programmed to be realized. The latter phenomenon has the potential to further worsen with the advent of AI, since, compared to the past, it is possible to automate further the activity of such a profile, from the automatic generation of posts and comments to its interactions: “likes”, tags to follow and target and shares are all interactions that social media’s algorithm counts to determine the visibility to assign to posts and profiles. By doing this on a large scale, it is possible to alter the perception of certain dynamics to real users, and, in case they are programmed to spread fake news and/or for propaganda purposes, they have the potential to make everything appear so credible as to make it practically indistinguishable from reality. This aspect seems irrelevant and secondary, yet in an interconnected and digitalized World such as ours, this really has the potential to influence huge masses of people. This is far from fiction, on the contrary it has been proved feasible and possible as the case of Cambridge Analytica has already proved, and is destined to be repeated in an increasingly pervasive manner and with growing magnitude if a way to counter such phenomena won’t be found. Currently, many companies are making a real “arms race”, as it is reasonable to think that whoever first manages to develop a sufficiently strong AI and implement it effectively will have a technology with “disruptive” potential both in terms of technological innovation and market revolution in the palm of their hands. At the moment, the favorite companies are OpenAI (Microsoft), Meta, Google, xAI and Apple, but many wonder whether it would be problematic to leave a technology with such expected potential in the hands of private companies, or at least if it is not the case to develop a worldwide regulation law capable of putting limitations and restrictions to protect workers and consumers.

Finally, there is one last aspect, namely an ethical-philosophical issue, which concerns a specific sub-category of artificial intelligence: strong AI or “General Artificial Intelligence”. Unlike the models analyzed in this paper, which are designed to perform a specific function or a circumscribed set of tasks, strong AI is capable of autonomously learning and understanding every task (of an intellectual nature) that a human being can learn [159] [160]. Furthermore, such an artificial intelligence should be sentient and self-aware. However, it is still a matter of debate whether self-awareness is necessary for the achievement of every human task, whether it is a consequence of it, or whether it is even possible to realize a self-aware artificial intelligence at all. In fact, many scholars seem skeptical about this possibility, for example the philosopher John Searle, who, using the metaphor of the "Chinese Room", argues that syntax (i.e. knowing how to process and execute a set of instructions) is not a sufficient condition for semantics (which would require intentionality), stating that *"(...) no purely formal model will ever be sufficient in itself for intentionality, because formal properties are not in themselves constitutive of intentionality, and they do not in themselves have causal powers (...)*" as well as the fact that "*(...) Unless one believes that the mind is separable from the brain both conceptually and empirically, dualism in a strong form, one cannot hope to reproduce the mental by writing and executing programs, since programs must be independent of brains (...)"* [161]. On the contrary, there are many who argue that it is, on the contrary, possible, and indeed a survey carried out in 2020 reported 72 active research and development projects for strong AI in 37 different countries around the world [162]. And yet, at the moment, the situation is at a standstill, as no one has managed to formally prove beyond reasonable doubt the impossibility of the existence of sentient AI, and neither vice versa. At this point, three questions arise. The first one concerns how detect if we deal with a sentient entity or with a system that is simply simulating self-awareness. Secondly, humanity needs to understand how we, as a species, should behave towards a strong AI, whether and how much we can trust it, and what rights for humans must be guaranteed. Lastly, it is reasonable to ask whether we would be able to truly understand such an entity. It must be taken into consideration that our thinking is also shaped, in part, by our experience of physical and biological life; we are dynamic systems that interact with the world with certain paradigms that influence our thinking capability, and since nobody is an isolated system, there is a mutual exchange and influence through the boundary of consciousness. Imagining a self-conscious AI that shares the same "thought patterns" with us is superficial, as such an entity will have a completely different experience of the world with completely different input, elaborated through schemes and patterns completely different from us or with a different "a priori" form. This, on the one hand, would be an invaluable opportunity for new insights and perspectives, but on the other hand, it could further complicate interaction, understanding and mutual coexistence. But for the moment, all we can do is to wait and see what the future holds.

Bibliography and References:

[1] Bai, Chunguang; Dallasega, Patrick; Orzes, Guido; Sarkis, Joseph. "Industry 4.0 technologies assessment: A sustainability perspective". *International Journal of Production Economics*. November, 2020.

[2] Mike Moore, Mike. "What is Industry 4.0? Everything you need to know". *TechRadar*. November, 2019.

[3] "Qlik-Top 10 Transformative Analytics Scenarios in Manufacturing", 2019.

[4] "Top 10 Predictions for Global Manufacturing in 2018: IDC," Industry Week, December 19, 2017.

[5] "Data and Analytics Use Cases for Midsize Enterprises", Gardner Research.

[6] "Data, BI and Analytics Trend Monitor", BARC Research Study. 2023.

[7]"Data Integration Report" Gartner Magic Quadrant™ for Data Integration Tools. 2022.
"5 Key Actions for IT Leaders for Effective Decision Making", Gardner Research.

[8] "5 critical components for successful data governance", Snowflake inc., 2022

[9] Nigel Slack, Michael Lewis. "Operations Strategy". 2002. Harlow, FT, Prentice Hall. ISBN 0273637819

[10] Foster Provost e Tom Fawcett, Data Science and its Relationship to Big Data and Data-Driven Decision Making, in Big Data, vol. 1, n. 1, 13 febbraio 2013, pp. 51–59, DOI:10.1089/big.2013.1508

[11] Vasant Dhar, Data Science and Prediction, in Commun. ACM, vol. 56, n. 12, dicembre 2013, pp. 64–73, DOI:10.1145/2500499.

[12] Cameron McKenzie, Embedded Business Intelligence (Embedded BI), Tech Target, February 2021.

[13] "What is Big Data?". spotlessdata.com. Arc hived from the original on 2017-02-17. Retrieved 2017-04-30.

[14] Patil, Preeti S.; Srikantha Rao; Suryakant B. Patil. "Optimization of Data Warehousing System: Simplification in Reporting and Analysis". IJCA Proceedings on International Conference and Workshop on Emerging Trends in Technology (ICWET). Foundation of Computer Science. 9 (6): 33–37.

[15] A. Bauer, H. Günzel: Data warehouse systems - architecture, development, application. dpunkt, 2013, ISBN 978-3-89864-785-4 .

[16] W. Lehner: Database technology for data warehouse systems, concepts and methods. dpunkt, 2002, ISBN 3-89864-177-5 .

[17] Dixon, J. Pentaho, Hadoop, and Data Lakes. 2010. Available online: https://jamesdixon.wordpress.com/2010/10/14/pentahohadoop-and-data-lakes/ (accessed on 27 October 2022).

[18] Alrehamy, H.; Walker, C. Personal Data Lake with Data Gravity Pull. In Proceedings of the IEEE Fifth International Conference on Big Data and Cloud Computing 2015, Beijing, China, 26–28 August 2015. [CrossRef].

[19] Nambiar, A.; Mundra, D. "An Overview of Data Warehouse and Data Lake in Modern Enterprise Data Management". Big Data Cogn. Comput 2022, 6, 132. https://doi.org/10.3390/bdcc6040132 .

[20] "Data Fabric Architecture is Key to Modernizing Data Management and Data Integration" Gartner. 11 May 2021

[21] Paul C. Tinnirello (1999). Systems Development Handbook. CRC Press. ISBN 0-8493-9822-3.

[22] CREATE VIEW (Transact-SQL) in SQL Server 2008 Books Online, Microsoft Corporation

[23] Tableau, Introducing Augmented Analytics, 2022.

[24] Qlik, "Introduction to AutoML", 2023.

[25] S. Gregor, M. Martin, W. Fernandez, S. Stern, M. Vitale, "The transformational dimension in the realization of business value from information technology", The Journal of Strategic Information Systems, 15 (3) (2006), pp. 249-270

[26] Sandra Vandermerwe & Juan Rada: Servitization of business: Adding value by adding services , European Management Journal, Volume 6, Issue 4, Winter 1988, Pages 314- 324.

[27] University of Magdeburg: An Introduction to Servitization - A Business Model Innovation for Manufacturing Companies, October 2014.

[28] Gawer, Annabelle (2010). Platforms, Markets and Innovation. Edward Elgar Publishing, chapter 2. ISBN 978-1-84844-070-8.

[29] PWC future insight, "The future of industries: Bringing down the walls", 2016.

[30] Industry 4.0 future project . Federal Ministry of Education and Research, retrieved on April 29, 2014.

[31] Gesellschaft für Informatik (GI): Digital Twin. February 15, 2018, retrieved February 17, 2018 .

[32] Dedić N. & Stanier C. (2016). "Measuring the Success of Changes to Existing Business Intelligence Solutions to Improve Business Intelligence Reporting" (PDF). *Measuring the Success of Changes to Existing Business Intelligence Solutions to Improve Business Intelligence Reporting. Lecture Notes in Business Information Processing*. Lecture Notes in Business Information Processing. Vol. 268. Springer International Publishing. pp. 225–236. doi:10.1007/978-3-319-49944-4_17. ISBN 978-3-319-49943-7. S2CID 30910248

[33] Miller Devens, Richard (1865). *Cyclopaedia of Commercial and Business Anecdotes; Comprising Interesting Reminiscences and Facts, Remarkable Traits and Humors of Merchants, Traders, Bankers Etc. in All Ages and Countries*. D. Appleton and company. p. 210. Retrieved 15 February 2014. business intelligence.

[34] Luhn, H. P. (1958). "A Business Intelligence System" (PDF). IBM Journal of Research and Development. 2 (4): 314–319. doi:10.1147/rd.24.0314. Archived from the original (PDF) on 13 September

[35] Ong, In Lih, Pei Hwa Siew, and Siew Fan Wong. "A five-layered business intelligence architecture". Communications of the IBIMA 2011 (2011): 1-11.

[36] F.W. Taylor, L'organizzazione scientifica del lavoro, Comunità, Milano, 1952.

[37] H. Fayol, "Administration industrielle et generale", 1916. (Translation: " Direzione industriale e generale" Angeli, Milano, 1961).

[38] F. Besta. "La ragioneria", Vol. 1. 1909. *Vallardi*, Milano.

[39] A.M. Arcari. "Programmazione e Controllo". 2014.

[40] Paola Ciambotti, "L'evoluzione dei sistemi di controllo e del ruolo del controller. Indagine sulle imprese marchigiane", 2019, cap. 3.

[41] F. Amigoni. "La controllership: rischi e opportunità, in "Economia &Management", Vol. 12, 1990, p.73.

[42] McDaniel, Lawrence J. Gitman, Carl. "The future of business: the essentials". 2009, (4th, student ed.). Mason, OH: South-Western Cengage Learning. p. 182. ISBN 978-0324590753.

[43] Kotler/Bliemel: Marketing Management , Schäffer-Poeschel Verlag, 1998, ISBN 3-7910-0882-X

[44] Injazz J. Chen, Antony Paulraj. "Towards a theory of supply chain management: the constructs and measurements". *Journal of Operations Management.* Vol. 22, No. 2, 2004.

[45] David Simchi-Levi, Philip Kaminsky, Edith Simchi-Levi. "Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies". 3. Edition. Boston 2008.

[46] Nigel Slack, Alistair Brandon-Jones, Pamela Danese, Pietro Romano, Andrea Vinelli. “Gestione delle Operations e dei Processi”. 2019, (quinta edizione). Milan: Pearson Education. ISBN 9788891910974 .

[47] A. Bhimani, A. Caglio, A. Ditillo, M. Morelli. “Performance management”. 2010. Egea, Milano.

[48] R.S. Kaplan, D.P. Norton. “The strategy Focused Organization. How Balanced Scorecard Companies Thrive in the New Business Environment”. 2001. Harvard Business School Press.

[49] Harreld, Heather. “Extended ERP technology reborn in B2B”. 2001. *Computerworld*, InfoWorld.

[50] “Cosa significa ERP?” 1C Italia Software gestionale. 1c-erp.it, 3 agosto 2020.

[51] Bardicchia, Marco. “Digital CRM: Strategies and Emerging Trends: Building Customer Relationship in the Digital Era”. 2020. *Amazon Digital Services LLC*, KDP Print US. ISBN 979-8-6455-7480-2.

[52] “Come scegliere un software MES: 3 fattori fondamentali”. 2018. DM Solution.

[53] *OECD Glossary of Statistical Terms*. OECD. 2008. p. 119. ISBN 978-92-64-025561.

[54] "Statistical Language - What are Data?". Australian Bureau of Statistics. 2013-07-13. Archived from the original on 2019-04-19. Retrieved 2020-03-09.

[55] Zins, Chaim. “Conceptual approaches for defining data, information, and knowledge”. *Journal of the American society for information science and technology*. 2007. 58.4: 479-493, 480.

[56] Bolisani, Ettore. “Gestione dell’informazione aziendale”, IN02103638. Handouts, slides and notes from the lessons. 2021.

[57] “Introduction to queries”. www.support.microsoft.com. 2023.

[58] “Tipologie di query”. syrusindustry.com. 2023.

[59] MAG Metadati Amministrativi e Gestionali. iccu.sbn.it. 28 marzo 2022.

[60] Roland Gabriel, Alexander Pastwa, Peter Gluchowski. „*Data Warehouse & Data Mining*”. 2009. W3l.

[61] Thomsen, Erik. “OLAP solutions: building multidimensional information systems”. 2002. John Wiley & Sons.

[62] Cuzzocrea, Alfredo. Saccà, Domenico. Ullman, D.; Jeffrey. “Big data: a research agenda” IDEAS '13: Proceedings of the 17th International Database Engineering & Applications Symposium. October, 2013. 198-203.

[63] AL-Jumaili, A.H.A.Muniyandi, R.C. Hasan, M.K. Paw, J.K.S. Singh, M.J. “Big Data Analytics Using Cloud Computing Based Frameworks for Power Management Systems: Status, Constraints, and Future Recommendations”. Sensors 2023, 23, 2952. https://doi.org/10.3390/s23062952 .

[64] Xiong, Z. Xu, K. “Lightweight job submission and file sharing schemes for a teaching ecosystem for parallel computing courses”. J. Ambient Intell. Humaniz. Comput. 2020.

[65] Badger, L. Patt-corner, R. Voas, J. “Cloud Computing Synopsis and Recommendations”. 2012. *Recommendations of the National Institute of Standards and Technology*. Nist Spec. Publ. 800, 81.

[66] Xu, X. Cao, L. Wang, X. “Adaptive Task Scheduling Strategy Based on Dynamic Workload Adjustment for Heterogeneous Hadoop Clusters”. 2016. IEEE Syst. J., 10, 471–482.

[67] Guo, Y. Rao, J. Jiang, C. Zhou, X. “Moving Hadoop into the Cloud with Flexible Slot Management and Speculative Execution. IEEE Trans. Parallel Distribution”. 2017. Syst., 28, 798–812.

[68] Zaharia, M. Chowdhury, M. Das, T.; Dave, A. Ma, J. McCauley, M. Franklin, M.J. Shenker, S. Stoica, I. “Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing”. 2012. *In*

Proceedings of the 9th Symposium on Networked Systems Design and Implementation. San Jose, CA, USA, 25–27. pp. 15–28

[69] Gopalani, S. Arora, R. "Comparing Apache Spark and Map Reduce with Performance Analysis using K-Means". 2015. Int. J. Comput. Appl. 113, 8–11.

[70] Tan, J. Meng, S. Meng, X. Zhang, L. "Improving ReduceTask data locality for sequential MapReduce jobs. In Proceedings of the IEEE". 2013. INFOCOM, Turin, Italy, 14–19. pp. 1627–1635.

[71] O'Leary, D. E. "Embedding AI and Crowdsourcing in the Big Data Lake". 2014. IEEE Intelligent Systems, 29(5):70–73.

[72] R. Hai, C. Koutras, C. Quix and M. Jarke. "Data Lakes: A Survey of Functions and Systems". in *IEEE Transactions on Knowledge and Data Engineering*, doi: 10.1109/TKDE.2023.3270101

[73] I. Gartner. Gartner Says Beware of the Data Lake Fallacy. https: //www.gartner.com/newsroom/id/2809117, 2014.

[74] "The growing importance of big data quality". The Data Roundtable. 21 November 2016. Retrieved 1 June 2020.

[75] B. Stein. A. Morrison. "The enterprise data lake: Better integration and deeper analytics". PwC Technology Forecast: Rethinking integration, 1(1-9):18, 2014.

[76] M. e. a. Wilkonson. "Commentary: The FAIR Guiding Principles for scientific data management and stewardship". 2016. NATURE Scientific Data, 3(160018).

[77] R. Hai, C. Koutras, C. Quix and M. Jarke, "Data Lakes: A Survey of Functions and Systems". 2023. *IEEE Transactions on Knowledge and Data Engineering*, doi: 10.1109/TKDE.2023.3270101/

[78] Manning, Christopher. "Artificial Intelligence Definitions". Human centered Artificial Intelligence (HAI), Standford University. 2020.

[79] Gardner Glossary. https://www.gartner.com/en/information-technology/glossary/artificial-intelligence . 2023.

[80] Van Duin, Stefan. Bakhshi, Naser. "Part 1: Artificial Intelligence Defined". *Deloitte*. 2017. https://www2.deloitte.com/se/sv/pages/technology/articles/part1-artificial-intelligence-defined.html .

[81] "Preparing for the Future of Artificial Intelligence". 2016. National archives, NSTC.

[82] Raphael, B. "The thinking computer". 1976. W.H. Freeman. San Francisco, CA.

[83] http://www-formal.stanford.edu/jmc/whatisai/node1.html.§

[84] Sestino, Andrea & De Mauro, Andrea. "Leveraging Artificial Intelligence in Business: Implications, Applications and Methods". 2021. *Technology Analysis and Strategic Management*. 34. 1-14. 10.1080/09537325.2021.1883583.

[85] Rock, Daniel. "Engineering value: The returns to technological talent and investments in artificial intelligence". 2019. *Available at SSRN 3427412* .

[86] "What is artificial intelligence". IBM. https://www.ibm.com/topics/artificial-intelligence#:~:text=At%20its%20simplest%20form%2C%20artificial,in%20conjunction%20with%20artificial%20intelligence. 2023.

[87] De Mauro, Andrea. "Big Data Analytics: Analizzare e interpretare dati con il machine learning". 2019. Apogeo Editore.

[88] Arthur L. Samuel, "Some studies in machine learning using the game of checkers". *IBM Journal of research and development*, 1959.

[89] Mitchell, M, Tom. “Machine Learning”. *McGraw Hill*. p. 2. 1997. ISBN 0-07-042807-7.

[90] Casella, George. Berger, Roger L. “Statistical Inference”. (2nd ed.). 2002. Duxbury. p. 290. ISBN 0-534-24312-6.

[91] Lucchetta, Giovanni. “Sistemi Integrati di Produzione”. IN04107628. Slides, handouts and lecture notes. Università degli studi di Padova, Corso di Laurea Magistrale in Ingegeria Gestionale, A.A. 2022/2023.

[92] Kaelbling, Leslie P.; Littman, Michael L.; Moore, Andrew W. (1996). "Reinforcement Learning: A Survey". *Journal of Artificial Intelligence Research*. 4: 237–285. arXiv:cs/9605103. doi:10.1613/jair.301. S2CID 1708582. Archived from the original on 2001-11-20.

[93] Delua, Julianna. “Supervised vs. Unsupervised Learning: What’s the Difference?”. *IBM*. (2022). https://www.ibm.com/blog/supervised-vs-unsupervised-learning/ .

[94] Hokey, Min. “Artificial intelligence in supply chain management: theory and applications”. *International Journal of Logistics: Research and Applications*. 13:1, 13-39. 2010. DOI: 10.1080/13675560902736537 .

[95] Krogh, A. “What are artificial neural networks?”. *Nat Biotechnol* 26, 195–197. (2008). https://doi.org/10.1038/nbt1386 .

[96] “Understanding the Algorithm for Gradient Descent: A Deep Dive”. *Stanford University*, KeepNotes, 2023. https://keepnotes.com/stanford-university/machine-learning/319-gradient-descent-intuition .

[97] Bottou, Léon. Bousquet, Olivier. “The Tradeoffs of Large Scale Learning”. In Sra, Suvrit; Nowozin, Sebastian; Wright, Stephen J. (eds.). *Optimization for Machine Learning*. Cambridge: MIT Press, 2012. pp. 351–368. ISBN 978-0-262-01646-9

[98] A. H. Land and A. G. Doig (1960). "An automatic method of solving discrete programming problems". *Econometrica*. 1960. 28 (3): 497–520. doi:10.2307/1910129. JSTOR 1910129 .

[99] “What is Simulated Annealing?". *www.cs.cmu.edu*. Retrieved 2023-05-13.

[100] Studer, Matthias; Ritschard, Gilbert; Gabadinho, Alexis; Müller, Nicolas S. (2011). "Discrepancy Analysis of State Sequences". *Sociological Methods & Research*. 40 (3): 471–510. doi:10.1177/0049124111415372. ISSN 0049-1241. S2CID 13307797.

[101] Rokach, L.; Maimon, O. (2005). “Top-down induction of decision trees classifiers-a survey”. IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews. 35 (4): 476–487. CiteSeerX 10.1.1.458.7031. doi:10.1109/TSMCC.2004.843247. S2CID 14808716 .

[102] Stehman, Stephen V. (1997). "Selecting and interpreting measures of thematic classification accuracy". Remote Sensing of Environment. 62 (1): 77–89. Bibcode:1997RSEnv..62...77S. doi:10.1016/S0034-4257(97)00083-7 .

[103] "Growing Decision Trees". MathWorks. MathWorks.

[104] Witten, Ian; Frank, Eibe; Hall, Mark (2011). Data Mining. Burlington, MA: Morgan Kaufmann. pp. 102–103. ISBN 978-0-12-374856-0.

[105] Breiman, Leo; Friedman, J. H.; Olshen, R. A.; Stone, C. J. (1984). Classification and regression trees. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software. ISBN 978-0-412-04841-8 .

[106] Larose, Daniel T.; Larose, Chantal D. (2014). Discovering knowledge in data: an introduction to data mining. Hoboken, NJ: John Wiley & Sons, Inc. ISBN 9781118874059

[107] “What is random forest?”. IBM. https://www.ibm.com/topics/random-forest#:~:text=Random%20forest%20is%20a%20commonly,both%20classification%20and%20regression%20problems

[108] Pawlak, Zdzislaw, Lech Polkowski, and Andrzej Skowron. "Rough set theory." *KI* 15.3 (2001): 38-39.

[109] Allen, Mary Kathryn. *The development of an artificial intelligence system for inventory management using multiple experts*. The Ohio State University, 1986.

[110] Sullivan, Gerald, and Kenneth Fordyce. "IBM Burlington's logistics management system." *Interfaces* 20.1 (1990): 43-64.

[111] Findler, Nicholas V., Cher Lo, and Ron Lo. "Pattern search for optimization." *Mathematics and computers in simulation* 29.1 (1987): 41-50.

[112] Jefferies, Margaret & Yeap, Wai-Kiang. "Robotics and Cognitive Approaches to Spatial Mapping". 2008. 10.1007/978-3-540-75388-9.

[113] DeLurgio, Stephen A. "Forecasting principles and applications." *(No Title)* (1998).

[114] Zha, X. F., S. Y. E. Lim, and S. C. Fok. "Development of expert system for concurrent product design and planning for assembly." *The International Journal of Advanced Manufacturing Technology* 15 (1999): 153-162.

[115] Sun, C. K., Uraikul, V., Chan, C. W., & Tontiwachwuthikul, P. (2000). An integrated expert system/operations research approach for the optimization of natural gas pipeline operations. *Engineering Applications of Artificial Intelligence*, *13*(4), 465-475.

[116] Kwong, Chun Kit, W. H. Ip, and J. W. K. Chan. "Combining scoring method and fuzzy expert systems approach to supplier assessment: a case study." *Integrated manufacturing systems* 13.7 (2002): 512-519.

[117] Yan, Jianyuan, Peggy E. Chaudhry, and Sohail S. Chaudhry. "A model of a decision support system based on case-based reasoning for third-party logistics evaluation." *Expert systems* 20.4 (2003): 196-207.

[118] Chow, Harry KH, et al. "Design of a knowledge-based logistics strategy system." *Expert Systems with Applications* 29.2 (2005): 272-290.

[119] Lawrynowicz, Anna. "Production planning and control with outsourcing using artificial intelligence." *International Journal of Services and Operations Management* 3.2 (2007): 193-209.

[120] Charles Elkan, The paradoxical success of fuzzy logic, in IEEE Expert, vol. 9, n. 4, 1994, pp. 3–49, DOI:10.1109/64.336150.

[121] Cortes, Corinna; Vapnik, Vladimir (1995). "Support-vector networks" (PDF). Machine Learning. 20 (3): 273–297. CiteSeerX 10.1.1.15.9362. doi:10.1007/BF00994018. S2CID 206787478.

[122] Joachims, Thorsten (1998). "Text categorization with Support Vector Machines: Learning with many relevant features". Machine Learning: ECML-98. Lecture Notes in Computer Science. Springer. 1398: 137–142. doi:10.1007/BFb0026683. ISBN 978-3-540-64417-0.

[123] Barghout, Lauren (2015). "Spatial-Taxon Information Granules as Used in Iterative Fuzzy-Decision-Making for Image Segmentation" (PDF). Granular Computing and Decision-Making. Studies in Big Data. Vol. 10. pp. 285–318. doi:10.1007/978-3-319-16829-6_12. ISBN 978-3-319-16828-9. S2CID 4154772.

[124] Maitra, D. S.; Bhattacharya, U.; Parui, S. K. (August 2015). "CNN based common approach to handwritten character recognition of multiple scripts". 2015 13th International Conference on Document Analysis and Recognition (ICDAR). pp. 1021–1025. doi:10.1109/ICDAR.2015.7333916. ISBN 978-1-4799-1805-8. S2CID 25739012.

[125] Cuingnet, Rémi; Rosso, Charlotte; Chupin, Marie; Lehéricy, Stéphane; Dormont, Didier; Benali, Habib; Samson, Yves; Colliot, Olivier (2011). "Spatial regularization of SVM for the detection of diffusion alterations associated with stroke outcome" (PDF). Medical Image Analysis. 15 (5): 729–737. doi:10.1016/j.media.2011.05.007. PMID 21752695.

[126] Hu, J.; Bhowmick, P.; Jang, I.; Arvin, F.; Lanzon, A. “A Decentralized Cluster Formation Containment Framework for Multirobot Systems”. *IEEE Transactions on Robotics*, 2021.

[127] Keskin, Gülşen Aydın, Sevinç İlhan, and Coşkun Özkan. “The Fuzzy ART algorithm: A categorization method for supplier evaluation and selection”. *Expert Systems with Applications* 37.2 (2010): 1235-1240.

[128] Prassl, W. F., J. M. Peden, and K. W. Wong. “A process-knowledge management approach for assessment and mitigation of drilling risks”. *Journal of Petroleum Science and Engineering* 49.3-4 (2005): 142-161.

[129] Dikici, E. Bigelow, M. Prevedello, L. M. White, R. D. Erdal, B. S. “Integrating AI into radiology workflow: levels of research, production, and feedback maturity”. 2020. *Journal of Medical Imaging*, *7*(1), 016502-016502.

[130] Matzka, Stephan. “Explainable artificial intelligence for predictive maintenance applications”. 2020. *Third international conference on artificial intelligence for industries* (ai4i). IEEE.

[131] Leeuwen, Jan van. “Algorithms and complexity”. 1998. *Handbook of Theoretical Computer Science*. Vol. A. Amsterdam: Elsevier. ISBN 0262720140. OCLC 247934368.

[132] Abu Zwaida, Tarek, Chuan Pham, and Yvan Beauregard. “Optimization of inventory management to prevent drug shortages in the hospital supply chain”. 2021. *Applied Sciences* 11.6: 2726.

[133] Biazzo, Stefano. Filippini, Roberto. “Management dell’innovazione”. 2018. ISEDI, ISBN-10: 8880083864.

[134] Xing, Fei, et al. "Driving Innovation with the Application of Industrial AI in the R&D Domain." Distributed, Ambient and Pervasive Interactions: 8th International Conference, DAPI 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings 22. Springer International Publishing, 2020.

[135] Schuh, G. Hicking, J. Stroh, M. F. Benning, J. “Using AI to Facilitate Technology Management–Designing an Automated Technology Radar”. 2020. *Procedia CIRP*, *93*, 419-424.

[136] Ibrahim, W. M. R. W., & Hassan, R. “Recruitment trends in the era of Industry 4.0 using artificial intelligence: pro and cons”. 2019. *Asian Journal of Research in Business and Management*, *1*(1), 16-21.

[137] Guenole, Nigel & Sheri Feinzig. “The business case for AI in HR”. 2018. *With Insights and Tips on Getting Started. Armonk: IBM Smarter Workforce Institute*, IBM Corporation.

[138] Borchert, P., Coussement, K. De Caigny, A. De Weerdt, J. “Extending business failure prediction models with textual website content using deep learning”. 2023. *European Journal of Operational Research*, *306*(1), 348-357.

[139] De Caigny, A. Coussement, K. De Bock, K. W. Lessmann, S. “Incorporating textual information in customer churn prediction models based on a convolutional neural network”. 2020. *International Journal of Forecasting*, *36*(4), 1563-1578.

[140] Lee, Hau L. V. Padmanabhan. Seungjin Whang. “The bullwhip effect in supply chains”. 1997. 93-102.

[141] Gunasekaran, A. “Supply chain management: Theory and applications”. *European Journal of Operational Research*. 2004. 159 (2), 265–268.

[142] Premkumar, G.P. “Interorganization systems and supply chain management: An information processing perspective”. 2000. *Information Systems Management*. 17 (3), 56–69.

[143] Carbonneau, Real. Laframboise, Kevin. Vahidov, Rustam. "Application of machine learning techniques for supply chain demand forecasting." *European journal of operational research* 184.3 (2008): 1140-1154.

[144] Gunasekaran, A. Ngai, E.W.T. “Information systems in supply chain integration and management”. 2004. *European Journal of Operational Research*. 159 (2), 265–527.

[145] Raza, Muhammad Qamar & Abbas, Khosravi. “A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings”. 2015. *Renewable and Sustainable Energy Reviews* 50: 1352-1372.

[146] Amirkolaii, K. N. Baboli, A. Shahzad, M. K. Tonadre, R. “Demand forecasting for irregular demands in business aircraft spare parts supply chains by using artificial intelligence (AI)”. 2017. *IFAC-PapersOnLine*, *50*(1), 15221-15226.

[147] Lucic, P. & Teodorovic, D. “Transportation modeling: an artificial life approach”. 2002. *14th IEEE International Conference on Tools with Artificial Intelligence*. (ICTAI 2002). Proceedings., Washington, DC, USA, 2002, pp. 216-223, doi: 10.1109/TAI.2002.1180807.

[148] Wamba-Taguimdje. S. L., Fosso. Wamba, S. Kala Kamdjoug, J. R. Tchatchouang, Wanko C. “Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects”. 2020. *Business Process Management Journal*, *26*(7), 1893-1924.

[149] Colaço, A. B. Mariani, V. C. Salem, M. R. dos Santos Coelho, L. “Maximizing the thermal performance index applying evolutionary multi-objective optimization approaches for double pipe heat exchanger”. 2022. *Applied Thermal Engineering*, *211*, 118504.

[150] Aditya Shastry, K. Sanjay, H. A. Sushma V. “Machine Learning for Business Analytics: Case Studies and Open Research Problems”. 2018. AI Case Studies. *Artificial Intelligence for Data Science in Theory and Practice*. Ch:3. ISBN 978-3-030-92244-3 .

[151] Faggella, D. “Furniture retailer saves time on customer support with routing and macros”. 2018. AI Case Studies. *Artificial Intelligence for Data Science in Theory and Practice*. ISBN 978-3-030-92244-3 .

[152] Scholz, M., Piller, G., Bock, N., & Böhm, K. (2015). ActOnAir: Data Mining and Forecasting for the Personal Guidance of Asthma Patients. *HPI Future SOC Lab: Proceedings 2015*, 109.

[153] Vermesan, Ovidiu. Bellmann, Ronnie. Bahr, Roy. Martinsen, Jøran. Kristoffersen, Anders. Hjertaker, Torgeir. Breiland, John. Andersen, Karl. Sand, Hans. Lindberg, David. “AI-Based Edge Acquisition, Processing and Analytics for Industrial Food Production”. 2022.10.3233/AISE220033.

[154] Razouk, Houssam & Kern, Roman. “Improving the Consistency of the Failure Mode Effect Analysis (FMEA) Documents in Semiconductor Manufacturing”. 2022. *Applied Sciences*. 12. 1840. 10.3390/app12041840.

[155] Cartledge, Alisa. “Business intelligence trends in 2020”. 2021. https://wiiisdom.com/ebook/business-intelligence-trends-2020 .

[156] Abruzzese, Francesco. “La digitalizzazione della pubblica amministrazione italiana: raffronto con le principali nazioni europee e prospettive future”. (2022).

[157] Palma, Valerio. “Gemelli di città. I modelli urbani digitali tra descrizione e astrazione”. *Politecnico di Torino*. (2021).

[158] Bower, Joseph L., and Clayton M. Christensen. “Disruptive technologies: catching the wave”. (1995).

[159] Hodson, Hal. “DeepMind and Google: the battle to control artificial intelligence”. *1843*. (2019).

[160] Shevlin, Henry. Vold, Karina. Crosby, Matthew. Halina, Marta. “The limits of machine intelligence: Despite progress in machine intelligence, artificial general intelligence is still a major challenge”. *EMBO Reports*, vol. 20, n. 10. 2019)

[161] Searle, John. “The Behavioral and Brain Sciences”. *Minds, Brains and Programs,* vol. 3, (1980).

[162] Seth Baum, Seth. “A Survey of Artificial General Intelligence Projects for Ethics, Risk, and Policy”. *Global Catastrophic Risk Institute Working Paper.* (2020).