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"IMPACT OF IIOT AND LEAN BUNDLES CONFIGURATIONS ON PROACTIVE WORK BEHAVIORS"

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Firma (signature) ……Xhestiana Brahimaj……

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INTRODUCTION

Industry 4.0 and Lean Production (in this work Lean Production/Management/Manufacturing will be used as synonymous to indicate the broad Lean conceptualization), at first stake, could seem contradictory concepts, since the first focuses on the technology dimension and the second on the human dimension. However, a deep understanding of these two paradigms shows many complementaries and potential synergies among them: both Lean Management and Industry 4.0 support the objectives of operational excellence, but they just use different tools to achieve these goals (BCG, 2017). Indeed, Lean implements value stream mapping, single-minute exchange of dies, visual controls, preventive maintenance and so on, while Industry 4.0 applies technologies such as big data analytics, advanced robotics, additive manufacturing, industrial internet, etc. (BCG, 2017).

The term "Industry 4.0'' has been used for the first time in an article published by the German government in 2011, after a discussion about high-tech strategy for 2020. In 2013, the German government focused its strategy for national industry's development on Industry 4.0. Following the German example, many other countries started to develop programs for the technological advancement of their industries.

The term and concept "Lean Production'' is many years older than the one of Industry 4.0, indeed it finds its roots in the book entitled "The machine that changed the world", published for the first time in 1991 by Womack, Jones and Roos. The book characterizes Lean Production as "a system of measures and methods which when taken together have the potential to bring about a lean and therefore particularly competitive state, not only in the manufacturing division, but throughout the entire company'', (Warnecke and Huser, 1995). This system of measures and methods has been pioneered by the "Toyota Manufacturing System", that represents the core of the book. The TPS (Toyota Production system) was different from all other production paradigms across four aspects: product development, chain of supply, shop floor management and after-sales service.

At the beginning of its spread, the Lean Production paradigm became known in the West thanks to its tools, such as kaizen workshops, where frontline workers solve problems, Kanban cards for just-in-time production, Andon cord for stopping the production process every time a problem occurs (McKinsey, 2014). Over the years, however, Lean concepts and principles started to be analyzed deeper, overcoming the simple observation of its tools or techniques.

Lean Production and Industry 4.0, if properly integrated, can reinforce and complement each other: Lean creates efficient and well-defined processes, where advanced technologies can be effectively applied and, on the other side, Industry 4.0 can support companies in the identification of what customers really value, through new technologies and analytical tools.

In the past few years an increasing number of studies have been published about the integration of these two dimensions and their potential repercussions. However, most of them are theoretical studies, not empirical and they focus on the understanding of how Industry 4.0 supports Lean or vice versa, and on identifying the performance implications of an integrated approach.

This present work deviates somewhat from these three clusters, focusing on the impact of IIoT (Industrial Internet of Things) technologies and Lean bundles' configurations on workers' proactivity.

The thesis starts with the introduction of the concept of Industry 4.0, trying to capture its peculiarities and core elements, then, a deep dive investigation is made on its main technologies: Additive Manufacturing (AM), Internet of Things (IoT) and Industrial Internet of Things (IIoT), Cyber Physical Systems (CPS), Data Analytics, Advanced Robotics, Artificial Intelligence (AI) and Machine Learning (ML). This chapter concludes with an overall analysis of the opportunities and challenges of Industry 4.0.

The Second Chapter focuses on exploring the concept of Lean Automation, performing a literature review on the relationship between the Lean dimension, including its practices, principles and tools, and the Industry 4.0 dimension. Regarding this interaction, three strands of thought emerge, namely "Industry 4.0 supports Lean'', "Lean facilitates the implementation of Industry 4.0'', "Performance implications of a Lean - Industry 4.0 integration''.

The first part of the Third Chapter mainly describes the Qualitative Comparative Analysis (QCA) approach, identifying its main characteristics: the set-theoretic configurations and the calibration of set membership, the concepts of consistency and coverage regarding set relations and the use of counterfactual analysis. The second part of the chapter is dedicated to the definition of the outcome (team proactivity) and causal conditions (Industrial Internet of Things, Total Quality Management, Just in Time, Human Resource Management) used for the empirical investigation and to the description of the data calibration and data analysis guiding the fsQCA (fuzzy set Qualitative Comparative Analysis) results.

Finally, in the last chapter the results of the fsQCA are presented and discussed. The analysis shows three main approaches a company can follow for increasing team proactivity: the implementation of Industrial Internet of Things technologies, the adoption of Human Resource Management practices and the joint application of Total Quality Management and Just in Time bundles. In none of these approaches there is a contradiction between the Industry 4.0 technology and the Lean bundles implementation.

Given the above considerations, it may be stated that this thesis studies the relationship between a specific Industry 4.0 technology and three Lean bundles, with a specific focus on team proactivity.

FIRST CHAPTER: INDUSTRY 4.0

1.1 Industry 4.0: concept

The term “Industry 4.0” was coined at the Hannover Fair in Germany in 2011 to indicate the “Fourth Industrial Revolution”, that involves fast and disruptive changes in digital manufacturing, network communication, computer and automation technologies, as well as many other areas (Pereira and Romero, 2017). Industry 4.0 technologies are based on improvements and developments of the technologies characteristic of the Third Industrial Revolution (Soete*,* 2018, p.30). The latter began in the 1960s and is defined as the “computer” or “digital” revolution, whose key factor was the “Internet”, that was conceived as a public infrastructure technology rather than a proprietary one (Hudson, 2017). In turn, the Third Industrial Revolution relied on the electricity and communication systems of the Second Industrial Revolution (late 19th century), which made possible the introduction of the telephone and the advent of Mass Production and which was preceded by the First Industrial Revolution in the 18th century, when was invented the steam engine that allowed the beginning of mechanical production. It is important to underline this succession of interdependencies among the different industrial revolutions because it shows that Industry 4.0 technologies adoption is best suited for systems and contexts with a high technological intensity (Philbeck and Davis, 2018).

The concept of Industry 4.0 has been conceived in many ways since the term was introduced: Pfohl et al. (2015) define it as “the sum of all disruptive innovations derived and implemented in a value chain to address the trends of digitalization, autonomization, transparency, mobility, modularization, network-collaboration and socializing of products and processes” and they identify in these seven trends the characterizing features of Industry 4.0. According to the authors, digitalization is believed to be the most important characterizing feature which enables all the others and it represents “the use of digital data and technology to automate data handling and optimize processes” (Buer et al., 2018). Autonomization refers to the capacity of machines and algorithms to make decisions and perform learning activities autonomously; transparency along the supply chain is increased thanks to the application of Industry 4.0 technologies which allows an easier monitoring of all value chain actors’ activities; the mobility feature indicates the mobility of devices that facilitates information sharing from all over the world; modularization is increased thanks to the application of new technologies.

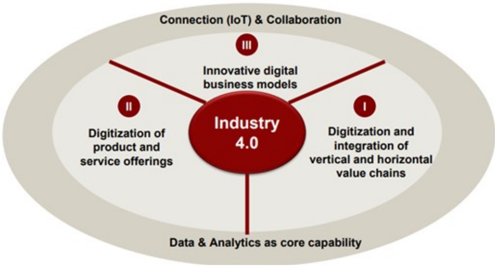
Finally, network-collaboration is enabled by the interactions between machines and people within specific networks inside and outside the company.

Another definition of Industry 4.0 has been provided by Hermann et al., (2015), for whom the concept of Industry 4.0 stems from the concept of Smart Factory: an autonomous manufacturing facility, characterized by the cooperation between virtual and physical systems, a virtual copy of the physical world and a decentralized decision making (Hudson, 2017). The Smart Factory is described also by an increasing cooperation across the supply chain, since production processes are not only integrated with other processes or departments inside the company, but also with suppliers and customers' operations systems (Cagliano et al., 2019).
Lasi et al., (2014) describe Industry 4.0 based on its fundamental concepts: "Smart Factory", "Cyber Physical Systems" and the creation of new systems in product/service development, distribution and procurement.
Regardless the peculiar definition of Industry 4.0, it can be stated that it does not only impact the factory dimension, but the whole supply chain from product development to outbound logistics leading to the optimization of production processes, increase in products' quality, strengthening of relations between all the stakeholders and to the development of new business models and way of operating (Pereira and Romero, 2017). Industry 4.0 can be considered as a new approach that brings together the digital and physical world, that enables the implementation of global supply chains characterized by a network of connections in which data are aggregated in disseminated servers and this means that every information is recorded in the system and stored in the cloud giving access to the whole value chain (Szozda,2017).
So, the Fourth Industrial Revolution, through smart and connected machines and systems, enables cooperation, along the entire value chain, between virtual and physical systems in a flexible way, leading to the absolute customization of products and the creation of new operating models (Schwab, p.12, 2016).
It is important to underline that Industry 4.0 has a broad scope, indeed it differs from previous revolutions because it involves breakthrough innovations in many fields other than manufacturing, like nanotechnology and gene sequencing for example; in this new ecosystem technologies interact with the physical, digital and biological world (Schwab, 2016).
However, the focus of this thesis will be, mainly, on the manufacturing sector.

1.2 Industry 4.0 technologies

Industry 4.0 involves internet and future oriented technologies, smart systems, that enable end-to-end information and communication across the whole supply chain, from inbound logistics to production, marketing, outbound logistics and services (Sanders et al., 2016). Pwc, in a paper entitled "The Industry 4.0 Opportunities", defined Industry 4.0 as a "new business model focused on exploiting opportunities deriving from new technologies" and identified three macro dimensions of exploration: digitization and integration of vertical and horizontal value chains, digitization of product and service offerings and innovative digital business models (*Figure 1*).

Figure 1: Industry 4.0 - explorable dimensions



Source 1: Pwc."Le opportunità Industry 4.0"

The exploitation of the opportunities embedded in these three macro areas will allow the company to reach a more integrated production, a higher level of production control, lower inventory and production costs, real time communication across the company's boundaries, an increased customer satisfaction and flexibility. Ultimately, the application of advanced technologies and the achievement of these results, will lead to the transformation of factories into Smart Factories, characterized by decentralized decision making and real-time data acquisition (Santos et al., 2021). Inside the Smart Factory it is possible to implement a real-time planning of production and a dynamic self-optimization, efficiency and flexibility are increased, as well as productivity and competitiveness in the market (Santos et al., 2021; Sony, 2018). Smart Factories are also indicated with the expression "dark factories" or "unmanned factories" because they do not need human intervention to perform production, that is entirely carried out by robotics systems, so they keep working even when the "lights are shut down" meaning when employees are not working (Oztemel and Gursev, 2020).

In the transformation process towards Smart Factories companies need the support of technologies that represent the core of the Industry 4.0 era.

According to a McKinsey research (2015), four clusters of technologies may be identified:

1. Data, Computational Power and Connectivity: this cluster includes Big Data, Internet of Things, Cloud Technology and is characterized by the ubiquitous use of sensors and actuators that allow for a powerful storage, transmission and processing.
2. Analytics and Intelligence: Artificial Intelligence, Machine Learning, Big Data and advanced statistical techniques enable digitization, automation of knowledge and advanced analytics.
3. Human-Machine Interaction: humans are able to interact in new ways with machines thanks to personal devices, the development of virtual and augmented reality, which

allow also an increase of the physical interaction between machines and humans, since they work together in the same space.

4. Digital-to-Physical conversion: the advances in Additive Manufacturing and Advanced Robotics had led to decreasing costs, the expansion of range of materials, advances in precision and quality.

In the following paragraphs the main technologies included in these four clusters will be investigated deeper to better understand their peculiarities, opportunities and applications.

1.2.1 Additive Manufacturing

Additive Manufacturing leads to the production of physical objects through a layer-by-layer fashion and it is the opposite of subtractive technology, where layers of materials are removed from an initial piece until the desired shape is obtained (Abdulhameed et al., 2019). One of the most important technology of Additive Manufacturing processes is 3D printing and that's why sometimes these two concepts are considered as equivalent: 3D printing is a process that takes a digital representation, which is then converted into a specific digital format and virtually sliced into a set of flat horizontal layers, that represent the instructions for the additive manufacturing machine to produce the object layer by layer, transforming a digital construction into a tangible work piece (Olsen and Tomlin, 2020). However, it should be specified that Additive Manufacturing is a broader concept, that includes different methods, techniques, technologies based on the state of input raw material, that could be solid-based, liquid-based or powder-based (Abdulhameed et al., 2019). 3D printing was initially applicable only to polymers and metals, while now it has moved to a wide range of materials, like glass, biocells, cement and sugar (McKinsey, 2015).

Additive Manufacturing creates many opportunities for companies (Olsen and Tomlin, 2020; Ford and Despeisse, 2016):

- It enables the production of complex shapes and geometries, in small batches, unreachable through the application of traditional manufacturing methods and creates lightweight components, reducing material and energy consumption in use.
- Set-ups are not required when switching between the production of objects with different shapes.
- The development of a new product design is an iterative and additive process, so waste of materials, costs, time and quality issues are reduced, improving time to market and prototyping.

- Additive manufacturing techniques enable “make to order” production, reducing inventory and the risk of unsold products.
- Technologies such as 3D printing enables a higher level of customization and are combined with new information, communication technologies and software (es. CAD).

However, Additive Manufacturing may present some disadvantages too, in terms of high variable costs, due to the high input raw materials cost, higher toxicity of material used for the production that offset the reduction in energy consumption, accuracy issues and limited material options. Moreover, this technology may imply a slower production cycle and, since different materials require different additive manufacturing technologies, there is a limited flexibility and ability to produce multi material products. So, Additive Manufacturing has the potential to make an organization more productive, proactive and responsive, while reducing risks and costs, but it also has some limitations that should be considered when implementing it (Haleem and Javaid, 2019).

Overall, it can be stated that Additive Manufacturing is best suited for markets with high variability, that requires highly customized products with low volumes, demanding fast deliveries and less dispersion of materials, energy and resources and high design complexity and changes. Indeed, additive technologies are highly used in the aerospace industry, to produce a small number of highly complex aircraft components and in this industry the implementation of additive manufacturing has reduced product lead time by up to 30-70% (Abdulhameed et al., 2019).

1.2.2 Internet of Things (IoT)

The Internet of Things (IoT) can be defined as “a collection of physical artifacts that contain embedded systems of electrical, mechanical, computing and communication mechanisms that enable Internet-based communication and data exchange” (Thames and Schaefer, 2017). The term IoT was first introduced in 1999 by Kevin Ashton, one of the founders of Auto-ID Center at MIT and he coined it by imaging a connection between the Internet and the physical world through sensors and platforms based on real-time feedback (Borgia, 2014). According to the Cluster of European Research projects on the Internet of Things, IoT represents a “dynamic global infrastructure with self- capabilities, where physical and virtual “things’’ have identities, use intelligent interfaces and are integrated into the information network’’ (Borgia, 2014).

Over the years, many other definitions have been provided depending, for example, on the kind of organization and the focus underlined, however, regardless of the peculiar characterization, two common elements, that are the concepts of “things’’ and “connectivity” should be underlined.

“Things’’ can be represented by anything that has the ability to store, process, share or exchange data (e.g. physical devices, vehicles, buildings) and, in the context of Industry 4.0, these “things’’ may be conceptualized as “smart’’, since they are embedded with electronics, software, sensors, which attribute them features as computation, data storage, communication and make them able to interact with the environment, integrated in the whole value chain as an active part of the system (Pereira and Romero, 2017; Oztemel and Gursev, 2020).
Connectivity is realized not only inside the factory or the single company, but in the whole supply chain, indeed, through the use of sensors, transmitter or radio frequency identification (RFID) tags, embedded in physical objects, companies have the opportunity to track any item as it moves along the supply chain and this makes remote monitoring one of the biggest applications of IoT (Schwab, 2016; Szozda, 2017; see Chen, 2016). Connectivity among “things’’ is enabled by the interconnection between the embedded sensors and actuators via wired or wireless networks that flow large amounts of data to computers, while physical objects communicate autonomously with each other and are able to “sense’’ the environment (McKinsey,2015).
To better understand the functioning of IoT, it should be briefly analyzed how the physical-digital world interaction takes place on three steps (Borgia, 2014):

1. Collection phase: information is gathered from the physical world, by attaching sensing technologies to devices. In this phase is very important the role of RFID, considered as the foundation technology of IoT, which allows microchips to transmit the identification information to a reader through wireless communication, leading to a richer information gathering (Da Xu et al., 2014).
2. Transmission phase: communication technologies are adopted to transmit the data to the network, so that anyone will be able to get access to the information.
3. Processing, managing and utilization phase: data are processes, analyzed and stored in the cloud or other central processing facilities, that will make decisions based on them and will send instructions to the different objects, enabling them to act intelligently.

IoT technologies allow real-time and remote monitoring of activities, items and machines, having a high impact on different parts of the company such as inventory management, because the application of RFID tags and readers allows high quality and timely inventory records (Olsen and Tomlin, 2020). Moreover, IoT leads to improvements in firm’s productivity and quality, because of the collection of vast amounts of information on productive assets, which impact workers’ performance too, since they gain awareness about the effect of their actions and behaviors and they have the opportunity to make adjustments (Freedman, 2017).IoT technologies also enable accurate and immediate decision making, due to the quality, completeness and timeliness of information, reached through the use of sensor-enabled devices, capable of real-time communication (Olsen and Tomlin, 2020).

Many other benefits can be mentioned in terms of reduction of overall waste and cost, decentralization and digitalization of production, enhancement of services, improvement of efficiency, higher flexibility and proactivity of production systems and vast applications opportunities. Indeed, it is important to underline that IoT applications do not limit to the manufacturing sector, they have an important role in other domains such as transportation and logistics, involving assisted driving and environment monitoring for example; healthcare, where IoT implementation should allow interconnection among heterogeneous objects, sensors and patients and the consequential real-time monitoring; IoT applications enable the creation of smart environment too, technological ecosystem of interconnected devices, which aim at improving people' lives (Atzori et al., 2010; Lampropulos et al., 2019).

IoT leads to many benefits for companies, it has a very broad range of applications, but it presents some challenges and issues as well, such as standardization, since to create an integrated network between different organizations it is necessary to develop some standards and to create a reference architecture (Ozmetel and Gursev, 2020).

Under IoT, machines can communicate with each other (Machine to Machine Communication, often indicated as M2M) and communication is one of the key pillar, but the heterogeneity of communication technologies implies the development of communication protocols able to interface with the different networks and the reliability of communication should always be ensured regardless the technology implemented (Borgia et al.,2014). Other challenges that companies should consider when implementing IoT are connected to data management, information confidentiality, privacy, network architecture, quality of service, lack of employee involvement and scarce leadership.

1.2.3 Industrial Internet of Things (IIoT)

Industrial IoT (IIoT) can be considered as a subset of IoT since they both contain computing and communication technologies (wired and wireless) and are focused on sensor technology, enhancing real-time responses and feasible reactions, leading to a decentralized decision-making. However, the "things'' of IIoT are limited to sensors, actuators, robots, manufacturing devices, automobiles, etc. IIoT technologies aim to connect industrial assets to a cloud over a network to enable autonomous production and real time information to users, customers and other processes, optimizing the overall production value (Boyes et al., 2018).

IIoT solutions provide insights and improve the capability of monitoring and controlling companies' assets and processes, increasing productivity, reducing time to market and unplanned downtime (Lampropoulos et al., 2019). Moreover, IIoT enables fast responses to critical situations thanks to real-time data acquisition and analytics and increases safety and working conditions for workers since dangerous tasks can be performed by devices (Sisinni et al., 2018).

IIoT systems are complex and they present many challenges that can be summarized as follows (Sisinni et al., 2018):

- Energy efficiency issue: many IIoT applications need to work for years with the same batteries and this means that low-power sensors are required, creating a demand for energy-efficient designs.
- Real time performance in dynamic environments: IIoT devices are often deployed in dynamic environments where timing is stringent, so the collection of data and delivery of control decisions should be on time and precise because IIoT technologies have to satisfy end-to-end deadlines of real time sensing and control tasks executed in the system. Moreover, the increasing scale and complexity of IIoT systems has favoured the occurrence of unexpected disturbances, making it more difficult to ensure real time performance.
- Need of coexistence and interoperability: different complex devices have to coexist in the same working environment and to work together, creating a high number of complex interfaces that should be handled in order to make these devices operational.
- Need of interoperability: interoperability has been defined by Sisinni et al. (2018) as "seamless data sharing between machines and other physical systems from different manufacturers''. Interoperability is key for the realization of a fully functional digital ecosystem and the lack of interoperability increases the cost and complexity of IIoT implementation and integration.
- Security and privacy: IIoT devices should be protected against potential physical attacks, data stored have to be encrypted to keep the confidentiality, the communication network among devices has to be secured and the system has to be always available within normal operation. Privacy challenges, instead, regard mainly data collection process and data anonymization process. For data collection it is easier to ensure privacy thanks to the restrictions on the collection and storage of private information, while it is more difficult to ensure privacy for data anonymization because of the diversity of the cryptographic schemes that can be adopted.

1.2.4 Cyber Physical Systems (CPS)

Cyber physical Systems are systems in which the physical space is integrated with the cyberspace: the physical space is monitored and controlled by embedded subsystems via networks with feedback loops, where physical processes affect computations and vice versa (Ashibani and Mahmoud, 2017; Putnik et al., 2019).

In CPS, data is collected from machines, then a cyber twin of each machine is created and it communicates with other machines' cyber twins to acquire knowledge across the network, enabling self-comparison, self-configurability and self-maintainability of the factory (Bagheri et al., 2015). A digital twin has been defined by NASA U.S. Air Force Vehicles as a "an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" and it is characterized by three main components: a physical object in real space, a virtual object in virtual space and data and information connections that converge the physical and virtual systems (Yang et al., 2017, ch.18; see Grieves, 2014).

So, based on the concept of digital twin, real-time data are collected by the physical dimension of the object, communication and sensor technology is employed to update the virtual twin of the physical object in real time, based on the data transmitted to a cyber simulation model, enabling the connection between the cyber and physical space (Yang et al., 2017).

CPS are characterized by a "5C'' architecture -smart connection, data to information conversion, cyber, cognition and configuration-, that covers the process from acquiring data (smart connection) until generating meaningful information and decision-making processes through feedback from the cyber space to the physical space (configuration). This architecture uses computing and communicating technologies (e.g. cloud computing) to provide connectivity between machines (Bagheri et al., 2015). The cyber level is responsible for analyzing all data coming from the physical world, thus acquiring system knowledge, thanks to machine learning technologies, and ultimately for releasing appropriate commands according to this data analysis.

CPS are different from IoT since the latter has no or simple control on the physical world, while the former is able not only to understand it, but to control it too, indeed CPS may be defined as "controllable, credible, scalable network physical equipment which deeply integrates the ability of computing, communication and control on the basis of info acquisition in IoT'' (Liu et al., 2017). While IoT is essentially a communication network connecting "things'', CPS is related to real-time systems that integrate communication and computation capabilities with monitoring and control of entities in the physical world, but it relies on IoT capabilities (Mahmoud and Ashibani, 2017). These two Industry 4.0 technologies have in common a high potential in terms of application domains, from transportation to the development of smart buildings, and in a certain way, CPS are able to perform many functions in manufacturing such as process monitoring, real time machine configuration, integration among different disciplines, and they enable self-behaving and decision making, an easier access to information, preventive maintenance and all these functions, together with many others, lead to improvement of resource utilization and productivity (Oztemel and Gursev,2020).

However, the increased connectivity of the physical and cyber world creates significant security challenges, mainly in terms of confidentiality, integrity, availability and authenticity, so companies need to develop and implement many countermeasures to resolve these issues such as data encryption, robust routing protocols, attack detection mechanism, end to end encryption and many other. CPS are characterized by traffic and storage issues as well, due to the high number of connected devices, so data clustering and analytics methods should be defined, avoiding the risk of delaying manufacturing processes (Mahmoud and Ashibani, 2017).

1.2.5 Data Analytics

The increasing digitalization of everyday life through advanced technologies and smart devices led to the generation of an enormous volume of heterogeneous data, with different volumes, structures, generated from different sources, making data analytics one of the most important technology of Industry 4.0 (Lampropoulos et al., 2019).

Big Data has been defined by The Federal Big Data Commission in 2012 as "a term that describes large volume of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management and analysis of information'' (Moors and Rogiest, 2018).

Volume, variety and velocity are the three main characteristics of big data. Web-based, mobile and sensor-generated data are increasing at huge volumes every minute, indeed in 2021 Statista estimated that in 2025 global data creation is forecasted to grow more than 180 zettabytes in 2025 (1 zettabyte is equal to 10^{21} bytes); variety is referred to the many different forms data assume, from messages, images to readings from sensors, GPS signals and more; velocity is the speed of data creation and it is very important because the collection of real-time data allows a company to become more agile and responsive to market demands (McAfee and Brynjolfsson, 2012). To these "3 Vs'' could be added value and veracity: data are valuable when useful for the business and they should always be true and reliable (Sheng et al., 2017).

Data analytics is a key technology, as previously mentioned, represented by a wide range of tools, techniques, methods, processes that allow to collect, analyze and transform data into valuable insights for the company; hence, the implementation of Data Analytics does not generate one-shot value for organizations, but it ensures the generation of a long-term sustained value (Moors and Rogiest, 2018).

Data Analytics improves company's performance, increases customers and competitors' knowledge and awareness about processes, improves business decision-making, since it enables organizations to make decisions based on real-time solid information, not on assumptions. However, to successfully implement data analytics companies have to overcome some obstacles and more precisely, McAfee and Brynjolfsoon (2012) identified five main challenges:

- Leadership: leaders should be change-oriented, able to understand technology and workforce needs, open to new ideas and with an innovative vision (Moors and Rogiest, 2018).
- Talent management: data is useless if nobody is able to understand and interpret them and to do so it is necessary to have professionals with specific skills and competences able to perform statistical analysis, data segmentation and clustering, create predictive models, thus creating new roles (Chen et al., 2012).
- Technology: to collect, manage, analyze and visualize data is crucial to have proper cyber-infrastructure, new algorithms should be developed to facilitate data analytics processes, to explore and leverage unique data characteristics (Chen et al., 2012).
- Decision-making: the increasing availability of data enables people at different levels of the organization to make decisions, leading to a more decentralized decision-making process and a consequential change in organizational management (Sheng et al., 2017).
- Company culture: every aspect of the organization has to be aligned with a data-driven approach, so not only operations and functions, but culture as well. Culture can be defined as a "pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked enough to be considered valid and be taught to new members'' and to fully benefit from Big Data, it should become more analytical, meaning more data-driven, cross functional, innovative and autonomous (Moors and Rogiest, 2018).

It can be stated that in order to successfully implement big data analytics, data should be reliable, management skills widened, strategic alignment implemented and Data Analytics should not be considered only as a new technology, but as a new way to work for the entire company.

1.2.6 Cloud Computing

The U.S. National institute of Standards and Technology (NIST), in 2011, stated that "Cloud Computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction''. Moreover, the NIST identified five essential characteristics of cloud computing (Mell and Grance, 2011):

1. On-demand self-service: computing resources, such as server time and network storage, are obtained as needed without the need of human interaction with the server provider.
2. Broad network access: resources are available over the network and accessed through standard mechanisms such as mobile phones, tablets, workstations.
3. Resource pooling: resources are pooled to serve multiple customers according to customer demand and the customer does not have an exact idea of the location where the provided resources (processing, storage, memory) are placed.
4. Rapid elasticity: resources are elastically provisioned and released, automatically sometimes, to dynamically face ups and downs of the demand.
5. Measured service: cloud systems automatically control and optimize resources.

Cloud Computing is delivered through different service model architectures such as Software as a Service (SaaS) , where applications are offered through software and are accessible via browser or program interface (e.g., Google Apps such as email and documents); Platform as a Service (PaaS), users can use platforms to build and adopt applications quickly (e.g., Google App Engine); Infrastructure as a Service (IaaS), this platform offers infrastructure services such as database, storage capacity and networking and the user has control over operating model and applications implemented (e.g., Amazon Web Services), (Attaran, 2017).

Cloud Computing differs from traditional IT services, since the latter is characterized by a one-to-one relationship between the vendor and the client, longer duration of contract - that is based on pricing and terms including the use of incentives-, and the outsourced work is specifically customized for the client (Vithayathil, 2017). While, Cloud Computing services are on demand, customers pay only for the services used and for the duration of use, the cloud vendor's defines service attributes to satisfy an aggregate demand, aiming at maximizing its own profit rather than customers' preferences and the vendor is usually external to the company and this external relation doesn't exist with an in-house IT department. In this new scenario, IT departments should evolve, adopting an intermediary role between the cloud vendor and the internal client, to fully capture cloud computing opportunities and to increase value generation (Vithayathil,2017).

Cloud Computing offers many advantages for companies in terms of lower upfront capital investment in software and hardware infrastructure, higher flexibility in increasing available storage, opportunity for dispersed groups of people to meet virtually and share information, delivery of reliable services through data centers, minimizing downtime and loss of productivity (Attaran, 2017).Cloud Computing services are critical for big data, since they allow to store huge amounts of data, they offer mechanisms to access virtual storage and by allocating or deallocating processes they face many issues such as data processing problems and information extraction (Borgia,2014). Cloud Computing disadvantages are mainly represented by reduced security, network vulnerability, undifferentiated cloud services or at least, a lower possibility of customization, agency problem since the cloud vendor is external to the company, business discontinuity (Vithayathil, 2017).

1.2.7 Advanced Robotics

Autonomous production is a key aspect of Industry 4.0 and it is enabled by a new generation of robots, able to perform tasks intelligently, focusing on safety, flexibility, versatility and collaboration, able to access information via the cloud and connect to each other without being programmed anymore (Bahrin et al., 2016). The MIT defined an intelligent robot as a "mechanical creature that can function autonomously'': a robot is constructed (mechanical), it seems to have its own motivation and decision-making processes (creature) and it is able to perceive and act (autonomous functioning), thanks to artificial intelligence and machine learning technologies (Bloem et al., 2014).

This new generation of robotic technologies is deployed alongside human workers, with whom they collaborate and this is the reason why they are called "collaborative robots'' ("cobot") too and why it is important to understand how employees perceive and interact with them (Olsen and Tomlin, 2020).

The adoption of human-robot collaboration is increasing, indeed in 2019 it reached a market share of 4.8% of the total industrial robots installed in the same year with an operational stock of plus 7% in Europe and USA, and these "collaborative robots" were applied in many industries such as automotive, electrical and electronics, metal and machinery, plastic and chemical products, food, for handling, welding and assembling functions primarily, (IFR, 2020).

Advanced Robotics leads to an increasing replacement of less skilled and educated jobs, characterized by routine and repetitive tasks, but, at the same time, it offers to workers the possibility to engage themselves in opportunities where they can use their skills more effectively and it offers learning opportunities too: through training activities employees could upgrade themselves and gain the required skills to work with robots (Vrontis et al., 2021). However, only if employees are able to realise this upgrade, adapting their capabilities to the changes involved by intelligent robots, they will be able to reach and exploit new opportunities.

To fully exploit the potential of new robots and create insightful solutions for companies, robots have to work closely to employees, communicating and learning from them, thus creating human machine interfaces (Vrontis et al., 2021; Bahrin et al., 2016).
The use of Advanced Robotics in industry positively affects four main dimension (Boston Consulting Group, 2019):

- Productivity: robots can work continuously, without never stopping, in dangerous and unfavourable conditions, carrying out things too big or difficult to be carried out by humans (Oztemel and Gursev, 2020). Moreover, advanced robots are easier to set up and reconfigure and able to learn quickly how tasks should be performed.
- Quality: advanced robots can deliver greater reliability and precision.
- Safety: the deployment of advanced robots, able to work in hazardous environments, increases safety for human workers, who are not required anymore to perform dangerous tasks.
- Agility: advanced robots enable the production of diversified and customized products and the redesign of products.

1.2.8 Artificial Intelligence (AI) and Machine Learning (ML)

Artificial Intelligence (AI) has been firstly defined by John McCarthy in the 1990s as "the science and engineering of making intelligent machines, especially intelligent computer programs'' (Cioffi et al., 2020). Artificial intelligence could be described as "computing technologies that simulate or imitate intelligent behaviours relevant to the ones of humans, despite that they act differently from them'', (Vrontis et al., 2021). According to Olsen and Tomlin (2020), industrial AI applications can be categorized into three groups:

1. Descriptive: AI describes an existing state, without necessarily predicting future outcomes or prescribing actions.
2. Predictive: the prediction of future outcomes with a consequential prescription of current actions is enabled by an understanding of the causal- effect relationship between specific phenomena.
3. Prescriptive: operational actions are generated by software.

AI introduces an interaction between humans and technologies, such as robots, creating human-machine interfaces: AI enables machines to complement human interactions, increasing problem solving effectiveness since machines become able to learn in real time, to process information and gain mathematical skills (Vrontis et al., 2021).
On one side, thanks to AI machines can perform many different tasks in a more productive way than humans, increasing the risk of losing jobs for people, while, on the other side, AI offers

many opportunities for employees too: an example can be given by “intelligent agents’’ that are used for training employees and that are able (thanks to AI) to learn in real time and, consequently, to tailor their training to employees’ preferences and external information, reducing the risk of low engagement, (Vrontis et al., 2021).

Machine Learning can be considered as a subfield of AI and it allows computers to use data and statistical techniques, analyzing any variability and clarifying ambiguous patterns, learning how to make good decisions without relying on any model (Olsen and Tomlin,2020).

A program can be defined as a ML program when “its performance on the task, measured by specific performance measures, improves with experience’’ and four types of ML can be identified: supervised learning, unsupervised learning, reinforcement learning and recommender systems, (Das et al., 2015). Supervised learning is based on the comparison between the computed output and expected output, leading to the identification of errors in the computed output and its consequential removal to reach the expected output, while unsupervised learning concentrates on the input pattern, learning on its own through discovering and adopting, enabling the division of data in different clusters. Reinforcement learning focuses on how an agent takes actions in the environment, offering him a reward when the output is correct and a penalty otherwise, while recommender systems are represented by techniques that allow an online user to customize its sites based on customer’s tastes.

In 2018, McKinsey identified some factors that can limit the adoption of AI and ML inside companies such as the need to train people in supervised learning especially, because they should be able to label and categorize the underlying training data, the necessity to have data sets enough large to train algorithms, giving advantage to companies able to obtain higher volume of data. There may also be issues in explaining the results obtained thanks to AI or ML techniques and in generalizing these results, meaning that AI models could have some problems in transferring learning from one set of circumstances to another, forcing companies to invest resources in the development of new models (McKinsey, 2018).

1.3 Opportunities and Challenges

Following the study of Industry 4.0 main technologies, it emerges how this new industrial paradigm implies many changes in companies’ organizational structure and in the way they operate and interact with other players along the supply chain.

As we have already mentioned, the implementation of advanced technologies can be challenging for companies from many points of view, which can be specific to the application of peculiar technologies, but their adoption leads to some specific benefits too. However, it can be worth underlining that there are some cross-technologies opportunities and challenges that derive from the implementation and adoption of Industry 4.0. Based on a literature review, some of these opportunities can be identified in: (1) *Customers' satisfaction,* (2) *Reduction of the time to market*, (3) *Optimization of production processes,* (4) *Increase in production efficiency and productivity.*

Instead, the main challenges are represented by: (1) *Organizational alignment,* (2) *Impact on employees,* (3) *Cybersecurity and* (4) *Management of data.*

1.3.1 Opportunities

One of the primary advantages of Industry 4.0 is represented by the increase in *customers' satisfaction,* in terms of an enhanced capability of companies to meet their expectations. Customers' preferences have deeply changed during the last decade, since they are not anymore looking for anonymous products, but they are increasingly demanding customized products, so companies in order to satisfy these new needs are moving from the Mass Production era to the Mass Customization era and this is enabled by a higher manufacturing flexibility reached through the adoption of disruptive information and communication technologies (e.g. IoT, Machine Learning, Cloud Computing, Big Data).

Another element that favours the customization of products is the opportunity for companies to create a sort of digital representation of the product along its lifecycle (digital thread), facilitating the sharing of information and the cross functional interaction and cooperation among all players involved in the supply chain, customers included (McKinsey, 2015). For example, through the support of big data and artificial intelligence customers are able to adjust product's specifications during the whole product lifecycle from design to testing, becoming co-producers (Li et al., 2017).

Customers' satisfaction is increased also in terms of "experience": consumers do not purchase a product anymore, they pay for the experience involved in the purchase and to enhance such experience is necessary to integrate products and services, further developing pre/after- sales services to generate new value and grow relationships with customers (Tortorella et al., 2021). The increasing need to deliver experiences to customers pushes companies to highly focus on customer service/journey, converting a product-oriented industry into a service-oriented industry, (Li et al., 2017). So, to satisfy customers' needs are emerging different operating models characterized by "customer-centricity", so by putting the client first, and that are strongly data driven. Indeed, hierarchical business models do not fit anymore into the new market conditions, since they represent "slower" operating models, less able to adapt to changes and to afford the level of agility**,** creativity and connectivity characterizing the new competitive environment (Thames and Schaefer, 2017). To remain competitive, companies need flexible, networked, and collaborative models able to adapt to real-time changing business conditions, due to higher market volatility, product complexity and to the creation of global supply chains (Schwab et al., 2016; Cagliano et al., 2019).

Another opportunity provided by modern technologies, such as 3D printing, that enable a rapid experimentation/prototyping of products, is a *reduction of time to market*, because of a faster development process. This enables an increasing company's responsiveness, meaning that the company can reach the market earlier creating additional value through increased revenues (McKinsey, 2015).

The optimization of production processes is reached thanks to the generation, by smart machines and devices, of high volume of data that are recorded and transformed into insights for improving the knowledge of manufacturing processes, for detecting any error or abnormalities, for creating new approaches, such as preventive assets maintenance and digital simulation that reduce the time and costs needed for physical prototypes and tests, pushing a proactive production management (Cimini et al., 2019). In this new scenario, scheduling, control and inventory management occurs in real-time properly supported by information and communication technologies (e.g. IoT and CPS).

Another important benefit represented by Industry 4.0 is the *increase in production efficiency and productivity*: technologies, such as CPS, that allow a broad control on manufacturing enables constant monitoring and proactive maintenance of companies' assets, maximizing their utilization (Schwab, 2016). McKinsey in a report of 2015 shows that big data and advanced analytics technologies can result in a 20/25 % increase in production volume and up to 45 % reduction in downtime. The use of more sophisticated systems and technologies reduces the cost of searching information, information asymmetry, the consumption of physical and human resources, since many repetitive tasks can be performed by machines, leading to an overall increase in production efficiency (Li, Hou and Wu, 2017).

1.3.2 Challenges

One of the main challenges companies have to face in the implementation process of new technologies is the need of *organizational alignment*: organizations need to move from hierarchical structures to flat organization, with a decentralized decision-making power at both team and operator level, while employees have to become multi-tasking and they have to be empowered to exploit the new technologies (Cagliano et al., 2019).

Indeed, a study performed by Cimini et al., (2019) on small medium enterprises demonstrates that organizational changes tend to adapt to technological changes through the introduction of organizational structures characterized by a wider span of control, a reduced number of hierarchical levels and a socio-technical evolution of the human role in the production (see Frank et al.,2019).

Moreover, to succeed in the adoption of new technologies it is necessary to first optimize the processes, to make them lean, clear and managed by people who know them very well, then to design the content of the work and, in the end, to introduce the technology (Furlan, 2018). In fact, technologies must be aligned with the organizational processes, otherwise there's a risk to introduce more complexity and variability in the processes themselves, making them more difficult to manage and control (Furlan, 2018). To be successful, technologies and organizations must co-evolve, so the latter will be able to embrace the new tasks and roles created by the former and to make this co-evolution possible it is crucial to elaborate clear guidelines for addressing the changes under consideration (Cimini et al., 2019).

A critical element for the organizational alignment is represented by *employees*, as already mentioned, because they should be able to adapt to changes implied by the adoption of new technologies and not to resist them. Employees should be trained, provided with standardized instructions for using modern technologies to ensure safety and precision in operations and it is crucial to communicate with them about the objectives of the company's Industry 4.0 project, about their role and their individual potential contribution, so that they will be more aware of what's the goal of the company, of what is going to happen inside the company, and it may increase their direct involvement in the transformation process.

Another important element to positively impact employees is the implementation of a continuous improvement strategy to stimulate agility, engagement, and ability to move into a new kind of organization (Moeuf et al., 2020). Considering the organization at the micro level, the introduction of smart technologies is expected to increase the job breadth and job autonomy of employees, their decision making, due to the higher decentralization within the company, and they are expected to perform more cognitive tasks, as monitor and supervision of machines' functioning, while more repetitive tasks will be performed by machines (Cagliano et al., 2019). The development of new tasks, leads to the necessity of new competences that can be grouped in four categories (Cimini et al.,2019):

- Technical: advanced use of IT devices, data analysis capability, management of computerized control machines.
- Methodological: management and planning abilities, problem-solving, project management.
- Personal: open mind-set, critical thinking, creativity, but especially leadership and ability to transfer knowledge to others.

- Interpersonal: flexibility, task management, self-organization.
- Social: ability to cooperate with others and teamwork, information sharing and networking capabilities

In this new technological environment, employees need to evolve and this evolution may lead, according to Weyer et al. (2015), to the creation of a new operator figure called "augmented operator'': this concept underlines the technological support of the worker, who addresses the knowledge automation in the systems, making them more flexible and adaptive, the variety of tasks he has to perform and his role as a strategic problem solver and decision maker in a context with increasing technological complexity (Koh et al., 2019; Mrugalska and Wyrwicka, 2017). In this scenario, there is the risk of increasing the gap between those who own the labour and those who own the capital (meant in this circumstance as intellectual capital), with an increasing risk of structural unemployment for people who mainly rely on repetitive manual labour, since it will be mainly performed by machines (Li et al., 2017). To deal with this risk, it is fundamental to train and develop people, upgrade employees, ensuring that nobody is "left behind'', so everyone will be able to deal with the new tasks, positively impacting the organization' s performance.

Indeed, a study performed by Tortorella et al., (2018) shows how the enhancement of Employees' Involvement (EI) positively mediates the relationship between Industry 4.0 technologies and operational performance. EI practices aim at "empowering employees to make decisions regarding problem solving at their level of organization'' and they influence employee satisfaction, quality of work life, operational performance outcome, profitability and competitiveness. Practices focused on organization openness, reputation, interpersonal trust and communication, career opportunities and so on, enhance EI on continuous improvement processes and are positively associated with the adoption of Industry 4.0 technologies. So, the availability of proper technology support enables employees to achieve their full potential, to become flexible problem solvers and decision makers and, at the same time, to reinforce the positive effect of Industry 4.0 technologies on operational performance, employees should be empowered and committed throughout their implementation. (Tortorella et al., 2018).

Moving from the organizational alignment and the consequential impact on employees, there are two main other risks connected with the implementation of advanced technologies, namely *cybersecurity* and the *management of data*.

Cybersecurity is one of the main challenges of the Fourth Industrial Revolution due to the increased connectivity that has the potential to enlarge the risk exponentially, especially considering that the IoT is the backbone of Industry 4.0 (Morrar et al., 2017). Cybersecurity is important both for individuals and companies in order to avoid any dispersion of private information in the case of natural disaster (e.g., equipment failures, user errors) and cyber-attacks (e.g. due to disgruntled employees or industrial espionage), reason why data rights and protection regulations have assumed an increasing importance for legislations around the world (Faheem et al., 2018). The risk of cyber-attacks makes technology's users more vulnerable, so, to protect themselves from cyber risk, companies should integrate cybersecurity strategies into their information technology system and they could deploy four practices mainly (Oztemel and Gursev, 2020; McKinsey, 2015). These four practices are represented by the (1) identification of the cyber risk connected with each asset and prioritize protection around key assets; (2) the integration of cybersecurity into core processes as part of the enterprise risk management process; (3) engagement of management and employees in activities aimed at mitigating and managing any compromission of security; (4) safeguarding of technology, meaning that technologies should be integrated with security practices.

The fear of data dispersion is also represented by the fact that most companies do not allow external organizations to manage their data, indeed, e.g., only 19% of American companies and 14% of German companies are willing to locate their servers outside their own territory (Szozda, 2017).

In the Industry 4.0 era it is not only crucial to protect data dispersion, but also to *manage data* effectively.

Thanks to the implementation of sensors, IoT, CPS, companies acquire an enormous quantity of data that need to be analyzed, managed, and transformed into useful insights for the organization. The ability to use the data available for improving the products' design and quality, production efficiency, costs, delivery, can be considered a critical success factor for the adoption of Industry 4.0 (Moeuf et al., 2019).

Data Analytics aims at identifying patterns and interdependencies from a pool of data to support intelligent decision-making, customer preferences, market trends and other valuable information for businesses (Faheem et al., 2018). So, it is critical to have a digital infrastructure to access high-quality data, but also to have the capabilities necessary to handle these data and to deeply analyze them to run the overall system aligned with the manufacturing goals (Ghadge et al., 2019; Oztemel and Gursev, 2020).

SECOND CHAPTER: LEAN AND INDUSTRY 4.0

2.1 Lean Production and Industry 4.0

The concept of Lean Production is based on the Toyota Production System (TPS), whose principles and practices were primarily introduced and developed in the 1950s by its Chief Production Engineer Taiichi Ohno (Womack et al., 2007, p. 50).

Lean Management aims to "align value creation with customer demand and to continuously eliminate waste in the process, requiring a continuous improvement approach'' (Rafael et al., 2019). Lean principles (identify value, value stream mapping, flow, pull and perfection) seek to reduce the overall variability in manufacturing processes increasing company's performance, offering simplicity and high effectiveness, and these are the reasons why Lean Production became one of the main production paradigms implemented by companies over the years (Pagliosa et al., 2019).

Early in their development, lean principles, practices and tools were mainly applied in the manufacturing industry (especially automotive industry because it was influenced by Toyota), but gradually they have been deployed in many other industries, including textile, services, food, medical, construction and so on (Santos et al., 2021).

Lean Production is a "synergic tool system'', since it involves the implementation of different tools and techniques to reach different goals: for example, Poka Yoke techniques are deployed to reach a reliable single piece flow, Heijunka levelled production techniques are applied within mixed product cells to achieve just-in-time delivery (Ruttimann and Stockli, 2016). Many other tools such as Total Quality Management (TQM), Kanban, 5S, Standard Work, Total Productive Maintenance (TPM), Human Resource Management (HRM) are adopted in Lean Production and they can be categorized into hard tools, mainly technical and analytical, and soft tools, such as training, supplier partnerships, problem solving and customer involvement (Santos et al., 2021).

The Lean paradigm offers many benefits for companies in terms of a faster reaction to market changes, production of smaller batches, higher variety of products, reduction of waste (muda, muri, mura) and the creation of transparent and standardized processes (Kolberg and Zuhlke, 2015). However, even though Lean Manufacturing supports the production of an increased variety of products, it is not suitable for reaching the "individual single-item production'' and consequently, for satisfying the level of customization required nowadays, due to a limited changeability of production lines and workstations (Kolber and Zuhlke, 2015; Kolberg et al., 2016). More specifically, the Lean approach presents some limitations relative to the fast and disruptive changes in the market demands, that can be summarized as follows: (1) there is a strong deviation in market demands versus the required lean levelled capacity, (2) Lean has not been designed for mass customization, (3) traditional Lean thinking does not take into consideration modern ICT technologies, (4) the “trial and error’’ approach adopted by Lean Manufacturing for improving processes require so much time, not matching the current required shorter product life cycle and the quick changes needed in production lines and (5) traditional tools such as value stream mapping are not fully able to manage the variation and stochastic behaviour of modern complex systems (Uriarte et al., 2018).

Industry 4.0 technologies help companies achieve the new required standards in terms of flexibility and “Mass Customization’’, enabling autonomous and dynamic production. Industry 4.0 is strongly IT driven, while Lean Production tries to reduce as much as possible IT dependence, being strongly human driven, since it considers people as a fundamental factor for sustaining continuous improvement (Pagliosa et al., 2019). This different characterization does not make the two approaches necessarily incompatible, since Lean Production does not completely exclude automation: in the 1960s, Taiichi Ono stated that repetitive and routine tasks should be automated, calling this principle “autonomation’’ (Kolberg et al., 2016). The integration between Industry 4.0 and Lean Production can be represented by the term “Lean Automation’’: advanced technologies are employed to achieve lean manufacturing (Sanders et al., 2016).

2.2 Lean Automation

Lean Automation attempts to combine Lean Production and Industry 4.0, taking the best from both worlds in order to help companies achieving operational excellence: lean production leads to the reduction in product and process complexity, increasing the efficiency of digitalization, while Industry 4.0 enhance the flexibility of lean processes, addressing the challenge of “mass customization’’, that is why the parallel implementation of both Lean and digitalization is estimated to yield 40% improvement potential (Rafael et al., 2019).

The term Lean Automation was first introduced in the mid-1990s after the peak of Computer Integrated Manufacturing (CIM), referring to the integration of automation technology into Lean Production, represented by the Japanese term “Jidoka’’ (translation: autonomation), which meant the interruption of machines every time an abnormality arose, followed by an interruption of the production line by employees (Ma et al., 2017). Over the years the concept of Lean Automation has widened its application range and nowadays, thanks to Industry 4.0 technologies, there are new opportunities of combining digitalization with Lean Production that can be grouped in the following way (Kolberg and Zuhlke, 2015; Mrugalska and Wyrwicka, 2017):

1. Smart Operator: the Smart Operator, thanks to devices such as smart watches providing signal lights, becomes immediately aware of any error inside the company, achieving the "Andon'' principle, by which employees should be notified as soon as possible about any failure inside the organization, so that anyone able to help can "run to lend a hand'' (Womack et al., 2007, p.99).
2. Smart Product: Smart Products can collect, process and analyze data, they can contain Kanban information to control production processes and they have properties such as adaptation, proactivity, self-organization and the ability to support their own production life cycle, pushing Kaizen processes. Thanks to all these elements, Smart Products enable the creation of a Current State Map, which shows wastes in processes and future strategic planning activities.
3. Smart Machine: Smart Machines coordinate themselves in the production processes, within decentralized self-organizations, realized by the integration of CPS within processes, that helps employees to avoid mistakes (Poka Yoke techniques), by data collection from sensors, actuators, RFID, that pushes continuous improvement and by Plug'n Produce applications which facilitate the introduction of Single Minute Exchange of Die into the whole production lines.

Regarding the concept of Lean Automation, from the literature three main strands of thought emerge *(Figure 2)*: Industry 4.0 supports Lean, Lean facilitates the implementation of Industry 4.0, the performance implications of a Lean - Industry 4.0 integration, (Santos et al., 2021).

Figure 2: Categorization of the studies investigating the relationship between Lean and Industry 4.0

Industry 4.0 supports Lean

- **General contributions** provided **by I4.0** technologies **to Lean** practices, tools and principles.
- Investigation of the **peculiar contributions** given by **specific I4.0** technologies **to individual Lean** practices, tools and principles.
- **Specification of the support** provided **by I4.0 to Lean** practices, tools and principles **through use cases** definition.

Lean facilitates the implementation of Industry 4.0

- **Lean prevails on I4.0** for operational improvement because **it creates waste-free and dynamic processes** where to introduce technologies efficiently.
- Investigation on **the individual relationship between Lean** practices and **I4.0** themes: there are Lean practices positively supporting I4.0 and other present a net neutral/negative supporting effect
- Analysis **of how Lean** practices **pushes** the **achievement of I4.0** characterizations

Performance implications of a Lean – Industry 4.0 integration

- The **integration** between **Lean and I4.0** leads to **improvement in** the overall **company's performance**, because they mutually reinforce each other, even though, sometimes, Lean should precede the introduction of I4.0.
- The **choice** of **which technologies to integrate** into Lean is **context-dependent**: different technologies may contribute to different Lean practices.

Source 2: Personal elaboration

2.2.1 Industry 4.0 supports Lean

There is a consistent part of literature stressing the different ways through which Industry 4.0 principles and solutions support Lean Manufacturing, tools and practices. Industry 4.0 enables better information sharing inside and outside the company, it provides real time data and an accurate information interpretation, which inevitably affect Lean Production, that is “driven by information’’ for the identification of everything that does not add value and of customer’s needs.

Sanders et al., (2016) show how Industry 4.0 technologies support companies becoming Lean, improving the overall productivity and eliminating waste, through an analysis of Industry 4.0 solutions for ten dimensions of Lean (identified by Shah and Warrad,2007), grouped in four management factors:

- Supplier factors (supplier feedback, JIT delivery by suppliers and supplier development): Industry 4.0 tools allow an immediate and automatic feedback to suppliers, thanks to improved communication channels, an increased JIT delivery by suppliers, enabled by wireless tracking, smart reallocation of orders and tags put to every item. Advanced technologies also push suppliers to develop themselves along with the manufacturer, through standardized interfaces and technological networks that enable the sharing of resources.
- Customer factor (customer involvement): advanced technologies allow customers to stay informed about the actual production stage, increasing customers’ involvement from the development of the product to the production. Hence, they enable higher product customization, better market research and customer analysis through Big Data deployment.
- Process factors (pull production, continuous flow, setup time reduction): pull production is facilitated by information and communication technologies that allow automatic material replenishment monitoring, schedule tracking and the development of e-Kanban systems. Continuous flow and setup time reduction is reached through different tools, such as RFID technology, that enable real time tracking of inventory and “plug and play’’ systems, which are equipped with machine learning, allowing companies to adapt machines based on the products and to produce in small batches.
- Control and Human factors (total productive/preventive maintenance, statistical process control and employee involvement): information and communication systems improve the overall productive and preventive maintenance in the factory, since machines become self-aware and self-maintained; processes are improved as well, enabling the creation of defect-free products. Employee involvement and empowerment is facilitated by smart feedback devices, worker support systems and improved man-machine interface.

This construct has also been used by a study of Tortorella et al., (2020) to stress how Industry 4.0 technologies can be integrated into Lean Production practices, supporting them, defining a Lean Automation framework. Indeed, their results evidence that in general there is a positive partial correlation between Lean Production practices and Industry 4.0 technologies; in particular, good communication with key suppliers is positively correlated to all Industry 4.0 technologies, while an integrated and collaborative engineering system is significantly correlated with almost all lean practices.

Lai et al., (2019), investigate deeper on how different Industry 4.0 technologies can have a positive impact on waste reduction, minimizing or eliminating all seven types of Muda. Overproduction is reduced thanks to a better order management and information, decisions taken instantaneously, real time data and autonomous machines; immediate feedback from stakeholders along the value chain minimizes production waiting time, while predictive and smarter maintenance reduce the risk of unplanned delays and interruption in processes, impacting the overall waiting time. Advanced technologies predict the best routes and the scheduling for WIP materials, minimizing as much as possible transportation; processes are determined, monitored in every step of the production flow thanks to the increased connectivity that provides accurate information, affecting over processing. The minimization of inventory is achieved through e- Kanban systems, real time communication between customers, suppliers and producers; unnecessary motion is identified and prevented by smart sensors, CPS, ML. Lastly, better equipment sensors, network integration that enhance monitoring of production, lead to the possibility of identifying any defect in advance, avoiding it.

Another Lean concept, that has been discussed in the literature in relation to how new modern and communication technologies can support and enhance it, is Jidoka. As previously mentioned, Jidoka consists of an automatic stop to processes every time a defect is detected by sensors, creating a pressure to act on employees to solve problems as soon as possible. Advanced technologies enable the prediction of potential errors before they occur (Predictive Process Monitoring), thanks to the application of effective measuring devices and a huge hardware capacity in terms of data storage, that leads to the collection of big data, which are continuously analyzed by powerful hardware (Deuse et al., 2020). This constant accumulation of knowledge is at the foundation of data based predictive models, characterized also by the use of Machine Learning and Data Analytics, that allow the deduction of conclusions about the evolution of processes and quality of the final product (Deuse et al.,2020).

So, thanks to new technologies, the Jidoka concept is improved and its focus changes from end-of-line quality control to a real-time monitoring of processes and quality prediction, making

possible the detection of a quality defect before it occurs and developing the ability to identify complex process relations.
To investigate how Industry 4.0 supports Lean, some authors focus on stressing how specific Industry 4.0 technologies enhance individual Lean practices.
According to Mayr et al. (2018), JIT, for example, can be supported by automatic guided vehicles, able to intelligently transport materials, avoiding empty routes, and by intelligent bins and smart products that pursue self-optimization; RFID can track materials in real time, reducing search time and enhancing transparency while, Big Data and Data Analytics provide insights about production processes supporting JIT as well. The levelled production, Heijunka, that aims at avoiding over/under production can be facilitated by Data Analytics to better understand customer needs and by software tools to help in planning processes. Simulation techniques ensure the identification of ideal parameters in terms of lot size, stock or delivery frequency, improving Kanban systems; Auto-ID technologies allow a constant monitoring of WIP, improving transparency of materials movement. This paper provides many other examples of lean practices that can be improved by the introduction of new technologies such as Value Stream Mapping, Total Productive Maintenance, SMED, Visual management and Poka Yoke, outlining how modern technological tools can support Lean.
A similar study has been conducted by Wagner et al. (2017), who, through the estimation and the rating of the impact of different technologies on Lean Production principles (5S, Kaizen, Heijunka, JIT, etc.), elaborate an Industry 4.0 impact matrix on Lean Production. Their findings prove that different technologies have a different impact on Lean principles: for example, most of advanced technologies contribute to Kaizen, other dimensions such as people and teamwork are improved only by human machine interaction technologies, while JIT can be strongly impacted by Big Data Analytics and vertical integration.
Also, Sanders et al. (2017) elaborate an interdependence matrix formed by Lean Manufacturing tools and Industry 4.0 design principles, to investigate the impact of the latter on the former. Most of Lean tools are either supported by Industry 4.0 principles or there is a neutral effect, except for takt time that is hindered by Industry 4.0 principles, probably because it is in contradiction them, since takt time is calculated as a fixed value, making real time data useless. Instead, Total Productive Maintenance practices are those that benefit more from Industry 4.0 design principles: real-time capability (I4.0 design principles) enables the constant monitoring of equipment and plant conditions, intelligent algorithms allow to predict failures before they occur, maintenance engineers can use augmented reality and 3D trouble-shooting to carry out maintenance activities and M2M communication allows eventually to contact other machines for taking over the workload. Moreover, real-time capability is the principle that offers the

higher support to Lean Manufacturing tools, however decentralization and interoperability are highly supportive too.
The importance of real-time capability can be deducted also in a study performed by Pagliosa et al. (2019), that identifies IoT and CPSs as the two main technologies with the largest number of high synergies with lean practices. After classifying nine Industry 4.0 technologies according to different levels of the value stream, the authors found out that there are technologies “more versatile’’ than others, meaning that they can be implemented successfully in more levels of the value stream, such as IoT and CPS. So, these technologies combined with Lean practices offer a higher number of synergies, favouring the achievement of better performance results.
In the analyzed literature, use cases are also presented as an instrument for stressing how the adoption of advanced technologies enhance the capabilities, the effectiveness or efficiency of Lean tools or practices.
In the previously mentioned paper, Wagner et al. (2017), the authors also present a use case that has been applied in the automotive industry: a “cyber-physical JIT delivery’’, which demonstrates how the use of CPS, Data Analytics and Big Data, sensors, RFID tags, leads to improvements in the factory, enhancing JIT. To develop this system, different Industry 4.0 technologies were assessed and all company’s processes were analyzed to better understand where there was improvement potential. It was needed to improve the JIT delivery of electrical assembly parts, so sensors were applied to every machine, Big Data Analytics was implemented as well as vertical integration. The incorporation of these technologies into Lean processes led to the virtual representation of every machine, increasing traceability and reliability. Later, other monitoring systems and simulation technologies were applied to increase system resilience, leading to a reduction in delivery time for online sales to 48 hours (Santos et al.,2021).
In 2021, Rahman et al., focused on the concept of a Lean Management - Decision support systems (LMDSS), to show how in the context of DSS (Decision support system) Industry 4.0 technologies can support Lean tools, leading to a process improvement. A DSS is a computer based information process and it is used by Lean companies to support their improvement processes, focusing on the waste elimination and productivity increase, but traditional decision making techniques alone are not able to face the complexity of big data in terms, for example, of storage capacity or analysis, so other tools such as Data Analytics and IoT should be implemented to improve the quantity and quality of information, to enhance production processes, management decision making capabilities and competences. The LMDSS framework keeps following Lean principles: identify value, measure (value stream mapping), analyse (establish flow), generate (pull value), execute (strive perfection).

Regarding Jidoka, Ma et al. (2017), design and implement a CPS-based smart Jidoka system, able to convert heterogenous data, analyze data, detect abnormalities and control feedback. The authors introduce a distributed architecture that integrates service-oriented architecture, cloud and IoT, to provide a flexible configuration, deployment and performance. They stress how CPS can make Jidoka smart, creating a more cost efficient and effective approach for improving production system flexibility (Ma et al., 2017).

Shahin et al., in 2020, described the use case of a "Cloud Kanban''. Traditional Kanban applications are limited to controlling the WIP inventory or managing software requirements, that is the reason why Kanban are usually defined as a "visual tool to monitor and control resource consumption and production" (Shahin et al., 2020). The introduction of Cloud technology in Kanban systems makes it possible to obtain an enhanced platform that provides a "holistic view of operations management" that, combined with continuous improvement processes and techniques, help operations managers to make conscious and effective decisions.

Many other use cases can be cited to stress how advanced technological solutions are able to enhance Lean practices, such as e-Kanban systems, where physical cards are replaced by virtual Kanban and missing or empty bins are recognized immediately through sensors; "Chaku Chaku lines'', characterized by automation technologies integrated in u-shaped assembly stations and tasks like the development of a local order management system, typically performed by ERP; iBin system, which represents an optical order system, developed as an extension to Kanban bin and so on (Satoglu et al., 2018).

2.2.2 Lean facilitates the implementation of Industry 4.0

Lean concepts, principles, practices are at the basis of the creation of robust waste-free processes, which can be considered a prerequisite for successfully implementing new technologies, otherwise the investments sustained for the adoption of these new digital solutions will be useless (Bittencourt et al., 2019).

Lean thinking facilitates Industry 4.0 implementation not only because it simplifies processes and eliminates waste, but also because it reduces the risk of compromising scarce resources and increases transparency across all the organization (Bittencourt et al., 2019).

This concept is also sustained by a survey performed by Jeske et al. (2021), in the German metal and electrical industry, whose results show that, in the year 2019, Lean Production is considered a requirement for the introduction of digitalization by more than 30% of respondents and it will be still used in the future by more than 50% of respondents, meaning that it is not only a prerequisite for the implementation of Industry 4.0, but also for its further development and establishment.

An empirical analysis performed by Rossini et al., (2019), on 108 European manufacturing companies shows that companies poorly (or highly) adopting Industry 4.0 are poorly (or highly) adopting Lean practices too and the high performance recorded for some companies in terms of productivity, delivery service level, inventory level, workplace safety (accidents) and quality (scrap and rework), is not significantly associated with Industry 4.0 technologies, but to well established Lean practices. Based on these results, the authors affirm that to reach process improvement, companies adopting higher levels of digitalization should concurrently implement Lean practices and the latter prevails on the former for operational performance improvement, since high performing companies claim higher levels of Lean Production implementation rather than advanced technologies application. So, companies that are willing to achieve better results in terms of performance, should primarily implement a certain level of Lean Production, create robust processes and then introduce Industry 4.0 technologies.

Coherently to this idea, Bittencourt et al. (2020), propose the 4P pyramid model of TPS (philosophy, processes, people and problem solving) as the pathway a company should follow for the implementation of new technologies. When a company introduces a new strategy or a new technology that should be integrated with existing ones, it is required a clear long-term vision about its business and management strategies (philosophy), that should focus on waste reduction and customer value. Processes are the second step of the pyramid, since after the vision has been defined, it is necessary to create waste-free, efficient processes before introducing any new technology, because "the automation of an inefficient process does not make it efficient'' (Bittencourt et al., 2020). Processes can be enhanced thanks to Lean practices and concepts, such as value stream mapping that enables a clear definition of the current state of a company's processes and status. The third step is represented by people, a crucial dimension for Lean thinking and Industry 4.0 deployment: it is important to give people the right tools for embracing the introduction of new technologies and their individual and team performance should be maximised to aim for perfection within the company. The final step is represented by problem-solving: continuous improvement behaviour and innovative thinking triggers Industry 4.0 implementation, making people able to select the best solutions to serve specific needs and purposes and to face the challenges implied by complex technologies. According to this paper, Lean thinking is an important agent in the implementation of Industry 4.0 for avoiding any future inefficiency or waste.

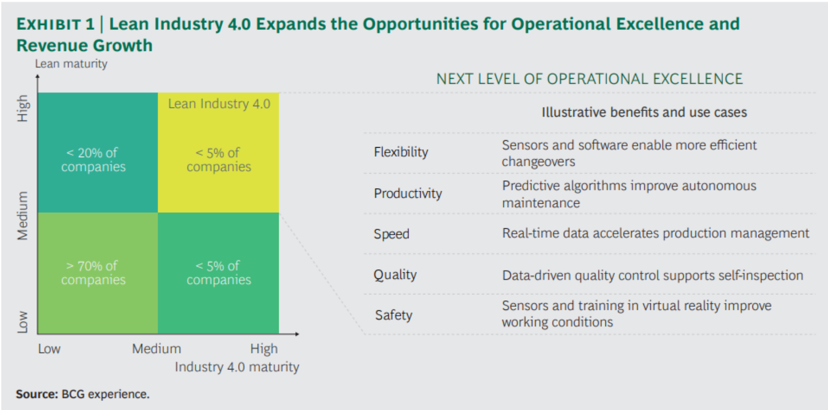
Saxby et al. (2020), try to investigate deeper into the level of support that Lean can give to Industry 4.0 through semi-structured interviews, with five Quality Specialists in manufacturing firms, regarding the individual relationship between nine Lean practices and eight consolidated Industry 4.0 themes. The authors state that, in general terms, most of answers (48% of responses) records a positive support given by Lean practices to Industry 4.0, however there may be cases where this is not verified (39% of responses were neutral and 8% negative). When considered individually, for some Lean practices is recorded a net positive response regarding their support to Industry 4.0, for others neutral/negative (these responses are grouped together). Specifically, practices positively supporting Industry 4.0 such as continuous improvement, supply chain engagement and customer value can be seen as complementary to Industry 4.0 requirements and objectives. While practices recording a net neutral/negative supporting effect to Industry 4.0 are, usually, in contradiction with its principles and goals: e.g. teamwork and employee involvement offer a neutral/negative support to Industry 4.0, probably because of the highly automated nature of the paradigm. The same reasoning can be applied in the reverse side, considering which Industry 4.0 technologies are more likely to be supported by Lean practices.

A research study performed by Sony (2018), starts from the characterization of Industry 4.0 to show how Lean practices and principles push the achievement of this industrial paradigm. In particular, the author sustains that Industry 4.0 is characterized by the achievement of three integrations within an organization: vertical integration, which happens inside the company's boundaries enhancing flexibility through smart machines and Big Data Analytics, horizontal integration, which is realized between different organizations across the value chain, creating an efficient digitalized ecosystem and end-to-end engineering, which refers to the integration that enables the creation of customized products and services (Sony,2018). According to Sony (2018), Lean Manufacturing principles represent the guidelines to follow when implementing advanced technologies to reach the three integrations of Industry 4.0. For example, to achieve vertical integration and transform the company into a flexible one, first, it is necessary to define value for customers, then a value stream mapping should be performed to identify and remove any non-value adding activity. So, when integrating technologies such as CPSs, waste should be primarily eliminated according to Lean thinking, then the creation of a flow process can enable cross functional cooperation and remove any bottleneck or delay. These steps will reduce delivery time leading to a pull system, so JIT philosophy could be applied and lastly, a continuous improvement culture should be implemented to reach perfection of systems. This approach can be followed to design the architecture of horizontal integration and end-to-end engineering integration too (Sony,2018).

2.2.3 Performance implications of a Lean - Industry 4.0 integration

The holistic integration between Lean and Industry 4.0 leads to valuable synergies for companies, but to capture the full benefits deriving from this integration, it is required to first identify and address its specific challenges across the whole supply chain and at factory level. This enables organizations to enhance their operational performance, reaching potential cost reductions related to poor quality by 20% and to WIP inventory by 30% (BCG, 2017). BCG (2017) highlights the impact of Lean Automation on operational performance across 5 dimensions: flexibility, productivity, speed, quality and safety (*Figure 3).*

Figure 3: Lean Industry 4.0 Expands the Opportunities for Operational Excellence and Revenue Growth



Source 3: BCG, 2017. When Lean meets Industry 4.0 – The next level of Operational Excellence

Among the papers analyzing the performance implications of a Lean - Industry 4.0 integration there is a study conducted by Rafael et al., in 2019, that focuses on the interrelation of Lean and digitalization in the Swiss manufacturing industry. The authors group the companies in four segments, based on the level of digital and Lean maturity, and then investigate each cluster's operational performance (relative performance in cost, quality and delivery compared to the industry), financial performance (change of revenue, EBIT, market share within last three years), organizational culture (open communication, alignment to overall goals, understanding of value stream and access to business intelligence) and continuous improvement (efforts towards waste reduction, feedback evaluation, joint improvement program and market screening for new technologies). The results of this study show that companies with a higher combined Lean and digital maturity tend to have better results in terms of the overall performance, compared to those implementing separately Lean practices and digital technologies. So, according to the authors, these two dimensions do not contradict or exclude each other, rather they can reinforce each other mutually:

- Industry 4.0 supports Lean: availability of real time and high-quality data increases transparency, information sharing, facilitating waste identification and digital solutions enhance flexibility, better satisfying customer needs and requirements.

- Lean supports Industry 4.0: lean ensures well defined processes, reducing the time required for the application of digital solutions, with a constant focus on customer value and waste reduction.

A study performed by Santos, in 2021, adopts a different approach for stressing how the adoption of Industry 4.0 technologies into Lean practices can help companies achieve better performance. The author focuses on six real case examples, each one deriving from a different industry (automotive, paper, machine manufacturing, furniture, healthcare and apparel), addressing Lean-digitalization integration, across different levels of the value chain and with different technologies involved. These six use cases stress not only the benefits achieved by the Lean Manufacturing-Industry 4.0 integration in terms of different performance indicators, but also the importance of a deep analysis of the starting situation of the company, since the choice about which technology to adopt is highly context-dependent. This implies that different technologies in different sectors contribute to the improvement of different Lean practices (Santos, 2018).

Moreover, Tortorella and Fettermann (2018) perform an empirical research on 110 Brazilian manufacturing companies, operating in different sectors, to investigate the relationship between Lean Production practices and Industry 4.0 implementation, focusing on how this relation influences companies' operational performance. Their results can be summarized as follows:

1. Companies widely implementing Lean Production and/or Industry 4.0 technologies have not recorded any relevant operational improvement and this "strange'' result can be due to a misunderstood or misapplied improvement approach.
2. High performance improvement companies present a significant association between Industry 4.0 and Lean practices, suggesting that companies widely implementing lean Production are more likely to adopt advanced technologies and their integration is more likely to positively impact operational performance.
3. As companies become more experienced on Lean Production implementation, there is an increasing significant association with Industry 4.0, because they acquire more awareness, a better understanding of their processes and practices, favouring a successful integration of advanced digital technologies, which in turn enhances Lean Production benefits.

Another empirical study was conducted in 2019 by Tortorella et al., always in the Brazilian manufacturing context, aiming to investigate how Industry 4.0 adoption (process-related and product/service-related technologies) moderate the relationship between Lean Production practices (pull, flow and low setup) and operational performance improvement. This research is based on the elaboration of a survey, a following set of Ordinary Least Squares (OLS) hierarchical linear regressions and the adoption of a contingency approach, identifying four contingencies: technological intensity, tier level, company size, and duration of Lean Production implementation. The final results show that the impact of Lean practices on operational performance can be supported by Industry 4.0 technologies, only the tier level has a significant effect on the interaction between Lean and Industry 4.0 and the impact of Industry 4.0 technologies (especially product/service related) as stand alone is not highly significant. However, it can be noteworthy to mention some peculiarities that emerged from this study: low set up practices and process related technologies have a positive impact on performance improvement when taken separately, but if the interaction term is taken into consideration, process-related technologies moderate the effect of low setup negatively. This result may be due to a lack of a deep understanding by Brazilian companies of the potential benefits of their concurrent adoption or to an improper implementation plan of technologies within processes. Product/service technologies positively moderate the relation between flow and operational performance improvement, so technologies such as rapid prototyping and cloud services that reduce time-to-market, create a reliable flow of value.

A similar research paper, but in the Norwegian manufacturing context, is represented by Buer et al. (2020). The authors test the synergistic effect caused by the integration of Lean Manufacturing and digitalisation on operational performance. They consider six Lean production practices (pull production, continuous flow, setup time reduction, statistical process control, TPM, employee involvement) and six advanced technologies. Their findings indicate the presence of a significant relationship between both Lean Manufacturing and digitalisation as stand-alone with operational performance as well as a positive interaction effect between Lean Manufacturing and factory digitalisation. A positive interaction effect means that the concurrent adoption of the two paradigms has an impact on operational performance, that is higher than the sum of their individual contributions. The authors conclude that Lean Manufacturing and factory digitalisation are complementary resources.

The complementary between Industry 4.0 and Lean Manufacturing has been further demonstrated by Rossini et al., (2021). Indeed, they show how Lean Automation enables companies to reach a competitive advantage thanks to the simultaneous application and integration of high technology solutions (Industry 4.0) and human based simplicity (Lean). The sample of this research was constituted by 293 leaders, representing European and Brazilian companies, who have been surveyed on four dimensions: operational performance indicators, Lean implementation time and company size (control variables), Lean production implementation and adoption level of Industry 4.0 technologies. Through various statistical analysis they identify “two Lean automation bundles’’:

- Operational stability (OS): it combines six lean production constructs (Statistical process control, TPM, Supplier JIT delivery, supplier feedback, supplier development and involved employees) and one Industry 4.0 construct (process related technologies). It focuses on suppliers and on preventing unexpected process variability, pursuing efficiency. An example of interplay between Lean and Industry 4.0 in this bundle is given by supplier involvement in product development processes with the use of integrated engineering systems for product development.
- Fast-to-market (FtM): it combines flow, pull, involved customer, low setup with one Industry 4.0 construct (product related technologies). It focuses on customers and on shortening and improving the delivery process, pursuing effectiveness. An example of integration between Industry 4.0 and Lean in this bundle is represented by the use of cloud technologies combined with customer involvement practices to enhance product development capabilities.

Both the Lean Automation bundles have a positive impact on the overall operational performance; in fact, they explain 31.2% of the variation in operational performance improvements. Moreover, the integration among the two paradigms creates very complex innovative systems which are difficult to replicate, providing a sustainable competitive advantage over competitors (Rossini et al., 2021).

2.3 Conclusions

Based on the literature review it can be stated that Industry 4.0 technologies can support Lean Production and vice versa. Advanced technologies facilitate waste identification, customer and supplier involvement, enhance Jidoka and JIT, enable Predictive Production Maintenance and pushes the development of traditional tools, increasing their effectiveness and efficacy.

The introduction of Industry 4.0 technologies should be preceded by a deep and accurate analysis of the starting point of the company, to understand its needs and the potential improvement opportunities, since the adoption of any technology is highly context-driven: the successful implementation of a technology depends on the context in which it is applied.

At the same time, Lean Production concepts and practices can create the basis for Industry 4.0 implementation process and may be critical also for its future development, because of the level of awareness lean thinking creates in a company. This result is shown also by a thesis conducted at University of Padua by Cazzaro (2018), who focuses on identifying and evaluating "the most probable features that characterize companies adopting Industry 4.0 technologies, in particular with respect to Lean implementation''. In this thesis it is demonstrated that companies

implementing Lean Manufacturing, for at least 3 years, have a higher probability of adopting Industry 4.0 and that Lean Manufacturing does not privilege a specific type of Industry 4.0 technology, but it's only connected to Industry 4.0 in general. The most peculiar result shown by this study is that most of companies that have adopted Lean for more than three years have implemented advanced technologies too, but not vice versa: the majority of companies that have implemented advanced technologies are not Lean implementers. According to the author, this result is probably due to the fact that Lean techniques are not easy to implement, because of the changes they imply inside the company, while the adoption of advanced technologies have been supported and facilitated by governments in the last few years. Regarding the implications of a Lean Management-Industry 4.0 integration, it emerges that, in general, it records a positive impact on the overall performance of the company, but the integration of Industry 4.0 technologies in the company's processes requires a deep understanding across the company of its potential benefits and should follow a clear and accurate implementation plan. The implementation of a "Lean Automation'' approach can lead companies to achieve a sustainable competitive performance, because it implies the development of very complex systems and processes, that if properly developed and deployed, are very difficult to imitate.
Another thesis, written by Zatta (2019), always at University of Padua, identifies, through a Qualitative Comparative Analysis, the combinations of Lean practices and Industry 4.0 technologies that ensure an outstanding performance for companies adopting them. The author's findings can be summarized as follows:

- Lean "hard practices" are essential conditions for high profitability, while "soft practices" are peripheral.
- The combination between hard practices, soft practices (even though they are peripheral) and technologies enabling a reduction of time to market leads to high ROA/high EBITDA margin.
- IoT, applied as an essential condition, combined with process technologies (peripheral) enhances ROA level.
- The right mix of process technologies and product technologies such as IoT, can lead to a positive financial performance.

This paper shows essentially that there are different ways through which it is possible to reach a good financial performance and among these possibilities there are also Industry 4.0 - Lean combinations, coherently to the findings of other authors already mentioned.
Overall, the literature review has shown a gap in the study of the effect of Lean practices and advanced technologies configurations on the human dimension, so the following chapters will be dedicated to this empirical investigation. In the following chapter, the Qualitative

Comparative Analysis approach will be introduced and implemented for empirically investigating how Lean bundles (in particular, three Lean bundles will be considered) and Industry 4.0 (specifically, the Industrial Internet of Things technologies will be involved) combinations impact team proactivity.

THIRD CHAPTER: QUALITATIVE COMPARATIVE ANALYSIS

3.1 Qualitative Comparative Analysis description

Qualitative Comparative Analysis (QCA) was introduced in 1987 by the American social scientist Charles Ragin to study comparative political science and sociological phenomena at macro-level with sample sizes too small for regression techniques, but too large for systematic cross-case comparisons (Misangyi, 2017). In fact, QCA can be considered as a "middle ground'' between a pure qualitative analysis and a quantitative one, since it adopts both a research approach, applying an iterative process of data collection, and analytical techniques to find empirical relevant patterns in the data (Wagemann and Schneider, 2010). QCA has been defined by Ragin (1987) as "asymmetric data analysis technique that combines the logic and empirical intensity of qualitative approaches, that are rich in contextual information, with quantitative methods, that deal with large numbers of cases and are more generalizable than symmetric theory and tools'' (Pappas and Woodside, 2021).

QCA employs a configurational approach that adopts a systematic and holistic view of organizations, stressing and studying non-linearity, synergistic effect and equifinality (Fiss, 2007). Non linearity means that relations between elements, variables, are not represented by singular causation and linearity (as in regression analysis techniques), but by complex causality; synergistic effect underlines that the conditions indicating an outcome are not evaluated as isolated entities, but as "configurations of interrelated structures'', more precisely a configuration can be defined as "specific set of causal synergetic variables used as a screen indicating an outcome of interest'' (Pappas and Woodside, 2021; Fiss, 2007). The term "equifinality'' has been defined by Katz and Kahn (1978) as the phenomena by which a system can reach the same final state, from different initial conditions and by a variety of paths.

A configurational approach is applied in set-theoretic methods and can not be fully adopted in techniques such as regression and cluster analysis: the former focuses on the impact of a specific variable on the outcome, holding constant the others, thus assuming that a specific relationship is relevant for all causes under examination, being unable to take equifinality into account, the former is not perfectly suitable either, because it does not study the contribution of individual elements to the whole or how different elements combine to achieve the outcome (Fiss, 2007).

Set-theoretic methods, such as QCA, are best suited for configurational theory implementation, because they explicitly consider cases as combinations (configurations) of different attributes,

and they evaluate the impact of these configurations, not of single attributes/variables, on the outcome of interest; moreover, they offer the opportunity to empirically examine equifinality and causality. An important concept in QCA is causal complexity, characterized by three main aspects: (1)conjunctural causation, that focuses on how attributes combine with each other and not on which one has the strongest effect on outcome, (2)equifinality and (3)asymmetric causal relationships, meaning that "causes leading to the presence of an outcome can be quite different from those leading to the absence of the outcome'', (Fiss,2011; Misangyi et al., 2017).
To better understand QCA, it is possible to summarize its main elements in three groups: set-theoretic configurations and calibration of set membership, set relations and counterfactual analysis.

3.1.1 Set-theoretic configurations and calibration of set membership

Cases (cases indicate the objects to which both the outcome and the causal conditions refer to) are considered configurations of attributes not as a disaggregation of them, thanks to the set-theoretic approach and the use of Boolean algebra. Causal conditions and outcomes are both conceptualized as "sets'' and the relationship between them (causal relation) is conceptualized as set-subset relation. For example, to analyze what configurations lead to high performance (outcome), first the members of set "high performance'' are examined, then the combinations of attributes leading to this outcome are identified, through the use of Boolean algebra and algorithms that simplify complex causal conditions into a reduced set of configurations that lead to the outcome (Fiss, 2011).
Thus, given that the outcome and the causal conditions (elements selected because of potential causes of the outcome) are conceptualized as sets, the relationship between the cases and outcome/causal conditions is expressed in terms of "set membership'' (Pappas and Woodside, 2021).
Initially, in the primary version of QCA, called Crisp set QCA (csQCA), set membership was defined only in the binary values [0,1], indicating full membership and full non membership. Then, gradually this version was developed becoming Fuzzy set QCA (fsQCA), that operates on fuzzy algebra - a general version of Boolean algebra-, (Wagemann and Schneider, 2010). Fuzzy set QCA allows to determine set membership adopting any value in the range [0-1], leading to the implementation of a more realistic and accurate approach (Pappas and Woodside, 2021).
To define set membership it is necessary to apply a calibration process: in the set of interest, three qualitative anchors indicating full membership, full non membership and the crossover point of maximum ambiguity regarding membership, have to be specified (Fiss, 2011). These

qualitative anchors are used for transforming the variables' scores into set measures: the variable scores are rescaled in a range of values from 0 to 1, based on these qualitative anchor values. For example, if a variable is measured on an ordinal Likert scale with values ranging from 1 (fully disagree) to 7 (fully agree), the three qualitative anchors will be: 1 (full non membership), 4 (crossover point) and 7 (full membership). After establishing these anchors, data are rescaled in a range of values from 0 to 1.

The definition of the qualitative anchors for full membership, full non membership and crossover point, requires theoretical and substantive knowledge since the anchors' values depend on how the variables are measured and on which phenomena researchers want to focus, (Ragin and Pennings, 2005).

Data calibration process can be characterized by many challenges: the theory and substantive knowledge that often guide calibration may be lacking, there may be issues in reconciling conceptual anchors with the actual distribution of data, calibration of qualitative data requires procedures to code them that can be very difficult to implement (Misangyi et al., 2017).

3.1.2 Set relations: Consistency and Coverage

To empirically identify all the possible causal processes leading to an outcome, after the transformation of all variables (both outcome and causal conditions) into sets, a truth table is built. A truth table has been specified by Ragin in 1999 as a list of all "logically possible combinations of causal conditions along with the cases conforming to each combination"; a truth table does not only show all the possible configurations of causal conditions, but it also enables the identification of those configurations leading to the outcome (Fiss, 2007).

The truth table is sorted by frequency, the minimum number of cases explained by a configuration needed to consider it a solution, and the minimum consistency level of the solution. Consistency has been defined by Ragin (2006) as "the degree at which cases sharing a given condition or combination of conditions agree in displaying the outcome in question". Set consistency is one of the two main aspects of set relations (the other one is coverage) because it measures how much a specific evidence is consistent with the argument that a set relation exists and it allows to evaluate necessity and sufficiency of set relations. In fsQCA, it can be stated that a subset relation exists when the membership score in one set is less or equal to the membership score in another set: for necessity, membership score in the outcome (Y) should always be less or equal to the membership score in the cause (X), while for sufficiency the opposite, the membership score in X should always be less or equal to membership in Y (Ragin, 2006). To better understand these rules, it is important to further specify the meaning of necessity and sufficiency. In order for a condition to be considered necessary it should be present in all possible paths that lead to the outcome and this can be summarized by the expression "whenever we find Y, we also find X, but not vice versa", suggesting that necessity focuses only on cases showing the outcome to identify necessary conditions, (Wagemann and Schenider, 2010). To evaluate sufficiency, instead, cases not showing the outcome are considered too, since are examined all the cases showing a particular condition or a combination of conditions to evaluate if they all (or almost all) experience or not the same outcome: if a combination is defined as a sufficient condition than every time it is not present, the outcome is not present either and this can be explained by the affirmation "whenever we find X (condition), we also find Y, but not vice versa" (Fiss, 2007; Misangyi, 2017). Moreover, necessary and sufficient conditions can be characterized by "core'' or "peripheral'' elements, two concepts defined by Fiss (2011) based on the causal relationship with the outcome: core elements have a strong causal relationship with the outcome, while peripheral elements present a weaker causal relationship with the outcome. The distinction between core and periphery, allows to introduce the concept of neutral permutations: the core causal conditions can be surrounded by different combinations of peripheral elements and these "permutations of peripheral causes'' can have the same effect on the outcome (equifinality), (Fiss, 2011). Neutral permutations can also be represented by the term INUS: insufficient but necessary part of a condition which is itself unnecessary but sufficient for the result (see. Mackie, 1965; Pappas and Woodside, 2021). Such conditions may be present or absent in a solution, or they may be conditions for which we "do not care".

As mentioned before, consistency is not the only relevant aspect of set-subset relations, but there is also coverage that should be evaluated. Set-theoretic coverage assesses the degree to which a cause or causal combination ''accounts for'' instances of an outcome and it is connected to the concept of equifinality and causal complexity, since it allows to identify the proportion of instances following each path that leads to the outcome (number of cases following a specific path to the outcome/ total number of instances of the outcome), (Ragin, 2006). Coverage is measured after consistency has been checked since it is meaningless to assess the coverage for inconsistent set relations (inconsistent subsets of the outcome), but coverage and consistency often contradict each other: a subset relation can be highly consistent, but it could be represented by a very low number of cases, because for example, there are many other potential paths to reach the outcome, leading to a consequential low coverage level (Ragin, 2006).

There are two final important considerations to be made:

- Consistency and coverage are descriptive measures, not inferential;

- Cases with a strong degree of membership in the causal condition/combination provide the most relevant consistent and inconsistent cases.

3.1.3 Counterfactual Analysis

Counterfactual Analysis allows to deal with the problem of limited diversity defined by Fiss (2007) as "a situation where one or more of the logically possible combinations of causal conditions specified in the analysis do not exist empirically''. The concept of limited diversity is inherent to causal complexity, since it implies that the diversity of cases, observed empirically, is limited by the tendency of the attributes to fall into coherent patterns because they are independent and usually change only discretely or intermittently (Misangyi et al., 2017). Moreover, limited diversity is critical in the choice of the number of causal conditions to include into the analysis because for every single causal condition added the number of causal combinations doubles, increasing the probability of having "logical remainders'', rows of the truth table that do not have empirical instances, and thus making the analysis more challenging (Meuer and Fiss, 2020).

Counterfactual Analysis represents a "reasoned evaluation of the outcome that an observed configuration would exhibit if it did exist'' (Misangyi et al., 2017). It enables the identification of two solutions: the intermediate solution that employs easy counterfactuals and the parsimonious solution that employs easy and difficult counterfactuals (Meuer and Fiss, 2020). Easy counterfactual refers to a causal condition that is added to a set of causal conditions that already by themselves lead to the outcome, meaning that adding this causal condition to the configuration does not make any difference (Fiss,2011). While difficult counterfactuals are represented by situations where a condition is removed by the set of causal conditions leading to the outcome, so removing that condition doesn't make any difference (Fiss, 2011).

A "solution" is a combination of causal conditions for which the rule "the combination leads to the outcome'' is consistent in a higher number of cases (Pappas and Woodside, 2021). The "complex solution" indicates all the possible configurations identified and it avoids the use of any logical remainders (Pappas and Woodside, 2021). Instead, the "parsimonious solution" allows the use of any remainder that will yield simpler solutions, so it includes all possible simplifying assumptions irrespective of whether they are based on easy or difficult counterfactuals (Ragin,2008). The "intermediate solution" includes simplifying assumptions regarding easy counterfactuals because this solution includes only theoretically plausible counterfactuals based on the application of theoretical and substantive knowledge and this type of knowledge links to the presence (easy counterfactuals), not the absence of a condition to the

outcome (difficult counterfactuals), that are much harder to determine (Fiss, 2011; Ragin, 2008).
The investigation of limited diversity could enable the design of configurations that offers robustness into organizations and it could allow the identification of additional conditions that may reinforce or improve existing configurations (Fiss, 2007).

3.2 QCA opportunities and issues

At the beginnings of its application, QCA had a little impact on management research and literature, it was mainly applied in situations with a small number of cases, but too high for a classical qualitative approach and too small for a quantitative one (Meuer and Fiss, 2020). Then, from the year 2007 it started to be applied more and more in management research and to be considered as a valid potential integrated research approach to the business literature; so, the number and variety of studies increased gradually, being employed in different subfields in combination with more qualitative and quantitative approach.
This expansion and increasing appreciation towards QCA has been reached thanks to the advantages and potential this approach has, such as the opportunity to study phenomena that are intrinsically configurational, to validate existing typologies, defined by Fiss (2011) as "conceptually derived interrelated sets of ideal types that identify multiple ideal types, each of which represents a unique combination of the organizational attributes that are believed to determine the relevant outcome(s)", but also to discover new ones (Meuer end Fiss, 2020). Moreover, QCA allows to address sufficiency and necessity both for causal conditions and combination of conditions, leading to the identification of some "common patterns'', resulting from different configurations of conditions, among all the possible paths that could lead to a specific outcome (causal complexity) (Ragin, 1999).
Another important opportunity provided by this approach is the consideration of the problem of limited diversity that exists also in quantitative analysis, but it is not addressed since it does not appear as a problem, because quantitative tools assume causal additivity and linearity that enable researchers to extrapolate general predictions even though some independent variables are not empirically represented by cases (Ragin,1999).
QCA provides a closer link between social theory and empirical evidence because social theory is largely verbal and verbal formulations are usually set theoretic in nature; moreover, it allows to study and distinguish among necessary and sufficient causal relations, identifying causal patterns that traditional techniques do not address (Ragin, 2008; Ragin and Pennings, 2005). The link between case-oriented methods (qualitative strategies) and variable-oriented

techniques (quantitative methods) is enabled by QCA, overcoming the limited range of cases typical to the first and the simplifying assumptions in the case of the second, being both an holistic approach (cases are treated as whole entities) and causal-analytical (Vancea, 2007).
Finally, truth tables allow to logical minimize data complexity and, thanks to the use of degree of membership rather than the binary in-out values, it allows a more accurate representation of categorical concepts (Vancea, 2007; Ragin and Pennings, 2005)
However, to offer a more complete view of QCA, it should be considered that this approach is represented by some issues too. An important issue regards the endogeneity connected with omitted variables and invalid reference, specifically, in small n-QCA it is easier to support the inclusion of all relevant variables in the study because of the closeness of the researcher with the issue and its knowledge about that, but when 'n' increases this closeness is more difficult to assess and the risk of invalid inferences increases; more studies are needed to study the issue of endogeneity in terms of omitted causal factors (Meuer and Fiss, 2020).
As stated by Meuer and Fiss (2020), another issue is the fact that QCA lacks a well established approach for including the time variable in analysis, being unable to fully capture the potential of temporal theorizing and time-series configurational analysis.

3.3 QCA process

3.3.1 Outcome definition

In this thesis the outcome to be investigated is team proactivity. Team proactivity is measured as the mean value of employees' proactive work behavior (PWB) within the same work unit.
PWB distinguishes people based on the extent to which they take actions to influence the environment, indeed PWBs are characterized by taking initiatives to improve the current situation or to change it by challenging the status quo, rather than passively accepting it (Crant, 2000).
PWB is connected with mainly two personality dimensions: extraversion and conscientiousness (Bateman and Crant, 1993). Extraversion is defined by the "need for stimulation, activity, assertiveness, quantity and intensity of interpersonal interaction'' and a proactive personality, in fact, seeks for new activities, opportunities and experiences, presenting a strong extraversion. Conscientiousness is determined by the degree of persistence and motivation in reaching objectives and it is connected with proactivity because proactive behaviors are strongly goal oriented, guided by a need for achievement (Bateman and Crant, 1993).
To better understand PWB, four proactivity constructs can be identified (Thomas et al., 2010):

1. Proactive personality: individuals are not shaped by the environment, but they actively initiate change in the environment.
2. Personal initiative: individual propensity to proactively engage in activities, behaviours in line with the organizational goals and mission with a long term focus.
3. Voice: proactively discuss change oriented and constructive ideas with the purpose of improving, even though others disagree.
4. Taking charge: efforts for pushing and reaching changes in the work environment, shaping new organizational processes and procedures.

These four proactivity constructs emphasize the key elements of proactive behavior, such as acting in advance to anticipate future problems and needs (personal initiative and taking charge), taking control and causing change, that means avoiding for something to happen and then passively respond to it (proactive personality and voice), and self-initiation, which consists on starting something by your own, without waiting people to tell you to do it and it is crucial for both taking control and being anticipatory, (Parker and Collins, 2010).

According to Grant and Parker (2009), PWB can be simulated by three main work design features: autonomy, ambiguity and accountability. Autonomy makes workers perceive they have the opportunity and ability to take on broader roles, stimulating proactive behaviors. Autonomy acts directly on role-breadth self-efficacy and flexible role orientation, which can be considered the two main antecedents of proactivity (Parker, 2000). Role-breadth self-efficacy (RBSE) represents the extent to which employees feel capable of performing tasks beyond strict technical requirements. Autonomy increases RBSE because employees feel more confident about performing a wider range of tasks and assuming more responsibility and this increased RBSE leads to an increase in proactivity (Parker, 2000; Grant and Parker, 2009). Autonomy increases flexible role orientation (FRO) too: FRO pushes employees to adopt a broader view of their roles and autonomy enables employees to define their roles in a more flexible way increasing FRO, which ultimately increases proactivity (Parker, 2000). Autonomy can increase proactivity through acting on role-breadth self-efficacy and flexible role orientation, but this change towards a proactive behavior is a learning process: in order for employees to a have a broader vision of their work and to engage themselves in different tasks and activities, they need to be trained and empowered through learning mechanisms that allow to develop their knowledge and expertise (Parker, 2000; Grant and Parker, 2009).

Ambiguity is another job feature that may increase proactivity and it can be defined as the "presence of uncertain or equivocal expectations'' (Grant and Parker, 2009). Ambiguity stimulates proactive behaviors because employees want to reduce uncertainty and to do so, they have to act in advance for avoiding future problems, improving tasks, and creating more stability. Ambiguity can also push employees towards a more information seeking and feedback seeking approach, creating a higher level of proactivity in order to improve their careers (Grant and Parker, 2009). Indeed, for individuals working under uncertain conditions, such as with job ambiguity, but also under other conditions, feedback can be a valuable resource for employees, since it could push them towards the achievement of their goals (Crant, 2000). Proactive feedback seeking and also information seeking attitudes are connected with a learning-goal orientation approach by workers, that represents the desire for learning new skills and acquiring new competences for personal and professional upgrade not for receiving positive judgements, avoiding negative ones (Crant, 2000).

The last work design feature identified by Grant and Parker (2009) as an important stimulator of proactivity is accountability, that represents the "expectation to justify one's actions to an audience''. Accountability makes employees feel more responsible for their tasks and this can lead to more proactive behaviors by employees to improve work, processes, and techniques (Grant and Parker, 2009).

These three work design features are not exhaustive, indeed there are other job characteristics that can positively affect proactivity such as job complexity and the social context and they represent contextual factors, but PWB can be influenced also by individual differences that represent the individual personal disposition towards proactivity (Crant, 2000).

3.3.2 Causal conditions definition

The purpose of this thesis is to investigate the impact of Industrial Internet of Things (IIoT) and Lean bundles configurations on team proactivity.

IIoT can be defined as the industrial application of the Internet of Things and has been already explained in Chapter One. While, for lean variables three bundles will be considered: JIT (Just in Time), TQM (Total Quality Management), HRM (Human Resource Management).

JIT aims at continuously reducing waste and it is represented by a series of practices implemented to deliver products at the right time, quantity and place and it is achieved through a smoothly flow of materials, set up reduction, small lots production that keeps in-process inventory at the minimum level, Kanban cards that enable a "pull'' system and level scheduling that stabilizes and balances production workload (Galeazzo and Furlan, 2018; Dal Pont et al., 2008).

TQM can be defined as a "management system used to continuously improve all areas of a company's operations aiming at reducing operational variability, which in turn leads to continuous improvement'' (Dal Pont et al., 2008). TQM practices, such as statistical process

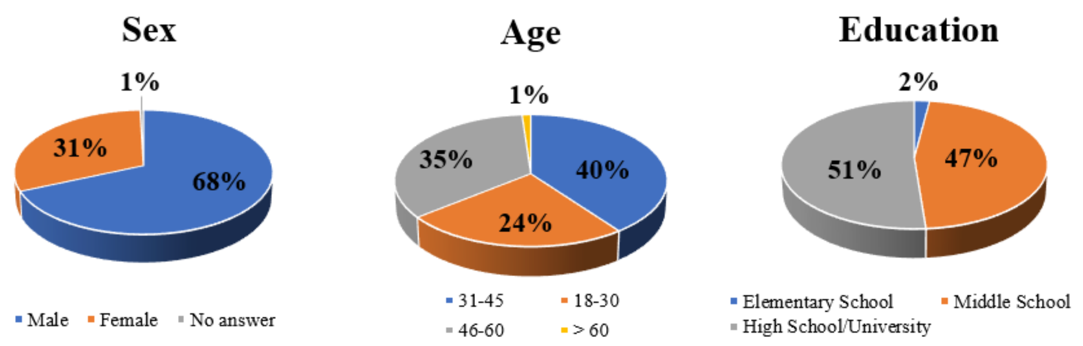
control and visual tools, are implemented to excel in quality products and processes (Galeazzo and Furlan, 2018).
HRM is represented by a "set of practices that emphasize the importance of employee involvement, the enhancement of employees skills and the support of top management'' (Galeazzo and Furlan, 2018). HRM practices, such as employee involvement, employee education and training, satisfaction and well-being, favour work flexibility and communication among employees, thus removing traditional barriers that impede innovation and continuous improvement (Dal Pont et al., 2008).

3.3.3 Database description

In this study secondary data, collected from February 2021 by Galeazzo and Furlan on medium to large size Italian manufacturing firms, are used. The data refer to companies selected from the AIDA database. Initially, 43 firms were involved in the study: the authors sent an e-mail to 326 key informants inside relevant Italian medium to large size companies, explaining their research purposes and the intended process of data collection, but only 43 firms replied to the e-mails. With these 43 firms, virtual meetings with two (on average) of their managers (usually operations managers, general managers and/or digital transformation managers) were arranged. After the virtual meetings, six firms decided to not proceed with the data collection process. The remaining firms accepted to receive a plant visit followed by questionnaires. During the plant visits, work units inside the firms were identified based on a purposive sample approach and they may be defined, in this research, as "production lines, workshops or cells that physically transform parts using either traditional technologies or a system of IIoT technologies". Indeed, the goal of the purposing sampling approach was to identify work units comparable in the database and that differ in terms of IIoT implementation. After the plant visits, four firms were unable to plan a date for completing the questionnaires in the required timeframe, so the final sample is characterized by 33 manufacturing plants, with 440 shop floor employees in 101 work units. For each work unit, employees were asked to fill an anonymous questionnaire involving questions about job characteristics, personality traits, demographic characteristics, proactive behaviors and the perception of HPWS (High Performance Work Systems) adoption.
In the sample investigated, 203 employees (46.1%) belong to traditional work units, meaning the remaining employees worked in work units that adopt some IIoT technologies. Moreover, the majority has a level of education ranging from Middle School License (47%) to High School Diploma/University Degree (51%), 68% are men and the sample age ranges, fundamentally

from 18 years old to 60 years old, with 40% of the respondents in the category 31-45 years old *(Figura 4)*.

Figure 4: Respondents' characterization



Source 4: Personal elaboration

In the database considered, the Lean bundles - JIT, TQM, HRM- are measured as constructs, meaning that they are calculated as a mean of different items that have been defined on a Likert scale with values ranging from 1(strongly disagree) to 7 (strongly agree) and the accurate representation of the variables construction is given in *Figure 5*. For measuring these items supervisors have been interviewed, indeed the degree of implementation of JIT, TQM and HRM is measured at work unit level.

The degree of IIoT implementation has been measured by the interviewers, not the supervisors, at work unit level too, on a scale of values ranging from 0 to 2, where 0 indicates no adoption of the technology, 1 indicates a low adoption level and 2 a high adoption level. In this study, the variable IIoT measures the extent to which the technologies that constitute IIoT have been adopted in the sampled work units. The database used for this study considers IIoT technologies divided into four groups: sensors, connectivity, components, interfaces and AI. Moreover, the authors of the database performed a clustering analysis: they implemented a hierarchical algorithm (Ward's method) combined with the Calinski–Harabasz index and the treelike structure of the dendogram to identify the number of clusters and, finally, a k-median clustering was performed. Implementing this approach, the authors identified three clusters: "Traditionalists", work units which do not adopt the technology, "Low adopters", meaning work units with a limited adoption of IIoT technologies and "High adopters" that indicate work units with a broad application of IIoT technologies.

Figure 5: Lean Bundles construction

Lean Variables construction	
JIT (7 elements)	We usually complete our daily schedule as planned The layout of our shop floor facilitates low inventories and fast throughput Suppliers and logistics partners deliver products and materials just in time Our clients receive "just in time" deliveries from us We have low setup times of equipment in our plant We use a kanban pull system for production control Production is in the smallest possible batch size
TQM (5 elements)	In our plant we give importance to putting all working tools in their place We actively develop proprietary machinery (i.e. made in-house for our specific needs) A large percent of the processes on the shop floor are currently under statistical quality control In our plant, working groups are formed to solve problems Our processes are effectively developed and implemented
HRM (8 elements)	Our team leaders encourage the people working for them to work as a team Management always explains to us why our suggestions have been implemented or discarded Our organizational structure is relatively flat Our employees are trained to multi-task. Our technicians have their offices located close to the production departments in order to provide prompt assistance when production stops During the last three years, many problems have been solved through small group meetings. Training and professional development of staff is carried out regularly in this establishment. Rather than adopting a static approach, we strive to continuously improve all aspects of products and processes

Source 5: Personal elaboration

The outcome to be considered in this study is team proactivity, that is a construct of four constructs: problem prevention, take charge, voice, personal innovation *(Figure 6)*. These four constructs consist of different items measured using a Likert Scale always ranging from 1 to 7: taking charge was measured using a three-item scale; voice was assessed with four items; individual innovation scale included three items and problem prevention was measured with four items. They are measured at individual level interviewing employees, but since the causal conditions are evaluated at work unit level, it was necessary to measure the work unit proactivity. Work unit proactivity has been calculated as the mean value of individuals' proactivity values. So, in this study proactivity is meant at the group level (work unit) not individual.

Figure 6: Proactivity construction

Proactivity construction	
Voice (4 elements)	Do you communicate your opinion on work issues to those who work with you, even if your opinion is different and others do not agree with you? Do you talk openly and encourage those who work with you to get involved on issues that matter to you? Do you keep yourself informed about issues where your opinion could be useful for your workplace? Have your say on new ideas or changes in procedures?
Take charge (3 elements)	Are you looking for improvements in procedures in your workplace? Do you try to introduce new ways of working that are more effective? Are you looking to implement solutions to urgent organisational problems?
Problem prevention (3 elements)	Do you try to develop procedures and systems that are effective in the long term, even if they slow things down in the beginning? Do you try to find the root cause of what goes wrong? Do you spend time planning how to prevent problems from recurring?
Personal innovation (3 elements)	Do you have creative ideas? Are you looking for new techniques, technologies and/or product ideas? Do you promote ideas in front of others?

Source 6: Personal elaboration

3.3.4 Data calibration and data analysis

In fsQCA data measures are converted into fuzzy sets in order to express the causal relationship between the outcome and causal conditions in terms of set membership. Set membership scores range from 0 to 1 and to determine them, it is required to establish three qualitative breakpoints: threshold for full membership (fuzzy score=0.95), threshold for full non membership (fuzzy score= 0.05) and the cross-over point (fuzzy score=0.5), (Ragin, 2017).

In this study, following the approach adopted by Pappas and Woodside in 2021, the values of 6.00, 4.00 and 2.00 are used, respectively, as anchors of full membership, cross-over point and full non-membership for JIT, TQM, HRM and proactivity. These qualitative anchors are established by observing the data distribution of variables that mainly range in the interval [2,6], since values are calculated as means.

While, for the degree of IIoT implementation three different thresholds are established to define the degree of membership, since this variable is measured following a different scale of values. Precisely, 2.00 represents the threshold for full membership, 1.00 the cross over point and 0.0 the threshold for full non membership.

After performing calibration, necessary conditions are evaluated and then the “truth table’’ algorithm is applied to compute all possible combinations of causal conditions. Indeed, the truth table represents a data matrix with $2^{\wedge k}$ rows, where “k’’ is the number of causal conditions used in the analysis, meaning that each row of the table is associated with a specific combination of

attributes (Fiss, 2011). The number of rows in the truth table is reduced based on frequency and consistency: frequency and consistency thresholds are established to indicate the minimum number of cases in the sample explained by a configuration (frequency) and to assess if each combination explains the outcome or not (consistency), (Ragin, 2017). In this analysis frequency threshold is established at 2, given the number of cases examined, and consistency threshold at 0.90. Consistency threshold has been established identifying breaking points in the consistency of values obtained in the truth table, before sorting it by frequency and consistency. Finally, the truth table configurations are simplified by an algorithm based on Boolean algebra. Specifically, this algorithm is based on a counterfactual analysis of causal conditions, that, as mentioned before, distinguishes among "easy'' and "difficult'' counterfactuals, leading to three types of solutions: complex, parsimonious and intermediate.
The results of the QCA process will be presented and analyzed in the following chapter.

FOURTH CHAPTER: RESULTS DISCUSSION

4.1 Analysis of the results

In the study performed the analysis of necessary conditions shows that both Lean bundles and IIoT implementation are not necessarily connected with team proactivity, since for a condition to be considered "necessary'' its minimum consistency level should be 0.90 and, in this research, causal conditions consistency ranges from 0.53 to 0.82 (*Figure 7*). However, it may be noticed that HRM and TQM present a high degree of consistency, 0.82 approximately, suggesting that the presence of these conditions is likely to lead to the outcome.

Figure 7: Necessary Conditions Analysis

Analysis of Necessary Conditions
Outcome variable: Work unit proactivity
Conditions tested:

	Consistency	Coverage:
JIT	0.765810	0.847420
HRM	0.817355	0.820078
TQM	0.821686	0.808266
IIoT	0.531042	0.790967

Source 7: Personal elaboration

The truth table algorithm enables the identification of sufficient conditions, which are represented in *Figure 8*, following the approach used by many other studies (Ragin and Fiss, 2008; Fiss, 2011; Galeazzo and Furlan, 2018; Pappas and Woodside, 2021).

In this table the presence of a condition in the configuration leading to the outcome (team proactivity) is represented by black circles, the absence by crossed out white circles and blank spaces indicate don't care situations, meaning that the conditions to which they correspond may either be present or absent. Moreover, big circles indicate core conditions (present both in the intermediate and parsimonious solution), while smaller circles represent peripheral conditions (present only in the intermediate solution).

The solution table shows three different paths leading to team proactivity (equifinality) with an overall consistency value of 0.83, higher than the acceptable threshold of 0.80 (Fiss, 2011), and an overall solution coverage of 0.71, meaning that the three combined models account for about 71% of membership in the outcome.

The first solution (C1) indicates that IIoT adoption, regardless of the implementation of Lean bundles, leads to team proactivity.

The second path leading to team proactivity is represented by a combination of HRM and the absence of TQM, despite the presence or absence of JIT and IIoT (C2).

The third path suggests that a combination of JIT and TQM, with the absence of HRM enables high team proactivity, regardless the adoption of IIoT (C3).

Figure 8: Sufficient Conditions Analysis

Team Proactivity			
Configuration	C1	C2	C3
Lean Bundles			
JIT			●
HRM		●	⊗
TQM		⊗	●
Industry 4.0			
IIot	●		
Consistency	0.79	0.99	0.98
Raw coverage	0.53	0.30	0.31
Unique coverage	0.29	0.08	0.04
Overall solution consistency		0.83	
Overall solution coverage		0.71	

Source 8: Personal elaboration

Notes: black circles indicate the presence of a condition, while crossed out white circles indicate the absence of a condition. Black spaces indicate a "don't care situation'', meaning that the condition may either be present or absent. Large circles indicate core conditions, small circles, instead, indicate peripheral conditions.

The first solution suggests that technological disruptions such as IIoT are important alone to foster team proactivity.

The second and third solutions suggest a sort of substitution effect between JIT and TQM with HRM, meaning that for reaching team proactivity JIT and TQM should be implemented together when HRM is not adopted, or, alternatively, HRM is a core condition for reaching team proactivity regardless of the other lean bundles. In the following section the results will be discussed further.

4.2 Results discussion

"IIoT adoption leads to workers' proactivity, regardless of Lean bundles implementation"

About the implementation of advanced technologies there are mainly two perspectives: technology-centric and human-centric. Many authors agree in stating that for successfully introducing new technologies a human-centric approach is required, otherwise there is the risk of making workers feel overwhelmed and stressed in the new environment, becoming resistant to change (Cagliano et al., 2019). Indeed, the introduction of IIoT systems inside a factory plant may enhance a feeling of uncertainty within employees, who are required to change and enhance their individual skills and who may fear losing their jobs, since routine activities can be performed by machines (Sievers et al., 2021).

To understand how IIoT can foster team proactivity (calculated in this paper as a mean of individual proactivity values), the approach adopted by Leyer et al., (2018) may be followed. In this study, the authors identify four dimensions (access to information, access to resources, access to support and access to opportunities) to which employee empowerment is connected and they explain how ICT (Information and Communication Technologies) can act on these four dimensions, ultimately increasing empowerment. This study has been replicated by Sievers et al., in 2021, who have focused not on ICT in general, but on IIoT. Based on this study, the adoption of IIoT technologies can act on the access to information, access to resources, access to support and access to opportunities.

The two main principles of IIoT are connectivity, meant as "access by anyone'' and accessibility, intended as "access everywhere and anytime'' (Hartmann and Halecker, 2015). In fact, IIoT systems and devices are able to collect and make available throughout the whole organization a huge volume of data, creating a mobile and ubiquitous information. In this situation, workers may access all the information they need to perform an activity, about a machine, a system or even about another colleague (Sievers et al., 2021). This increased access to information makes it easier for workers to identify current or future problems and initiate solutions by themselves, pushing workers to take charge (e.g. to look for improvements) and prevent problems (e.g. try to find the root cause of a problem) two elements that lead to an increase in proactivity.

IIoT also enables the access to resources, that are inclusive not ophysical resources such as tools or spare parts, but also intangible resources such as time (Leyer et al., 2018).

Inside the manufacturing plant, workers may need a lot of time to find out where tools are located, who is using them, which resources are available and which not and so on. Thanks to devices such as sensors and tags, employees have the opportunity to identify all the issues regarding resources at the beginning of the working day, for example, optimizing their search and saving time (Sievers et al., 2021). The time saved may be used for training and learning activities that are critical for employees' involvement when a new technology is implemented, it may also be exploited by workers for "reflection'', meaning for thinking analytically and creatively about a situation (Garvin et al., 2008). This critical investigation of situations and problems may push personal innovation, since workers have the time needed for developing creative ideas and then promoting them, for searching and testing new techniques, and it may increase employees' voice as well, since they may use the time available to become informed about other issues happening inside the company, develop a thorough opinion about them and then communicate them.

Access to support is facilitated by IIoT technologies, since the interconnected dashboards not only provide data about activities or processes, but they also provide the opportunity to identify who are the experts about a specific issue or task and how to reach them (Leyer et al., 2018). Workers should feel free to ask questions and support to coworkers, supervisors or managers, when they need it, since, as stated in the first chapter, to enhance EI (employees' involvement) on continuous improvement activities, practices focused on organization openness and communication are key. Moreover, the opportunity to receive information or feedback about a task or a job is strictly connected to proactivity and pushes employees towards their achievements. Another aspect of having access to support is that it may represent a learning opportunity for workers, that may ultimately push them towards the proactive development of new ideas or solutions, and their respective sharing inside the organization to promote change. In a context characterized by IIoT, devices and sensors themselves are able to support workers in their decision-making processes by providing them real-time feedback, such as status updates or instructions (Sievers et al., 2021).

Finally, IIoT facilitates access to opportunities that, in general terms, may be interpreted as learning opportunities. IIoT enhances the awareness of what is happening inside the whole company, enabling workers to have a deeper understanding of processes, which helps them to find solutions and foster learning. In fact, instruments such as dashboards that provide not only current data, but also previous data are useful for the identification of the root causes of a problem, facilitating problem prevention, personal innovation, taking charge and voice.

To conclude, IIoT may foster proactivity in different ways, but to make it beneficial for the company it should be combined with learning: workers need to be trained, to acquire knowledge about the technical aspects of specific devices, systems and so on, to develop new competencies and skills.

If a “learning organization’’ is created, employees could proactively create, acquire and transfer knowledge to improve their individual performance and to openly discuss improvement opportunities and possible issues (Leyer et al., 2018; Garvin et al., 2008).

“The configuration HRM and not TQM leads to workers’ proactivity/ TQM with JIT and not HRM leads to workers’ proactivity”

HRM, JIT, TQM are three different lean bundles, where for a bundle is intended a set of practices that work together towards the achievement of a specific goal. JIT and TQM are often considered as more technical practices, HRM, instead is commonly referred to as a social bundle. There are many studies that sustain the complementarity of these bundles referring to the impact on the company’s operational performance, meaning that the adoption of one bundle increases the marginal returns of the other and vice versa (Furlan et al., 2011).

Indeed, Shah and Ward (2003) consider four Lean bundles that are TPM, TQM, JIT and HRM, and demonstrate how they have a positive impact on company’s operational performance both when implemented separately and when combined together, supporting the idea that a synergistic effect is created among these four bundles. Moreover, Dal Pont et al., (2008) demonstrate that JIT and TQM have a positive direct effect on a company's operational performance, while HRM is not directly connected with the operational performance, since its impact is mediated by JIT and TQM. HRM is also considered a necessary condition for JIT and TQM successful implementation.

HRM is considered as an enhancer of JIT and TQM complementarity by Furlan et al., (2011) too: HRM pushes employees to be innovative and autonomous, thus enabling quality improvements and JIT because they become able to identify new ways of reducing set-ups, ultimately facilitating pull production flows and by implementing practices such as education and training.

These studies, as many others, focus on the company’s performance and the creation of complementarities among the Lean bundles. This thesis moves away from this literature, since it focuses on the worker dimension, studying proactivity and showing the presence of a substitution effect between HRM (social dimension) and the combination of JIT and TQM (technical dimensions).

Indeed, the fsQCA shows that HRM is a sufficient condition for reaching team proactivity with the absence of TQM and regardless of the implementation of the other two causal conditions (IIoT and JIT). HRM implements practices such as job rotation, job design, training programs, problem solving activities, employee involvement that lead to the development of a flexible cross-functional work force (Shah and Ward, 2003). A flexible role orientation is one of the antecedents of proactivity, so by acting on this dimension HRM increases proactivity.

Moreover, HRM acts on all the four dimensions of proactivity, voice, take charge, problem prevention and personal innovation:

- Voice: HRM pushes a reduction in organizational layers and an increased communication between management and workers, making them more comfortable on manifesting their opinions even when they may be different from what the majority sustains and on being, consequently, more open to other people's ideas too.
- Take charge: HRM practices increase employee involvement, empowering workers with the appropriate tools for the development of new solutions that can potentially lead to improvements inside the organization.
- Problem prevention: education and training increase workers problem solving capability, that translates in the identification of root causes of problems and the consequential understanding of how to prevent the occurrence of these problems.
- Personal innovation: HRM impacts how workers perceive their role inside the company, since they feel more involved in the company's goals and objectives and this motivates them to be more “innovative’’. Indeed, workers are more motivated when they perceive a company's interest in the long-term development of their careers and this is enabled by higher employee involvement, training programs, openness by management and coworkers and so on (Bonavia and Garcia, 2011).

On the other hand, fsQCA results show that TQM combined with JIT increases workers’ proactivity. The impact of these two Lean bundles on workers’ proactivity may appear less intuitive since they are usually associated with more technical aspects, as already mentioned, such as lot size and cycle time reduction (JIT) or statistical process control and poka yoke techniques (TQM).

In general terms, the synergistic effect between JIT and TQM has been demonstrated by various studies such as Furlan et al. (2011), as previously stated, Sriparavatsu and Gupta (1997), who show that the joint application of TQM and JIT practices increases performance variables such as quality, productivity, employee involvement, cost reduction. Moreover, Galeazzo and Furlan (2018) through a qualitative comparative analysis demonstrate that the combination of JIT and TQM leads to a high financial performance; Sulistyowati et al., 2020, with a study performed on Indonesian companies, evidence that JIT has a positive direct effect on operational performance and an indirect effect through TQM. However, there are no relevant studies that show the synergistic effect among these two bundles on the workers proactivity.

Both TQM and JIT are characterized by information and feedback as key elements for continuously reducing waste and increasing quality of products and processes (Cua et al., 2001).

Additionally, JIT practices enable the creation of a flexible workforce since, to deliver "the right product at the right time in the right place", workers have to be flexible and autonomous in their tasks when an emergence is faced, because they have to find a solution very fast otherwise there will be delays or defects in the products.
On the other hand, according to some authors, such as Agus and Selveraj (2020) and Chen (2015), TQM includes many technical oriented practices (also referred to as "hard TQM'') such as process improvement and statistical process control analysis, but it comprehends some people- oriented practices too (also referred to as "soft TQM''), such as workforce commitment, teamwork, customer and supplier relationships. Indeed, TQM does not only facilitate the reduction of rework, the re-design of processes, competitive benchmarking, but it also increases employee participation and teamwork by pushing both behavioral and individual's learning process, that, in turn, has a positive impact on job involvement, job satisfaction, organizational commitment (see Miguel, 2003; Agus and Selvaraj, 2020).
Workers' flexibility and autonomy, pushed by JIT, combined with teamwork and employee involvement, enabled by TQM, ultimately increase workers' proactivity since, as has been already cited, elements such as flexibility, autonomy, teamwork and employee involvement are key for proactivity.
The difference between HRM practices and TQM with JIT is that, HRM acts directly on the workforce dimension with the purpose of improving its well-being, satisfaction and involvement, while the combination of TQM and JIT has a more indirect effect on workers proactivity: proactivity is achieved through practices employed to reach some technical results, not with the primary goal to focus on employees.
The results of this paper evidence that:

1. The adoption of IIoT technologies is a sufficient condition for the achievement of team proactivity and there is no contradiction in the joint adoption of IIoT and Lean bundles. Indeed, all the three configurations show that when IIoT is adopted Lean practices may or may not be adopted, with no difference and when Lean bundles are adopted, the presence or absence of IIoT is irrelevant.
2. HRM alone is a sufficient condition for the achievement of team proactivity. This may suggest that when the outcome variable is connected to the work organization at micro level (such as proactivity in this case), a human-centric approach should be adopted with a primary focus on the employee's involvement and well-being. Moreover, a social bundle such as HRM, should not be jointly implemented with other bundles, such as TQM, that involve some social practices too.

3. The combination of JIT and TQM, and not HRM, is sufficient for reaching workers' proactivity. This result suggests that technical bundles, when combined together, present synergistic benefits, and for reaching team proactivity a bundle focusing almost exclusively on technical aspects, such as JIT, should not be combined with a highly social bundle (HRM), but with a set of practices that mainly focus on technical aspects, but that consider some social aspects too (TQM).

CONCLUSIONS

This thesis investigates how Lean bundles and IIoT technologies interact for improving workers' proactivity and demonstrates that there are different ways through which it may be achieved.

Indeed, to push team proactivity managers do not have to necessarily implement all Lean bundles and IIoT jointly, but they need to carefully consider how to allocate resources between the different practices. As stated by Galeazzo and Furlan, (2018), managers should focus on the integration of those practices that best fit their company's needs and its context. Furthermore, since different configurations lead to an increase in proactivity, managers must first define what ultimate goals their company needs to achieve through increased proactivity.

This means that if the primary goal of the company is to improve processes for quality and speed improvements by increasing proactivity then, the most appropriate approach is to implement JIT and TQM jointly (third solution) (Galeazzo and Furlan, 2018).

While the approach based on the implementation of HRM practices may be best suited when the underlying priority of the company is less narrowed, meaning that it aims at improving the general well-being and satisfaction of employees for increasing their active and proactive participation in companies' activities and goals for, ultimately, improve processes, maintenance, quality, work organization, etc.

The adoption of IIoT technologies may be the most appropriate approach when the main priority of the company is to increase productivity, since it requires the availability of huge amounts of data on productive assets and awareness by employees about the effect of their actions and behaviors.

So, based on the previous discussion, it may be stated that this thesis provides managerial contributions by suggesting that there is not a unique solution for the adoption of proactive work behaviors by employees, but there are different approaches and, based on the underlying priorities of the organizations, managers should choose among them.

Overall, the benefits provided by Lean practices on the human dimension have been demonstrated from previous literature, mainly from a theoretical perspective and on a general perspective that implies an overall consideration of the paradigm of Lean Production. The effect of Industry 4.0 technologies on employees has been less investigated and it is probably due to the fact that the Industry 4.0 paradigm is more recent than Lean. This thesis provides a comprehensive approach to the investigation of employee proactivity considering both Lean bundles and an Industry 4.0 technology (IIoT). However, this thesis is characterized by some limitations too. First, it investigates the potential complementarities between three Lean bundles and one Industry 4.0 technology, when there may be other Lean sets of practices, such as TPM, and other Industry 4.0 technologies, that combined together may push proactivity. Indeed, especially when considering the vast amount of Industry 4.0 technologies, it may be crucial to investigate further how other technologies may impact the human-dimension. Moreover, the inclusion of different Lean bundles may contribute to the further understanding of how technical practices and social practices interact with each other, potentially identifying other synergies or trade-offs.

Another limitation is inherent to the fsQCA approach, since its results are limited by the number of causal conditions applied and the cases considered. So, it may be useful to perform studies with an even higher number of cases and a higher number of causal conditions: for example, job characteristics may be included to see if and how they may change the results and eventually, how they interact with lean bundles and IIoT.

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To myself, to the commitment and efforts of a lifetime,
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