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Investments in digitalization and business growth

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INVESTMENTS IN DIGITALIZATION AND BUSINESS GROWTH

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INTRODUCTION

The concept of Digital Transformation refers to the profound changes driven by digital technologies, which affect not only individual firms but also the economy and society as a whole. This transformation fosters the emergence of new business models in which digital technologies play a central role. Innovations such as artificial intelligence (AI), the Internet of Things (IoT), robotics, and 3D printing converge to create intelligent and interconnected production systems, thereby opening new frontiers in terms of efficiency, flexibility, and product customization.

Chapter 1: Digitalization and Company Growth analyses the impact of Industry 4.0 and Industry 5.0 on business models. Particular attention is devoted to the role of digital technologies, especially AI, in modernizing business structures and ensuring sustainable competitive advantage. The chapter also explores the relationship between digital adoption and productivity, considering the broader effects on employment, wages, and international competitiveness. In order to provide a comprehensive framework, it reviews the main studies on the relationship between AI and productivity, as well as the debates surrounding the concepts of the productivity paradox and the digitalization paradox.

Chapter 2: Econometric Analysis will focus on the relationship between digital technologies, especially AI technologies, and productivity in the case of Italian firms. We will show that the firms investing in digital technologies have a higher labor productivity by 12.2% than the non-investing firms and that the impact is higher for the firms investing in AI technologies that have a labor productivity higher by 19.7%.

We will also analyse the effect of different AI technologies on productivity, with particular attention to the importance of the number of technologies adopted and the role of training. We will arrive to demonstrate that a higher number of AI technologies will lead to a higher effect on labor productivity and that the relationship between digital technologies and labor productivity raise across firms investing in training activities.

Finally, we will outline the main guidelines, presenting the key challenges that different countries must face to ensure that the effect of adopting digital technologies, and in particular AI, is maximized.

CHAPTER 1: Digitalization and company's growth

1)Definition of Digitalization and Digital Transformation

The term digitization, along with the expression Digital Transformation, has been extensively discussed in numerous academic articles but lacks a universal definition. However, from the analysis of the main literature sources, it is clear that the distinction between "digitization", "digitalization", and "digital transformation" is essential. According to Verhoef, P. C. et al (2021), these three expressions represent the phases of Digital Transformation. The authors argue that digital transformation is driven by certain external drivers and that specific strategic actions are necessary for successful implementation.

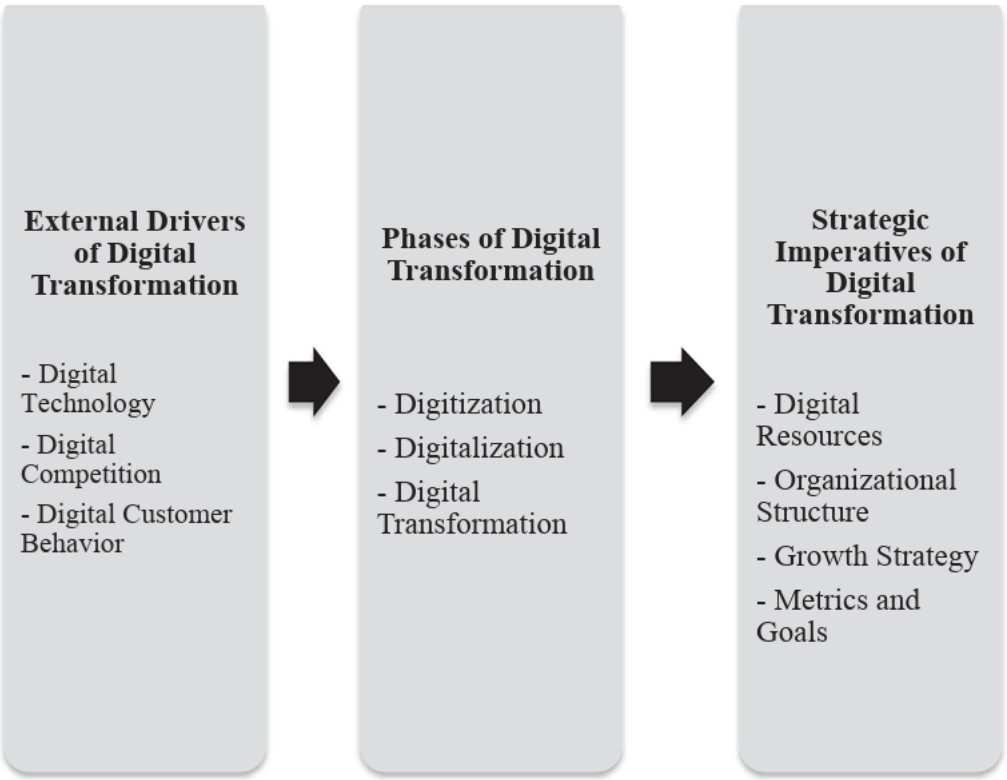

Fig. 1. Flow Model for Discussion on Digital Transformation.

Figure1: Flow Model for Discussion on Digital Transformation

Source: Verhoef, P. C. et al, 2021

To analyze the phenomenon more comprehensively, we will describe the three expressions in detail.

Digitization is a term introduced in 1960, describing the action of converting analog informations into digital informations so that computers can manage and transmit it (Dougherty and Dunne, 2012; Loebbecke and Picot, 2015). In addition to this definition, which focuses solely on the conversion of internal or external company documentation into a digital format, some scholars use the term to refer to the shift from analog to digital tasks (Li et al., 2016; Sebastian et al., 2017) or as the integration of IT technologies into existing processes, resulting in greater operational efficiency, reducing costs, and making resources more accessible, precisely through the adoption of digital technologies (Lai et al., 2010; Vendrell-Herrero et al., 2017).

Digitalization describes how IT or digital technologies can modify various business processes (Li et al., 2016). According to Kim, S., Choi, B., & Lew, Y. K, (2021), digitalization can influence both business processes and products or services. Process digitalization refers to the conversion of a business process carried out in the real world into multiple stages performed virtually. Product digitalization refers to transforming a physical product into a digital version that can be exchanged virtually. Finally, service digitalization refers to the provision of a service, which was previously offered in a physical space, now offered in a virtual space (Kim, S. et. Al., 2021).

In digitalization, IT becomes a key element in seizing new business opportunities by changing pre-existing business models, such as communication (Ramaswamy & Ozcan, 2016; Van Doorn et al., 2010), distribution (Leviäkangas, 2016), or business relationship management (Baraldi & Nadin, 2006). Through digitalization, companies adopt digital technologies to optimize current business processes through greater coordination among them, often resulting in increased value for consumers due to a better user experience (Pagani & Pardo, 2017).

Ultimately, digitalization not only allows companies to reduce their costs but also impacts the business model by affecting business processes and, in many cases, changing the relationship with the end consumer, who benefits from an increased perceived value.

Digital transformation, on the other hand, refers to the drastic change brought about by digital technologies not only to individual companies but also to the economy and society as a whole (Kim, S. et. Al., 2021).

At the corporate level, this term refers to the change undergone by companies, typically resulting in the creation of new business models (Iansiti & Lakhani, 2014; Kane et al., 2015; Pagani & Pardo, 2017), a key element for maintaining a competitive advantage. Digital transformation introduces new business logics aimed at creating and capturing value (e.g., Pagani & Pardo, 2017; Zott & Amit, 2008). In fact, it not only influences business processes and tasks, as digitalization does, but impacts the entire company, affecting the business model (Amit & Zott, 2001).

Digital transformation is particularly crucial for incumbents, meaning companies already established in a sector, which often face challenges and barriers when trying to innovate the existing business model through the adoption of digital technologies. The choice must consider the various trade-offs between the existing and the new business model (Christensen, Bartman, & Van Bever, 2016; Markides, 2006).

In general, most definitions focus on the concept of change, understood as a structural change in the business model and the value that the change generates.

Cheng Gong & Vincent Ribiere (2021), in an attempt to create a universal definition that could be referenced by both academics and managers, define digital transformation as "A fundamental change process, enabled by the innovative use of digital technologies accompanied by the strategic leverage of key resources and capabilities, aiming to radically improve an entity[1] and redefine its value proposition for its stakeholders."

The importance of resources and capabilities is also highlighted in a study by Ebert & Duarte (2018). Digital Transformation is depicted as the result of the convergence between hard power (technology) and soft power (people and business), generating value through the resulting processes. It also highlights how value is created not only through traditional means but also through digitalization. In this context, software and technologies act both as a driver and a consequence of digital disruption.

2) From Industry 4.0 to Industry 5.0: Differences and New Perspectives

2.1) Industry 4.0

The term Industry 4.0 was first introduced at the “Hannover Messe 2011” fair by Siegfried Dais and Henning Kagermann, the main proponents of the project implemented by the German government to realize the high-tech strategy. (Mario Rupp et. Al., 2021)

After the term was coined, several initiatives were observed in other countries aimed at achieving the same goal. In the United States, for example, the ‘Advanced Manufacturing Partnership (AMP)’ and the ‘Smart Manufacturing’ initiatives were

[1] An entity could be: an organization, a business network, an industry, or society.

launched. China, on the other hand, implemented a ten-year plan called ‘Made in China 2025’ to transform its manufacturing industry. (Mario Rupp et. Al.,2021)

Despite this, an unanimously agreed definition is still lacking. In an attempt to formulate a universally valid definition based on a bibliometric analysis and a literature review, Rupp, Schneckenburger, Merkel, Börret, and Harrison (2021) state that Industry 4.0 “is the implementation of Cyber Physical Systems for creating Smart Factories by using the Internet of Things, Big Data, Cloud Computing, Artificial Intelligence and Communication Technologies for Information and Communication in Real Time over the Value Chain.” (Mario Rupp et. Al.,2021)

This interpretation is consistent with the themes addressed in the main academic articles and with the technological characteristics observed.

Thus, the term Industry 4.0 was coined in advance to indicate a planned Fourth Industrial Revolution. Beginning with advanced digitization within factories, characterized by the merging of Internet technologies with innovative technologies in the field of so-called smart objects (products and machines), it seemed natural to witness a paradigm shift in industrial production (Lasi, H. et. Al.,2014).

The production of the future envisions modular production systems, functional because of their extreme efficiency, where the products themselves autonomously control their own production processes. In this context, it would be possible both to produce customized items in batches of one and to maintain the economic advantages typical of mass production (Lasi, H. et. Al.,2014).

These changes are driven by two main directions of development: application pull and technology push (Lasi, H. et. Al.,2014).

The first element emphasizes the stronger demand pull (application pull) resulting from social, economic, and political changes. In particular, the reduction in development times, on-demand customization, flexibility, decentralization, and resource efficiency are key elements.

Reducing development times is fundamental since the ability to innovate is becoming the primary factor for business success. For these reasons, it is necessary to innovate and develop rapidly.

On-demand customization, meanwhile, is the element that best reflects the shift from a seller-dominated market to one dominated by buyers. The latter set the terms of exchange, thereby necessitating an increasing individualization of products.

Flexibility is essential due to the new operational requirements and is necessary in both the development and production of products.

Decentralization represents the need for faster decision-making processes by reducing organizational hierarchies to address the numerous challenges companies must face in an increasingly unpredictable environment.

Resource efficiency is necessary given the heightened attention to industrial sustainability (Lasi, H. et. Al.,2014).

On the other hand, there is a strong technological push in the industrial context. Several directions of technological development can be identified: increased automation and mechanization, digitization and interconnection, and miniaturization.

The increase in automation and mechanization not only supports work practices with technological tools but also enables complex analytical, managerial, and operational tasks to be performed by automatic solutions such as autonomous production cells, which manage and optimize processes independently.

The increasing digitization of production processes and machinery allows for a larger amount of data to be collected via actuators and sensors, thereby improving the control and analysis of processes. Moreover, the greater interconnection among various technical components, machinery, sensors, or digital systems, along with the increased digitization of products and services, promotes the creation of digitized environments that enable the development and implementation of new technologies such as simulation, digital protection, and virtual/augmented reality.

Miniaturization, on the other hand, opens up new application opportunities, especially in production or logistics contexts where the use of small-sized electronic devices with high performance is fundamental (Lasi, H. et. Al.,2014).

Within a production system, the human component, machines, products, and processes are all connected and self-regulating. This not only allows for strategies to respond to changes but also fosters the implementation of solutions. The objective of Industry 4.0 is to increase productivity by enhancing stakeholder value.

Various academic studies have identified six design principles: Interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity (Davis et. Al., 2020).

These six principles represent fundamental guidelines that, if adopted in strategic and methodological choices, promote the creation of advanced production systems that are flexible, scalable, and capable of handling sudden changes (Davis et. Al., 2020).

Within a production system, the term interoperability refers to the ability of two or more systems to exchange and interpret large volumes of data. This enables the creation of a new integration environment among products, services, and processes. However, technological barriers often exist between various segments of the value chain, hindering efficiency and process integration. Standardized IT protocols would be necessary to facilitate communication (Davis et. Al., 2020).

Virtualization consists of the virtual reproduction of the company, which facilitates the control of products and processes as well as production planning. A true “digital twin” is created not only for the product or process but for the entire value chain. This allows for a reduction in the time needed to plan new products, making it easier to identify potential errors in configuration or simulation (Davis et. Al., 2020).

Real-time capability refers to analytical systems that must be able to interpret large volumes of data, extract value from them, and respond immediately. This reduces reaction times and increases productivity (Davis et. Al., 2020).

Service orientation focuses on the ability of companies to use digital technologies and interconnection to offer personalized, high-quality services. It provides machines, people, and software with access to key information, enabling them to make real-time modifications to the system based on customer preferences (Davis et. Al., 2020).

Modularity refers both to the standardization of individual products, making them modular, that is, composed of standardized components that can be combined in different ways to create customized versions of the product, and to the production system in general, where machines and production lines can be easily adapted to the company’s needs. This makes it easier to customize goods, effectively responding to market demand (Davis et. Al., 2020).

The combination of these six design principles allows companies to move closer to the vision of Industry 4.0, characterized by high flexibility and low complexity.

Numerous studies are also examining the connection between the principles of Industry 4.0 and those typical of Lean Production Systems, a term used to refer to a business management methodology aimed at increasing a company’s productivity value by minimizing waste. In fact, Industry 4.0 enabling technologies can enhance the principles of LPS, further improving efficiency and productivity.

The European Commission defines enabling technologies as “technologies with high knowledge intensity and associated with high R&D intensity, rapid innovation cycles, substantial investment expenditures, and highly qualified jobs. They enable innovation in processes, goods, and services across all economic sectors and therefore have systemic relevance. They are multidisciplinary, involve technologies from different sectors, and tend to converge and integrate. They can help leaders in technologies from other sectors to take full advantage of their research activities.” (European Commission, 2012).

The main enabling technologies of Industry 4.0 have been defined by the Boston Consulting Group and adopted in Italy in the National “Impresa 4.0” Plan of the Ministry of Economic Development. They are: Advanced Manufacturing Solutions, Additive Manufacturing, Augmented Reality, Simulation, Horizontal/Vertical Integration, Industrial Internet, Cloud, Cyber-security, Big Data and Analytics.

Advanced Manufacturing Solutions include technologically advanced production systems, characterized by high interconnection and modularity that ensure flexibility and performance attainment. The main systems include interconnected, quickly programmable collaborative robots.

Additive Manufacturing refers to production systems that increase the efficiency of material usage, such as 3D printers connected to digital development software.

Augmented Reality consists of using augmented reality vision systems to support production processes.

Simulation encompasses the ability of intelligent and interconnected machines to perform simulations that enable companies to increase productivity and optimize processes.

Horizontal/Vertical Integration ensures the exchange of information and data across all areas of the production chain, from the supplier to the final consumer.

Industrial Internet and IoT refer to the multidirectional communication between production processes and products. Communication occurs among all internal and external elements of the company via the Internet.

Cloud facilitates the diffusion and implementation of cloud computing solutions and data management on open systems. The concept of open systems refers to technological solutions that adhere to open standards, use shared protocols, and allow interoperability among different services and platforms.

Cyber-security and business continuity involve adopting new security standards to protect data, which is increasingly at risk of breaches due to the interconnections between the internal and external environments.

Big Data involves the analysis of large databases to optimize products and production processes.

2.2) Industry 5.0

Industry 4.0 has revolutionized the manufacturing sector by introducing numerous technologies such as the Internet of Things (IoT), cloud computing, cyber-physical systems (CPSs), cognitive computing, and artificial intelligence (AI). Many of these technologies have been analysed in detail in the previous paragraph and are used to make the manufacturing industry "smart," where all machinery and business software are interconnected and control the production process (Maddikunta et al., 2022).

The adoption of enabling technologies by companies, along with the analysis of the data these technologies generate, has facilitated mass production by reducing management,

production, and logistics costs. However, in an attempt to lower costs, Industry 4.0 has overlooked the impact and importance of the human component, leading to increased unemployment (Maddikunta et al., 2022).
Industry 5.0, on the other hand, recognizes the fundamental role of human creativity and aims to integrate critical and cognitive thinking into machines and software (Maddikunta et al., 2022).
The goal of synergy between humans and machines is to make production more efficient and faster, also thanks to constant monitoring.
Industry 5.0 focuses on increasing customer satisfaction. It builds upon the technologies and applications of Industry 4.0 and establishes a relationship between collaborative robots (cobots) and human workers. One of the key contributions of this revolution is mass personalization, which allows customers to choose customized products according to their specific needs (Maddikunta et al., 2022).
Since Industry 5.0 is still evolving, there is no universally accepted definition.

Michael Rada, leader and founder of Industry 5.0, states that:
"Industry 5.0 is the first industrial evolution led by humans based on the 6R principles (Recognize, Reconsider, Realize, Reduce, Reuse, and Recycle) of industrial upcycling, a systematic waste prevention technique and logistics efficiency design to enhance life standards, innovative creations, and produce high-quality custom products." (M. Rada, Industry 5.0 definition, 2020).

Additionally, Friedman and Hendry argue that Industry 5.0 pushes companies and industry experts to recognize the importance of including human factors in industrial systems (Friedman & Hendry, 2019).

Industry 5.0 is therefore a natural evolution of Industry 4.0, and according to Maddikunta et al. (2022), the additional features of Industry 5.0 include Smart Additive Manufacturing, which leverages AI and computer vision for more sustainable and precise production; Predictive Maintenance, which utilizes IoT and predictive analytics to reduce failures and optimize maintenance; Hyper Customization, which enables highly personalized production through the collaboration between robots and human intelligence; and Cyber-Physical Cognitive Systems (CPCS), which integrate cloud computing, big data, and IoT to enhance coordination between humans and machines.

Smart Additive Manufacturing allows products to be created layer by layer, making them lightweight yet durable. This method reduces resource waste and pollution throughout the entire development cycle. With recent technological advancements and the introduction of AI, IoT, cloud computing, big data, CPS, 5G, digital twins, edge computing, and manufacturing, smart empowering technologies are becoming increasingly popular, enhancing sustainability, productivity, and industrial profitability.

Predictive Maintenance enables the detection of faults and interventions before they occur, thereby avoiding scheduled or corrective maintenance. This is made possible primarily through the use of advanced technologies such as IoT (Internet of Things) and cyber-physical systems (CPSs). Machinery gains self-awareness through the use of smart sensors and advanced computational agents, software used in predictive modeling. This optimizes production while reducing downtime and maintenance costs.

Industry 5.0 also emphasizes hyper-personalization, leveraging advanced technologies such as artificial intelligence (AI), machine learning (ML), and computer vision to analyse data in real time and offer personalized products and services for each customer. Achieving mass customization is possible by integrating human intelligence with robots. Production processes are adapted based on customer needs and market changes.

Technological advancements in various sectors have led to the increasing adoption of Cyber-Physical Cognitive Systems (CPCSs). Compared to the Cyber-Physical Systems (CPSs) typical of Industry 4.0, these new systems have additional cognitive capabilities, primarily due to the greater emphasis on artificial intelligence and machine learning. While CPSs focus on automating industrial operations, CPCSs enable direct collaboration between robots and humans, where human decision-making enhances production processes. Machine learning and predictive analytics allow these systems to effectively analyse and observe their environment, quickly adapting to changes and evolving market demands by making intelligent decisions (Maddikunta et al., 2022).

Industry 5.0 introduces several enabling technologies that, when integrated with cognitive skills, can facilitate product customization while simultaneously increasing production. These technologies include Edge Computing (EC), Digital Twins (DT), Internet of Everything (IoE), big data analytics, cobots, 6G, and blockchain (Maddikunta et al., 2022).

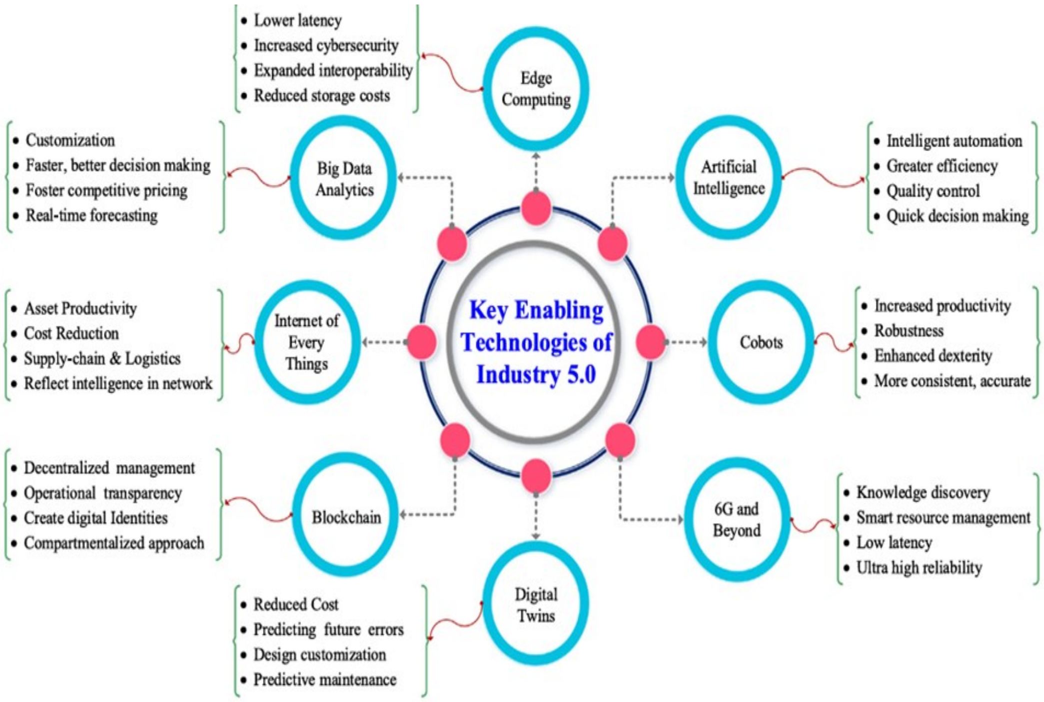

Figure 2: Key enabling technologies of Industry 5.0.

Source: Maddikunta et al., 2022

For more details on Industry 5.0 technologies, see Appendix A.

2.3) The Importance of Artificial Intelligence for New Business Models

In recent years, several studies have analysed the impact of Automation, Big Data, Artificial Intelligence (AI), and the Internet of Things (IoT) on business model innovation.

Jorzik et al. (2024) conducted a systematic literature review, highlighting key trends and gaps in the research on AI-driven Business Model Innovation (AI-driven BMI).

Artificial intelligence is one of the most revolutionary technologies of the 21st century. To capture the value from AI applications, companies must introduce appropriate business models (BMs).

There are many definitions of AI, but Jorzik et al. (2024) base their study on the widely accepted definition of AI as "a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." Therefore, the term AI is considered by the authors as a generic term that includes several tools, most of which are related to Machine Learning (ML) techniques (Jorzik, Klein, Kanbach, & Kraus, 2024).

When talking about Machine Learning, we refer to a set of mathematical methods and algorithms that learn and improve autonomously by analysing computerized data. There are three types of learning: supervised, unsupervised, and reinforcement learning.

With supervised learning, the algorithm is trained with labeled data and identifies patterns between input and output data. In this way, it can label new data based on previously learned patterns. A typical example of this type of learning is classification using decision trees and solving problems with regression, which can help companies make predictions.

Unsupervised learning does not require a predefined output because the model identifies patterns in the various unlabeled data it receives. In the context of business innovation, this method mainly allows the personalization of offers to potential customers and segmentation of customers based on their preferences and behaviors.

Reinforcement learning, on the other hand, allows companies to adapt and optimize their processes through the ability to perform a specific task by learning and reacting in a constantly evolving environment (Jorzik, Klein, Kanbach, & Kraus, 2024).

In addition to these types of learning, deep learning (DL) has gained increasing importance. Inspired by the structure of the human brain, deep learning (DL) can process large amounts of data, making it particularly effective in image classification and object recognition. It is also useful for understanding, interpreting, and generating human language. Thanks to the use of artificial neural networks, DL offers great potential for business model innovation (Jorzik, Klein, Kanbach, & Kraus, 2024).

Business model innovation (BMI) can be defined as "designed, novel, and nontrivial changes to the key elements of a firm's BM and/or the architecture linking these elements." However, many companies are unprepared to face the necessary changes because they lack the skills and knowledge for effective implementation. These factors often lead to the failure of projects that include AI in various business models (Jorzik, Klein, Kanbach, & Kraus, 2024).

To make the most of innovations, companies must invest in employee skills. Managers must train a competent workforce that has the necessary skills to drive innovation and meet emerging challenges (Jorzik, Klein, Kanbach, & Kraus, 2024).

Jorzik et al. (2024) identified six key elements for understanding and guiding AI-based business model innovation: triggers, restraints, resources and capabilities, application of AI, implications, and management and organizational issues.

The first dimension seeks to explain why companies feel the need for AI-driven business models. A major driver comes from the need to change consumer needs by distributing value and simultaneously involving them in its creation. The integration of AI with Industry 4.0 technologies amplifies the ability to innovate too. Another important element to consider is the business ecosystem, which can facilitate this transition by including various stakeholders such as suppliers and partners. Moreover, factors such as the entry of new competitors, competitive dynamics, government initiatives, regulatory compliance, changes in the business context, sustainability trends, and social pressures stimulate companies to adopt innovation in business models through artificial intelligence.

However, the elements that push a company to introduce AI into its business models are also closely related to the restraints that make its application difficult.

Barriers include ethics, safety, legality, employee resistance, and the black-box nature of AI. Ethical problems arise from potential algorithmic biases that lead to discrimination or unethical implementations, while security problems refer to the improbability of achieving a 100% accuracy rate of AI while maintaining data security and privacy. Another issue is that deep learning algorithms, by processing large amounts of data, identify patterns and relationships but often without providing a clear explanation of the decision-making process. For this reason, they are compared to a "black box," as the user or final decision-maker does not have full access to the internal logic of the system. Consequently, people might not fully trust the results generated by AI. Employees may also resist change, making everything more complicated.

The third dimension of the research focuses on what companies need as a foundation to implement an AI-based business model. Data plays a significant role, and big data experts describe the five key characteristics: validity, speed, volume, variety, and value. Effective data management also allows companies to leverage information from machine sensors and Internet of Things (IoT) applications. However, the use of this data is efficient only with an adequate IT infrastructure. Storage systems, being expensive, push companies to either obtain significant internal or external financial resources or develop the necessary skills, routines, and activities for implementation.

The fourth dimension focuses on the steps needed to implement AI in business models. First, it is crucial to analyse the pre-existing business model by evaluating the value proposition, the customers to whom the value will be delivered, and the revenue model. From this, an AI strategy aligned with the company's vision should be implemented, satisfying the needs of the customers previously identified. Therefore, it is essential to develop solutions that answer crucial questions, solve customer problems, and focus on the most relevant application areas through the work of multidisciplinary teams dedicated to AI use. When implementing the solution, it is important to choose the technologies and tools that best suit the project, training the algorithms properly. A pilot project can be particularly useful for gathering feedback that aids in continuous improvement and achieving the required efficiency. In this way, transparency, userfriendly structures, and involving consumers in the development are crucial elements for achieving the goal.

The fifth dimension focuses on the roles that AI can assume. The roles are: support, enabler, innovator, and disruptor.

AI as a support does not change the core operations of the business but makes existing processes more efficient, increasing workers' capabilities. This refers to incremental improvements rather than radical change. However, the added value from AI implementation is high and allows the company to gain a competitive advantage or explore new opportunities more easily.

AI as an enabler transforms business processes, creating new ones. This leads to the development of new business capabilities that the company did not think it could develop before.

AI as an innovator leads to the creation of new products, generating a new value proposition, expanding the business. As the business model evolves, it changes the way value is generated and distributed.

AI as a disruptor represents the highest level of its transformative power, revolutionizing practices and standards across an entire industry. Its adoption challenges traditional business models in the sector and redefines the core characteristics of the products or services offered to customers. For example, autonomous vehicles have disrupted the entire automotive industry, pushing companies to reconsider their business models and integrate new essential features for consumers.

The sixth dimension focuses on managerial and organizational issues, which play a fundamental role in the effective application of AI technologies.

Management and organizational decisions greatly influence how a company uses artificial intelligence (AI) and how it can transform its business model. To fully leverage AI, companies must adopt new leadership approaches and develop specific skills, yet they often lack the capabilities to do so. In fact, many AI-based initiatives fail precisely because companies do not have the appropriate structure. AI must become part of the corporate culture and be aligned with business objectives, involving all relevant stakeholders. To achieve this, it is necessary to first understand the technology, then implement it in the company's processes, and finally reach a certain level of digital maturity. Startups, due to their more flexible structure, are generally more open to innovation and can implement AI-driven projects more effectively than larger companies (Jorzik, Klein, Kanbach, & Kraus, 2024).

Towards the end of their study, Jorzik et al. (2024) identify four types of AI-driven Business Model Innovation (BMI), each with distinct characteristics. The four perspectives are: technology implications, reconfiguration, focused BMI, and transformative BMI.

The technology implications perspective does not consider AI as the central element of value creation but rather as a supporting tool that enables gradual improvements in existing processes. Business model innovation (BMI) occurs in an evolutionary manner, as a result of incremental improvements derived from the progressive use of AI, making operations more efficient and effective over time.

The reconfiguration perspective focuses on how AI adoption can support value creation by improving or expanding the current business model. In this context, management also plays a fundamental role in organizing the company in a way that facilitates AI exploitation.

The focused AI-driven BMI perspective highlights how companies can deliberately use AI to innovate their business models. Here, the strategy focuses on innovating specific dimensions of the business model or the entire model itself, with AI as the central element of value creation. To make this transformation effective, management must develop new leadership skills and foster an AI-oriented corporate culture.

Finally, the transformative BMI perspective considers AI as a central driver of value creation, with an impact extending beyond corporate boundaries to involve the entire business ecosystem, stakeholders, and society. As companies must adapt to technological evolution, changes in consumer preferences, and social trends, AI is not simply used to optimize internal operations but becomes a key element in transforming the business model. However, to fully harness AI's potential, companies must also contribute to building a broader ecosystem where developers, partner companies, and customers actively participate, driving innovation and business evolution over time (Jorzik, Klein, Kanbach, & Kraus, 2024).

In conclusion, technological change proves to be essential for business development, influencing the economic sustainability of companies in the medium to long term. The 28th CEO Survey conducted by PWC confirms CEOs' expectations of increased revenues resulting from the integration of AI into business models. This optimism drives many companies to integrate new technologies, particularly generative AI, into their business processes and operational procedures (28° Annual Global CEO Survey by PwC).

We also analysed the importance of skills and having a flexible structure in creating a sustainable business. This year's PwC survey found that 35% of Italian CEOs (compared to 23% globally) identified the skill gap, the mismatch between sought-after skills and those found in the workforce, as the primary threat for the coming year.

The importance of revolutionizing the business model and value creation strategies is evident from the fact that 69% of CEOs in Italy have taken at least one significant action to redefine how their company generates, distributes, and captures value: a percentage higher than the global average of 63%. The most common transformation initiatives include developing innovative products and services and implementing targeted changes to reach new customer segments (28° Annual Global CEO Survey by PwC).

However, the greater proactivity and willingness to change, along with many leaders' awareness of the need to evolve business models, do not appear to have made the actions taken by companies sufficient to achieve a concrete transformation.

Although it has been observed that CEOs who have undertaken more actions to transform their business model have reported higher net profit margins for their companies, significant attention is still given to business transformation strategies and exploring all potential growth opportunities.

A company facing periods of significant change requires a CEO capable of translating their vision into a corporate strategy through well-thought-out, informed, and impartial decisions. To achieve this, it is important to incorporate the following best practices into decision-making processes: making decision criteria transparent, considering information that may contradict one's opinion, encouraging perspectives different from those of the leadership, and acknowledging the possibility of pursuing the wrong choice (28° Annual Global CEO Survey di PwC).

However, most leaders do not adopt these practices, exposing decision-making processes to the risk of confirmation bias. This cognitive phenomenon leads individuals to seek and select information that aligns with their pre-existing knowledge without questioning their assumptions. As a result, they develop a partial and often distorted view of reality, compromising decision quality. Furthermore, many CEOs evaluate strategic decisions based on expected outcomes rather than the quality of the decision-making process (28° Annual Global CEO Survey di PwC).

Ultimately, technological advancements have made companies increasingly aware of the importance of changing their business models both to meet new consumer needs and to enhance profitability in a highly competitive environment. At the same time, managers face numerous challenges in ensuring a proper and effective business transformation, particularly in developing clear skills and adopting a flexible structure.

2.3.1) Artificial Intelligence and Labor Productivity: a global perspective

AI technologies are those most widely used to revolutionize business models and to increase productivity. In the following framework, we analysed the results of the main studies on these technologies, allowing us to gain a clearer picture of their effectiveness on labor productivity and on employment levels.

Paper	**Empirical study**	**Main results**

Babina et al.(2023)- *Artificial intelligence, Firm Growth and Product Innovation*	Yes (USA, firm-level panel data using AI hiring and investment signals)	Firms investing in AI experience substantial growth: +19.5% in sales, +18.1% in employment, and +22.3% in market valuation, relative to similar firms. The effects are robust across specifications and IV strategies. Growth is driven by product innovation, evidenced by increased trademarks and new product launched, rather than cost-cutting or productivity gains. Larger and resource-rich firms benefit most, suggesting a concentration-enhancing effect. AI adoption does not significantly affect TFP, indicating that performance gains stem mainly from expansion and innovation.
Brynjolfsson, Li & Raymond (2023) – *Generative AI at Work*	Yes(field study on call center)	AI support increases productivity by +15% (chats resolved per hour). Largest gains (+30%) among low-skill and less experienced workers; no or negative effects for top performers. Also improves employee retention and customer sentiment.
Czarnitzki et al. (2023) – *Artificial Intelligence and Firm-Level Productivity*	Yes(Germany, European Commission's Community Innovation Survey (CIS))	AI adoption increases productivity: +5–14% in sales (OLS), and up to +30% with instrumental variable (IV) methods. Similar results found for value added, with AI adopters showing +14.6% higher value added (OLS). AI intensity (number of AI technologies × application areas) is also positively associated with productivity: firms using AI more broadly achieve significantly higher gains (e.g., a 0.05 increase in AI intensity → +42% sales, IV estimate). The effects are stronger for firms in capital- and tech-intensive sectors.
Zhai & Liu (2023) – *Artificial intelligence technology innovation and firm productivity: Evidence from China.*	Yes (China, sample of Chinese listed companies)	AI innovation (measured by patent counts) leads to +8.9% TFP (OLS), confirmed by IV, OP, and GMM models. AI also has stronger effects in large firms, SOEs (state-owned enterprises), and labor-intensive sectors. Mechanisms include: cost reduction (AI → ↓ operating costs), labor upgrading (↑ high-skilled share), digital transformation, and enhanced innovation efficiency.
Damioli et al. (2021) – *The impact of Aritificial Intelligence on Labor Productivity*	Yes (worldwide sample of firms having filed at least a patent related to the field of AI between 2000 and 2016)	AI patenting has a causal impact on labor productivity. A doubling of AI-related patents is associated with a +3% increase in labor productivity (turnover per employee). Effects are significant only for SMEs (not large firms), and concentrated in the service sector, where the effect of AI patent applications on labor productivity turns out to be relative strong, elevating at 7.7%. No measurable effect before 2009; positive impact only emerges after 2009, consistent with the rising maturity and adoption of AI technologies. Robust to firm controls, sector fixed effects, and use of system GMM.

International Labour Organization (ILO), (2023)- *Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality.*	No	Clerical and administrative workers are by far the most exposed group: approximately 24% of their tasks are highly automatable, and 58% moderately so. Generative AI is expected to augment, not replace, most jobs by automating routine components. Advanced economies, which have a higher share of knowledge work, are more exposed: up to 5.5% of jobs are fully automatable, compared to only 0.4% in low-income countries. Meanwhile, a larger share of workers may see some of their tasks optimized by AI without losing their jobs: around 10.4% in low-income countries and 13–13.5% in high-income countries. Gendered impacts are notable, with women more affected in high-income countries due to their overrepresentation in clerical roles. The most significant effects may be on job quality: task composition, worker autonomy, and work intensity may all be affected. Positive outcomes will depend on policy frameworks that promote worker empowerment, algorithmic transparency, and inclusive upskilling strategies. Generative AI is expected to reshape jobs rather than eliminate them
OECD Employment Outlook (2023)– *Artificial Intelligence and the Labour Market*	No	AI influences work through three channels: automation (displacement effect), complementarity (productivity effect), and the creation of new tasks (reinstatement effect). So far, no negative aggregate effects on employment have been observed, either at the national or sectoral level. Firms more exposed to AI tend to reduce hiring in non-AI roles, while increasing demand for workers with AI-related or complementary skills. The most exposed occupations are high-skilled (such as managers, engineers, and professionals), while lower-skilled workers are more vulnerable to displacement and harder to retrain. However, the report emphasizes that many studies find a positive relationship between employment growth and AI exposure for high-skill (high-income) occupations, but not for low- and medium-skill occupations. The overall impact will depend on how broadly the productivity gains driven by AI are reinvested. AI adoption remains relatively limited, and firms tend to adjust employment through attrition rather than through layoffs.
Chih-Hai Yang (2023) – *How Artificial Intelligence Technology Affects Productivity and*	Yes (firm-level data on AI innovations in Taiwan's electronics	There are two measures: treatment measure (0/1) and the number of AI patents. AI patents → +13% TFP, after inclusion of non-AI patents the impact of AI patents lower to 7,85%, confirmed across LP, OP, and GMM models.

Employment: Firm-level Evidence from Taiwan	industry for the 2002–2018 period)	Instead, a 10% increase in AI patents induces a 0.589% increase in TFP, while a 10% increase in AI patents induces a 0.374% increase on labor productivity. This result implies that AI technology has a greater effect on capital productivity. Firms with AI patents see +0.369% employment growth per 10% patent increase. However, the employment effect is weaker or negative in large, exporting, and multinational firms. AI adoption reshapes workforce composition, reducing low-skilled labor share and increasing demand for high-skilled workers.
Acemoglu, Autor, Hazell, Restrepo (2022)- *AI and Jobs: Evidence from Online Vacancies*	Yes (USA, online vacancy data)	A one standard deviation increase in AI exposure (Felten index) is associated with a +15% increase in AI-related job postings and a –13.8% reduction in non-AI vacancies. This negative hiring effect on non-AI roles remains robust when controlling for sector and firm size (–11.9%) and is particularly strong in the post-2014 period (–11.94%). With the Webb index, the decline in non-AI vacancies is even more pronounced in the baseline model (–17.2%), and moderates to –6.7% in more saturated specifications with extensive controls. The SML index, by contrast, yields weaker and statistically insignificant results. The authors also document significant "skill churn": AI-exposed firms stop listing older, less-relevant skills and begin demanding new ones. However, at the aggregate level, no significant effects on total employment or wages are detected, indicating that AI's labor market impacts are currently concentrated at the firm level rather than systemic.
Alderucci et al. (2020)- *Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata*	Yes (Own data on AI patenting matched with U.S. Census microdata collected on the innovating firms)	Within-firm effects: Filing an AI patent is associated with an 8.3% increase in revenue per employee, 8.9% in value-added per employee, and 7% in TFP. There is no significant change in production worker share, we see a rise in income for the 90th percentile and 50th percentile workers relative to the lower worker. This rise is highest among the 90th percentile workers, suggesting increased demand for the highest-skilled worker. Between-firm effects: AI-innovating firms show 25% higher employment growth and 40% higher revenue growth than matched non-adopters, indicating a structural advantage. However, productivity gains seen within firms do not consistently appear in the event-study comparison.

Bessen (2019)- *AI and Jobs: The Role of Demand*	No	The paper argues that employment outcomes from AI depend critically on product demand elasticity. If AI boosts productivity and lowers costs in sectors with elastic demand, employment can increase rather than decrease, as greater output offsets labor-saving effects. Historically, most automation has been partial, not total, and the same is expected with AI in the near term. Thus, demand growth is key: rapid technical change alone does not imply job loss. The study calls for empirical research on how AI reshapes task automation, sectoral demand, and job creation across industries.

3) Digitalization Paradox and Productivity Paradox

3.1) Productivity Paradox

To introduce the analysis of the productivity paradox, we have compiled a summary table that gathers and compares the main academic contributions on the topic, highlighting the different interpretations provided in the literature regarding the relationship between technological innovation and productivity growth. The so-called productivity paradox refers to the apparent contradiction observed since the 1970s, whereby the widespread adoption of information technologies, particularly computers and digital systems, did not appear to be accompanied by a corresponding increase in aggregate productivity. In essence, the concept points to the fact that growing investments by firms in advanced technologies did not translate into measurable gains in macroeconomic indicators, especially in terms of productivity improvement. Several scholars have investigated this phenomenon both at the firm level and from a macroeconomic perspective, generating a rich debate with varying interpretations and empirical findings.

Authors and Year	Independent Variable	Dependent Variable	Key Findings
David (1990)	Adoption of Computers (IT)	Aggregate Productivity	Through an analogy with electrification (1890-1913), demonstrates that integrating a general-purpose technology requires time to reorganize processes and

			develop skills; traditional statistics fail to capture qualitative benefits (human-machine interactions, information overload) that emerge only in the long term.
Brynjolfsson (1993)	IT Investments	Aggregate Productivity	Confirms Solow's paradox: productivity growth does not keep pace with IT spending. Proposes four causes: mismeasurement of benefits, time lags in impact, redistribution of competitive gains without net increase, and managerial/organizational deficiencies in IT usage.
Oliner, Sichel & Triplett (1994)	IT Capital (Hardware, Software, IT Labor)	Productivity and Economic Growth	1. Hardware alone: accounted for only 2% of total capital in 1993 and depreciated rapidly, contributing marginally to growth. 2. Complete IT ecosystem: including software and specialized labor, the total contribution to GDP growth doubles (up to 4-5%). 3. Mismeasurement of benefits: many qualitative impacts (better internal coordination, faster decision-making, data quality) remain invisible to official statistics. 4. Time lags: full effects of technology require time for organizational adoption and skill development, creating a gap between spending and observed benefits.
Brynjolfsson & Hitt (1998)	IT investments at firm level	Firm-level Productivity	Shows that short-term IT benefits are modest, but

			when accompanied by organizational changes (process redesign, training), they become substantial in the long term; IT acts as an efficiency catalyst only with proper organizational complements.
Triplett (1999)	Diffusion of Computers (IT)	Aggregate Productivity	Identifies seven explanations for the paradox: low economic share of PCs, hedonic bias, incomplete measurement of IT services, time lags in effects, rapid obsolescence, conversion costs, and statistical scaling errors; concludes the phenomenon is multi-causal and requires integrated approaches.
Oliner, Sichel & Stiroh (2008)	IT Diffusion and Software/Server Investments	Aggregate Productivity (USA)	1995–2000: IT drove efficiency and TFP in many sectors; post-2000, direct IT effects diminish, and growth is sustained by corporate restructuring, reallocation of resources to more productive activities, and accumulation of intangible capital (know-how, training, software).
Guo, Li, Wang & Mardani (2023)	Digital transformation	Firm Performance (Asset Turnover, Operating Costs, Administrative Expenses)	Digitalization in the short-term increases operating and administrative costs and reduces asset turnover, worsening profitability; managerial myopia amplifies these effects by delaying adoption and neglecting human capital development.

3.2) Digitalization Paradox

Despite the opportunities to increase revenues through digitalization, many companies struggle to achieve an adequate economic return on their substantial digitalization investments. These challenges have led to the introduction of the term Digitalization Paradox. Unlike the Productivity Paradox, which focuses on cost reduction and efficiency improvement, the Digitalization Paradox centres on revenue growth (Gebauer et al.,2020).

In the previous section, the analyses conducted by Guo, Li, Wang, and Mardani (2023) were included, which focused on the relationship between digital transformation and firm performance. However, the causes of this paradox and possible ways to overcome it were not explored in depth. Gebauer et al. (2020) argue that when cumulative investments in digitalization are relatively small, revenue growth aligns with expectations. However, when companies make more substantial investments, revenues do not follow the projected trend.

Digitalization leads companies to change their business models, particularly altering individual components. The inability to effectively modify the business model may explain the Digitalization Paradox. When designing their business model, companies focus on three main components: value proposition, value creation (or delivery), and profit equation (Gebauer et al.,2020).

The value proposition encompasses all aspects of a company's offering that generate value for customers, addressing their needs and solving their problems.

To deliver a compelling value proposition, companies require specific resources, capabilities, and processes. The manner in which they implement these elements to create value is referred to as the firm's value creation activities.

The profit equation represents the financial manifestation of both the value proposition and the value-creation mechanisms. It establishes how value is extracted from customers and how the cost structure should be designed to support value creation (Gebauer et al.,2020).

Business models, therefore, are not merely a collection of separate activities but rather a system of interconnected components working together in a specific way. Consequently, modifying one of these components can have unintended effects on the others. When harmony and consistency between these elements are disrupted, companies may fall into growth traps that hinder revenue enhancement through digitalization (Gebauer et al.,2020).

Gebauer et al. (2020) identify three growth paths for revenue enhancement through digitalization: commercializing digital solutions, utilizing product connectivity, and establishing an IoT-platform-based application business.

The first growth path highlights the importance of digital solutions, driven by the increasing availability of digital technologies and the growing demand for personalized experiences. To commercialize digital solutions, companies integrate digital technologies to develop digitally enabled solutions capable of addressing complex customer needs. In doing so, they modify their value creation activities by focusing on structured processes that leverage digital technologies to better serve customers. This approach allows firms to stimulate demand, identify new sales opportunities, and introduce innovative digital solutions. To offer these solutions at sustainable costs, companies must modularize, standardize, and customize solution components, thereby increasing revenues through digital offerings (Gebauer et al.,2020).

Despite the seemingly straightforward nature of these changes, companies may become trapped in growth constraints. Gebauer et al. (2020) identify four primary pitfalls: prioritizing technical possibilities over customer needs, relying on a single digital technology for digital solutions, developing digital solutions with insufficient perceived customer value, and overemphasizing either standardization or customization.

The second growth path revolves around leveraging product connectivity. The increasing number of internet-connected products drives this path, allowing firms to monitor and analyse product usage, thereby creating competitive advantages through improved availability, uptime, utilization, and performance. An additional factor supporting this growth path is the shift in customer preferences toward paying for product usage and performance rather than outright ownership.

Through connectivity, companies can guarantee specific performance levels to customers, enabling them to adopt pay-per-use models instead of direct product sales. The ability to monitor, inspect, and diagnose products remotely plays a crucial role in this transformation. By accurately predicting failures, companies can align their value proposition with performance guarantees. Furthermore, real-time monitoring and analysis of product usage and lifecycle costs enable firms to facilitate pay-per-use models, aligning costs with customer usage levels.

However, certain growth traps may emerge along this path. These include an incomplete and ambiguous accounting of cost savings, the assumption that product connectivity will cannibalize existing service revenues, the failure to enable component condition monitoring with key suppliers, the risk of attracting only highly demanding and low-usage customers, and the promotion of payment schemes based on performance levels and product usage (Gebauer et al.,2020).

The third growth path involves establishing an IoT-platform-based application business. The vast amount of data generated by interconnected products enables customers to enhance the efficiency and effectiveness of both products and processes. After identifying key consumer pain points, companies can address them using data collected from various connected products. To do so effectively, it is essential to create a new digital ecosystem by investing in the development of platforms for data management and analysis, while distributing costs through collaborations (Gebauer et al.,2020).

The profit equation for this approach must incorporate payment models such as subscriptions, licenses, and freemium strategies, similar to those used in the software industry. Additionally, it must account for investment and implementation costs associated with IoT platforms and applications.

Companies seeking to establish such a digital ecosystem may encounter several challenges. For instance, collaboration with partners is often necessary, but a lack of mutual trust may undermine these partnerships. Another critical issue arises when companies remain overly committed to the freemium model, leading customers to resist upgrading to more advanced, paid versions of the service (Gebauer et al.,2020).

Ultimately, Gebauer et al. (2020) identify three revenue growth paths: commercializing digital solutions, leveraging product connectivity, and developing an IoT-platform-based application business. While commercializing digital solutions directly increases digital revenues, product connectivity does not necessarily generate direct revenue growth but rather transforms the existing revenue model associated with products and services. Meanwhile, the development of an IoT application business fosters growth by integrating these applications into digital offerings.

Overall, companies are shifting from a simple adaptation and customization of products toward a vision in which digitalization serves as a fundamental driver of innovation and growth. This transformation enables value creation not only through physical products but also through digital solutions.

Analysing these growth paths helps clarify how companies can enhance revenues through digitalization and the accompanying business model changes. Growth traps, however, hinder firms from increasing their revenues and contribute to the Digitalization Paradox. To avoid this, companies must adapt and align all aspects of their business: what they offer customers, how they create value, and how they generate profits. If they successfully implement these changes, they will be able to achieve higher profits (Gebauer et al.,2020).

4) The effect of digital technologies on firms' performance

4.1) The effect of digital technologies on productivity

Digitalization is a broad phenomenon that encompasses numerous technologies and applications and is among the factors that most strongly affect firms' performance and firms structural and organizational changes. In theory, adopting digital technologies should produce a significant increase in productivity, since digital inputs are a key driver of aggregate productivity growth (Anghel et al., 2024).

Nucci et al. (2023) suggest that more intense digital adoption occurs mainly in larger firms and in high-technology manufacturing sectors. The adoption of digital technologies is less likely in all other economic sectors, both manufacturing and services. Even in knowledge-intensive services, extensive use of digital technologies is less common than in high-tech industries. Moreover, older firms are considered more inclined to make extensive use of digital technologies (Nucci et al., 2023).

It has also been found that firms spending relatively more on services, rather than on material inputs, are more motivated to use digital technologies; this may be because this cost category can include ICT-related complementary services such as IT consulting and staff training. At the same time, organizations with a higher share of labor costs in the value of production are less likely to adopt digital technologies (Nucci et al., 2023).

Recent evidence confirms that adopting digital technologies can generate substantial improvements in firms' performance, particularly in productivity and revenue growth.

In a study on the benefits of Industry 4.0 technologies in Italian firms, Cirillo et al. (2023) show that adopting new digital technologies significantly increased labor productivity and sales growth: digital investments raise labor productivity by 5 %, and the sales of the analysed firms increased on average by 4 %. This result is also consistent regarding sales per employee, which rise by about 6 % in firms investing in new technologies compared with those that do not. (Cirillo et al., 2023).

Cirillo et al. (2023) also argue that productivity effects are concentrated among SMEs, more mature firms, and highly productive firms, those positioned at the top of the labor-productivity distribution. In contrast, larger firms, younger firms, or less productive firms display little or no positive impact.

This may be explained by different timelines for realizing productivity gains: in large companies, adopting new technologies may require lengthy adjustments to existing production processes, so in these more complex organizations the benefits of Industry 4.0 investments likely take longer to materialize. Alternatively, more productive firms are better able to harness productivity gains from reorganizing production activities through digital-technology adoption than less productive firms (Cirillo et al., 2023).

Similarly, a firm-level analysis for Italy by Nucci et al. (2023) finds that firms classified as "highly digitalized" recorded, in the 2015-2018 triennium, labor-productivity growth rates about 2.7 percentage points higher than less digitalized firms (Nucci et al., 2023).

However, the impact of digital technologies on firms' productivity and business growth varies by sector and firm age. Nucci et al. (2023) distinguish between manufacturing and service firms: the estimated effect of digital adoption on productivity change is stronger in manufacturing firms than in service firms, with coefficients of 0.031 and 0.028, both statistically significant at the 1 % level**.** Furthermore, the productivity boost is larger in younger firms compared to older firms (0.051 vs. 0.020) and in smaller firms compared to larger firms (0.044 vs. 0.023), all effects also significant at the 1 % level (Nucci et al., 2023).

The result regarding firm age from Nucci et al. (2023) diverges from that of Cirillo et al. (2023). This divergence may stem from the different scope of the technologies considered or from differences in the time periods and methodologies employed.

Overall, these results align with other international studies. For example, Babina et al. (2024) also argue that AI investments are linked to a significant increase in sales and market value: a one-standard-deviation rise in the share of AI workers over an eight-year period corresponds to an additional 19.5 % growth in sales, while the same increase is associated with a 22–24 % rise in firm market value (Babina et al., 2024).

They identify a stronger positive link between changes in AI investments and growth in larger firms. Typically, large firms face constraints on scaling due to higher costs of new-product innovation; the results suggest that AI may offer a way for large firms to overcome innovation and scaling barriers by leveraging their data assets (Babina et al., 2024).

Anderton et al. (2023) focus on the impact of digital technologies on the most productive laggards who can use digital technologies to accelerate TFP growth, becoming more efficient over time. In their study, the estimated coefficient for these firms is two to three times higher than the impact found for the average laggard (Anderton et al., 2023).

Digital-technology investments help the more productive laggards achieve better outcomes, increasing their productivity, but do not automatically transform them into sector leaders (Anderton et al., 2023).

This is because digitalization affects TFP growth in the average laggard to a degree comparable with that in the average frontier firm. Frontier firms do not benefit more directly from digitalization than laggards, but they can more successfully monitor and implement innovations introduced by their peers than the average laggard firm (Anderton et al., 2023).

Firms already close to the frontier, those that are more productive, can exploit digital technologies more effectively and further improve their TFP. Laggard firms, instead, do not obtain the same initial productivity boost and thus struggle to close the gap. Consequently, in sectors where digitalization advances, the group of firms already at the top grows stronger, while few new companies enter the leadership ranks. If frontier leaders manage to enhance their TFP at an even faster pace, it becomes harder for laggard firms to catch up, thereby raising exit rates among other firms (Anderton et al., 2023).

Anderton et al. (2023) also argue that the impact of digital investments on firm-level TFP growth is greater and more significant than that of intangible assets. Nevertheless, an increase in intangibles can foster TFP growth, especially in frontier firms, thanks to their complementarity with digital technologies (Anderton et al., 2023).

An OECD study on Dutch firms confirms the importance of intangibles and shows that the adoption of digital technologies and intangible assets is positively and statistically significantly associated with productivity growth (Borowiecki et al., 2021).

Borowiecki et al. (2021) highlight that investments in ICT hardware and high-speed broadband are positively and statistically associated with productivity growth, especially in services relative to manufacturing. The authors include ICT hardware, though not itself a digital technology or an intangible asset, because it is essential for implementing more advanced digital technologies and intangibles such as software (Borowiecki et al., 2021).

The study also argues that accumulating ICT-specialist and software-specialist skills in the workforce is linked to greater productivity gains, particularly in the service sector and for younger firms (Borowiecki et al., 2021).

Moreover, specific investments such as adopting advanced software have a significant impact on low-productivity firms, helping them close the gap with frontier firms. This may be because introducing new software entails lower fixed costs and greater scaling-up opportunities (Borowiecki et al., 2021).

In conclusion, the importance of intangibles shows that investing in digital technologies must be carefully planned and is not, by itself, sufficient to automatically generate a productivity leap for all firms. Digitalization appears to be a true productivity engine for companies in certain sectors that already have relatively high productivity levels, whereas for most firms it may constitute a marginal element. The latter firms invest in digital technologies mainly to stay in the market and avoid becoming obsolete, but they cannot use these technologies effectively to generate innovation. Only 30 % of the most productive laggards benefit from digitalization. Without a clear plan or a specific innovation on how best to leverage the digital investment, firms may be unable to capture the productivity gains stemming from these technologies (Anderton et al., 2023).

4.2) The effect of digital technologies on wages and occupation

Beyond boosting productivity and sales, digital transformation also affects firms' labour markets, influencing both wages and the level and composition of employment.

Cirillo et al. (2023) found a positive link between the adoption of digital technologies and wages, showing that firms adopting such technologies pay average wages about 1.9 % higher than comparable non-adopters (Cirillo et al., 2023).

At the same time, the authors showed that in small and lower-medium-sized enterprises, with fewer than fifty employees, investment in digital technologies leads to a 2.3 % rise in average wages, whereas no effect is found in medium and medium-large organisations (Cirillo et al., 2023).

The absence of effects in larger firms may reflect not only longer adjustment periods for productivity and wages, but also wide internal wage dispersion in which pay increases for some workers can be diluted by stagnation or declines for others (Cirillo et al., 2023).

A second interesting point that emerges is that, although wage increases are observed in groups where productivity gains occur, the share of value going to labour remains lower than the productivity increases attributable to digital technology adoption; the gap is almost three percentage points, signalling weak redistribution of the returns to technological change and consistent with the wage–productivity decoupling seen in many countries over the past decade (Cirillo et al., 2023).

Moreover, Cirillo et al. (2023), distinguishing between younger and more mature firms, find a positive effect of Industry 4.0 investments on wages in mature firms, with average pay rising by about 2.6 % (Cirillo et al., 2023).

Firms that pay high wages are usually the most productive ones and are those in which I4.0 technologies have a strong distributive effect, bringing higher productivity (6 %) and higher wages (5.4 %); by contrast, in less productive, low-wage firms no significant link is found between I4.0 adoption and wages (Cirillo et al., 2023).

The adoption of new technologies may also affect labour markets, but current evidence on their overall employment impact is heterogeneous.

For example, AI-based automation can displace workers, eliminating certain jobs, but can also create new roles through task reassignment and through employment gains stemming from higher productivity (Anghel et al., 2024).

Recent U.S. literature argues that automation, while tending to reduce employment in low-skill occupations, has a net positive effect on total jobs. However, these results are not confirmed by recent studies conducted in France, which show that the introduction of automation can also yield a positive effect on the employment levels of less-skilled workers (Anghel et al., 2024).

Anghel et al. (2024) find a positive link between AI adoption and changes in employment shares. This relationship is driven mainly by the hiring of young, high-skilled workers (Anghel et al., 2024).

Albanesi et al. (2023) observe, in an aggregate European sample, a positive association between AI-enabled automation and changes in employment shares, irrespective of the proxy used. Moving up one decile in the AI-exposure ranking is associated with a 1.04 % increase in sector-occupation employment when using Webb's indicator and 1.7 % with Felten's indicator (Albanesi et al., 2023).

The study shows that these aggregate results are an average of a marked increase in high-skill jobs and a null effect in other groups.

Indeed, Albanesi et al. (2023), using country-level data, divide sector-occupation cells into terciles by the average age of workers (young, core, older) and by the share of education (low, medium, high). Each tercile in the analysis therefore comprises all the sector-occupation cells falling into that age or education band (Albanesi et al., 2023).

The results reveal significant employment changes linked to AI only for the high-education tercile, where moving up one decile in the AI-exposure ranking raises sector-occupation employment by 1.25 % with Webb's indicator and 2.66 % with Felten's measure (Albanesi et al., 2023).

A positive relationship is also found for the tercile characterised by younger workers. Thus, Albanesi et al. (2023) show that AI-enabled automation is associated with an overall employment increase driven mainly by occupations with relatively higher skills and younger workers (Albanesi et al., 2023).

In addition, the positive link between AI an employment appears in individual countries despite heterogeneity in effect size.

These findings are consistent with Babina et al. (2024), who show a positive association between digital adoption and employment growth: a one standard deviation rise in AI investment over an eight-year period translates into an 18.1 % employment increase. Such effects are observed across all major industry sectors, confirming the notion of AI as a general purpose technology (Babina et al., 2024).

Overall, these results suggest that AI adoption does not, on net, displace firms' workforces, even if the possible reallocation of workers across functions or tasks is not examined (Babina et al., 2024).

4.3) The effect of digital technologies on international competitiveness

Numerous studies have highlighted the importance of firms' digital reorganization and the benefits it brings to the entire economic system. The adoption of digital technologies (DT), that is, the suite of technologies ushering in the Industry 4.0 paradigm, allows companies to reconfigure their processes, thereby increasing their competitive advantage in global markets. Thanks to DT, firms can reduce transaction costs, lower distances and market-entry costs, overcome many of the barriers that limit small enterprises' international expansion, and exploit new channels for product distribution and sales. Digital technologies also facilitate integration into global value chains by improving coordination with consumers, suppliers, partners, and distributors (Pini et al., 2018).

To remain competitive, firms must do more than simply invest capital in DT: a true organizational transformation is essential. Product and process innovations bring about significant organizational changes both internally and in relationships with other firms. Consistent with the Resource-Based View, numerous studies underscore the need to develop complementary resources, such as human-capital training and revised procedures and processes, in order to make competitive advantage sustainable. Without these resources, technology investment alone does not translate into superior performance (Cassetta et al., 2019).

The literature has extensively examined the impact of DT on firm outcomes: productivity, economic performance, innovation, and export growth have been analysed at national, regional, and sectoral levels. Regarding internationalization, many authors show that a higher degree of digitalization is associated with a greater propensity to export and more rapid growth in foreign markets (Cassetta et al., 2019). DT improve knowledge of foreign markets, enable product adaptation to local demand, broaden access to competitor information, and make data exchange with international customers and partners more efficient, thus promoting integration into global value chains (Pini et al., 2018).

However, implementing DT alone is not enough to guarantee success abroad: the benefits fully materialize only when accompanied by adequate organizational changes and the development of internal digital and managerial capabilities. SMEs achieve real competitive advantage when they integrate new technologies into operational processes and business models (Cassetta et al., 2019).

Pini et al. (2018) demonstrate that the likelihood of increasing exports rises significantly only when advanced DT are combined with organizational innovations; similarly, Cassetta et al. (2019) find that internal digital reorganization, that is, the adoption of DT alongside process changes and personnel up-skilling, is crucial for international growth. These findings invoke the principle of resource complementarity and the role of absorptive capacity: only firms capable of effectively acquiring and leveraging new knowledge transform digitalization into superior export performance (Cassetta et al., 2019).

Dos Santos et al. (2025) confirm that the effect of DT on export reaches its maximum when digital intensity exceeds the threshold of adopting two technologies, investments are paired with training, and the strategy is based on twin innovation, integrating digital and green innovation (dos Santos et al.; 2025).

Despite some non-uniform evidence on the direct impact of digital technologies on export activity, the connection between digitalization and internationalization, often encapsulated by the neologism "internetization", opens new perspectives, especially for SMEs (Quarato et al., 2020).

For example, Pini et al. (2018) note that SMEs investing in ICT tend to be larger and experience faster growth in foreign sales: by offering new channels for information, marketing, and sales, and by reducing distance and market-entry costs, DT help overcome many of the barriers that limit small enterprises' international expansion (Pini et al., 2018).

In summary, the literature converges on the idea that digitalization, when integrated with internal reorganization and capability development, is a key factor in strengthening competitiveness and expanding firms' presence in international markets.

CHAPTER 2: Econometric Analysis

1) Introduction

In recent years, economic literature has increasingly focused on the role of digital technologies, and in particular AI technologies, in driving firms' productivity growth. Several studies have also shown that the use of digital technologies not only improves production processes but also fosters innovation and the adoption of new business models. Nevertheless, empirical results are not univocal: while some studies find a positive and significant impact of digital technologies on productivity, others underline that positive effects vary depending on the sector, firm size, investments in complementary resources, or the ability to integrate new digital technologies into existing processes. Still others, referring to the so-called productivity paradox, argue that overall results are not significant.

In general, the literature has focused on two specific elements: the complementarity between different digital technologies and the importance of their combined use, as well as the role of human capital and training as enabling factors that allow firms to fully exploit the potential of digital technologies.

However, some fundamental questions remain open. Beyond the lack of univocal results, we still do not know, for example, whether the impact on productivity depends more on the number of technologies adopted or on the specific type of technology. Moreover, detailed results are lacking for the Italian context, which is characterized by a production system mainly composed of small and medium-sized enterprises, often making limited investments in innovation and training.

Consequently, it is particularly stimulating to investigate whether, in the presence of investments in digital technologies, Italian firms experience an increase in productivity, even though the Italian production ecosystem has unique characteristics compared to other advanced economies. Our study thus contributes to enriching the international debate.

Secondly, empirical evidence can provide concrete insights for the definition of public policies and business strategies aimed at maximizing the benefits stemming from the adoption of digital technologies.

In light of the findings from the literature and the existing gaps, this chapter aims to address the following research questions:

1. What is the effect of adopting digital technologies, and in particular artificial intelligence, on the productivity of Italian firms?
2. Does adopting a larger number of AI technologies lead to a more significant impact on productivity?
3. To what extent do training and the development of internal skills influence the effectiveness of AI adoption on productivity?
4. Are there significant differences across sectors or between firms of different sizes in the relationship between AI and productivity?

2)Variables description

Table VD – Variables description

Variables	Type	Description
Dependent variable		
Labor prod	Continuous	labor productivity, value added per employee (log terms)
Main independent variables		
Tech.all	Dummy	1 = if the firm has invested in at least one technology among internet technologies, AI technologies or other technologies in the 2016-2018 period. Tech.all=1 if Tech.int =1 or Tech.ia=1 or Tech.other =1
Tech.int	Dummy	1 = if the firm has made investments in at least one of the following internet-based technologies [ultra-broadband fiber optic internet connection; mobile internet connection (4G-5G); Internet of Things (IoT)] during the period 2016–2018 primarily to increase its level of competitiveness; 0 = otherwise.
Tech.ia	Dummy	1 = if the firm has made investments in at least one of the following AI-based technologies [immersive technologies; Big Data processing and analysis; advanced automation, collaborative robots, and intelligent systems] during the period 2016–2018 primarily to increase its level of competitiveness; 0 = otherwise.
Tech.other	Dummy	1 = if the firm has made investments in at least one of the following other technologies [3D printing; simulation among interconnected machines; cybersecurity] during the period 2016–2018 primarily to increase its level of competitiveness; 0 = otherwise.
Tech.ia.immersive	Dummy	1 = if the firm has made investments in AI immersive technologies; 0 = otherwise.
Tech.ia.bigdata	Dummy	1 = if the firm has made investments in AI big data technologies; 0 = otherwise.
Tech.ia.robot	Dummy	1 = if the firm has made investments in AI robot technologies; 0 = otherwise.
Tech.ia.intensity	Ordinal	0 = if the firms did not invest in any AI technologies (*Tech.ia.zero*); 1 = if the firms invested in only one AI technology (*Tech.ia.one*); 2 = if the firms invested in two AI technologies (*Tech.ia.two*); 3 = if the firms invested in three AI technologies (*Tech.ia.three*)

Control variables		
Industry	Dummies	Dummies 2-digit Nace rev.2
Size	Continuous	Number of employees
Geographical location	Dummies	Dummies regions (NUTS-2)

3)Summary statistics

The following charts show the distribution of the firms analyzed, including the percentage of firms adopting various technologies, their size, geographic location, and sector of activity.

The chart below shows the percentage of firms analyzed that have made investments in various types of technologies during the period 2016-2018.

66,9% of the firms analyzed have invested in Digital technologies (*Tech.all*), namely in at least one technology among internet-based technologies, AI-based technologies, and other technologies. 58,5% of the firms have made investments in Internet-based technologies (*Tech.int*), namely in at least one of the following internet-based technologies: ultra-broadband fiber-optic internet connection; mobile internet connection (4G–5G); Internet of Things (IoT).

10,8% of the firms have made investments in AI-technologies (*Tech.ia*), namely in at least one of the following AI-based technologies: immersive technologies; Big Data processing and analysis; advanced automation, collaborative robots, or intelligent systems.

Finally, 36,1% of the firms have made investments in Other-technologies (*Tech.other*), namely in at least one of the following other technologies: 3D printing; simulation among interconnected machines; cybersecurity.

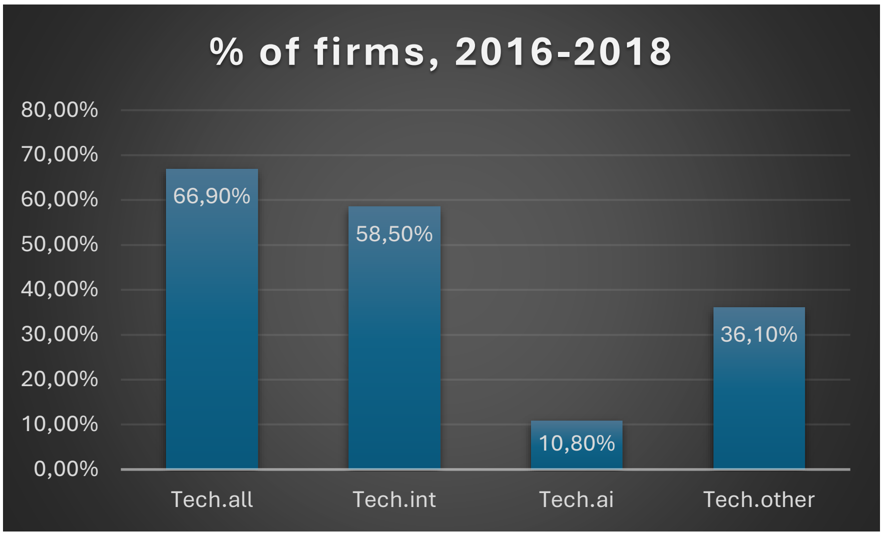

Figure 2: Percentage of firms that have invested in digital technologies

Source: elaboration on ISTAT data

The chart below shows the distribution of firms' sizes. It allows us to observe that 77,7% of the firms are small-sized, 19,0% are medium-sized, and only 3,4% are large-sized. It is also worth noting the absence of micro-enterprises.

According to the geographic distribution, 32,5% of the firms are in the North-West, 27,9% in the North-East, 20,2% in the South, and 19,5% in the Center.

From the sector point of view, 38,3% of the firms belong to the manufacturing sector, 51,9% to the services sector, and the remaining 9,8% fall under other sectors.

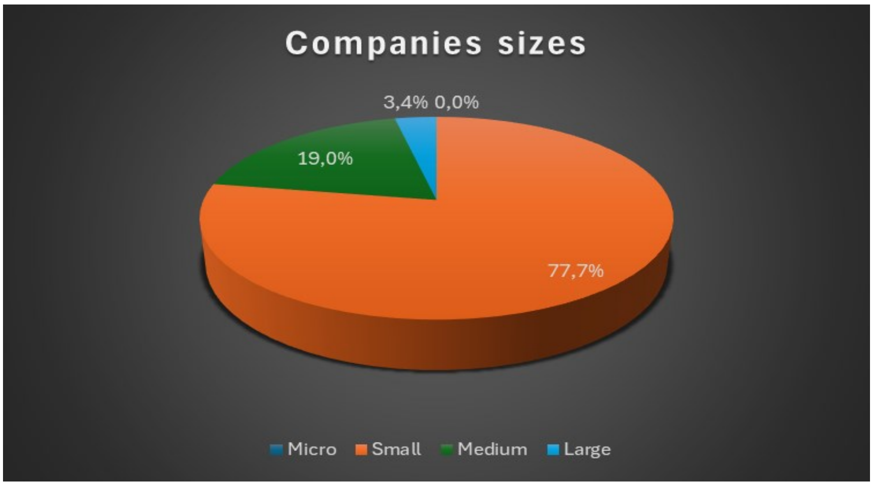

Figure 3: Distribution of firms' sizes

Source: elaboration on ISTAT data

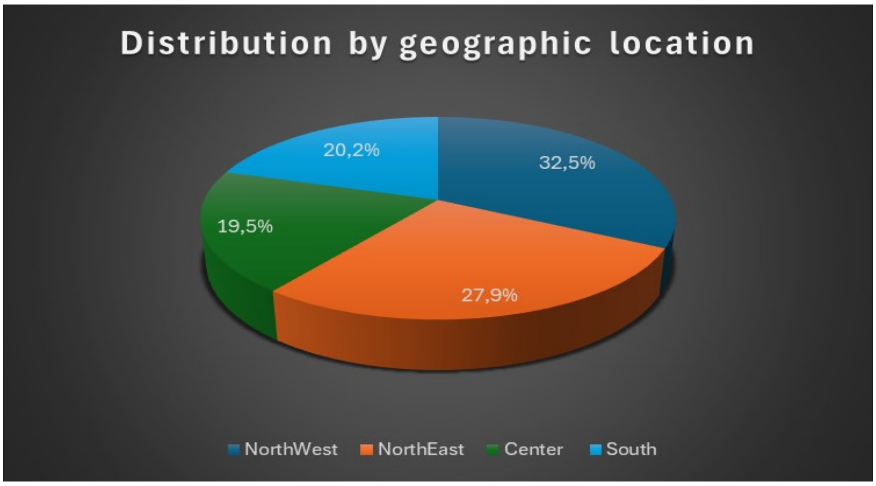

Figure 4: Distribution of firms by geographical location

Source: elaboration on ISTAT data

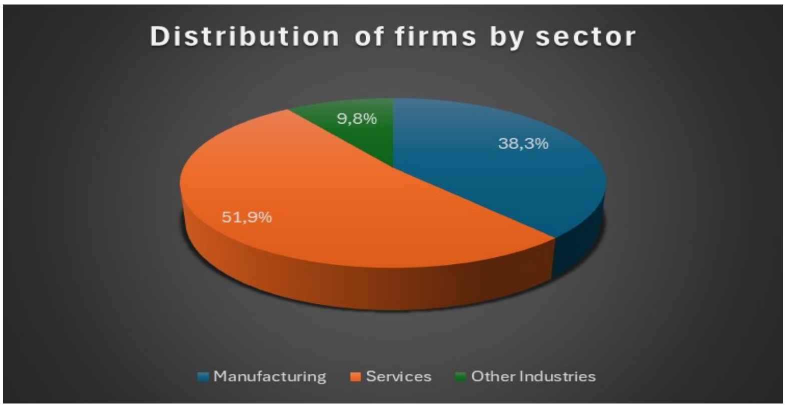

Figure 5: Distribution of firms by sector

Source: elaboration on ISTAT data

4) Method

We estimated the relationship between digital technologies and labor productivity through a log-linear cross-section regression. Analytically:

$$lnlpi = \beta 0 + \beta 1 \mathrm{DT} i + \beta 2 C i + \varepsilon i \quad [1]$$

where *lnlp* represents the (logarithm of) labor productivity of firm i; DT is the vector of variables capturing digital technologies; C is the vector of control variables; and ε_i is the error term. For further details, see the section "Variables description".

Given the log-linear nature of the model, coefficient B indicates the percentage difference in labor productivity between firms that invest in digital technologies and those that do not.

5) Digital technologies and labor productivity: our results

Table X reports the results about the relationship between digital technologies and labor productivity, controlling for a set of variables to deal for potentially confounding effects of various firm's characteristics that may influence the labor productivity growth (age, industry and geographical location).

We find that all types of technologies are positively associated with labor productivity (hence there is a "productivity premium"). Overall, the firms investing in digital technologies have a higher labor productivity by 12.2% than the non-investing firms (Model A). More specifically, we find that in all types of technologies the coefficient is positive and statistically significant at the 1%. However, the results show that the highest magnitude arises for AI technologies: the firms investing in AI (*Tech.ia*) are a labor productivity higher by 19.7% than the other firms (Model C); while for other technologies (*Tech.other*) the difference is 16.2% (Model D) and for the Internet technologies (*Tech.int*) the productivity premium is 9.3% (Model B). Also, when we consider simultaneously all three types of technologies the highest magnitude of AI is confirmed (Model E).

Thus, concerning the first research question RQ.1 "Are digital technologies positively associated with labor productivity?" our results show that there is a positive relationship between digital technologies and productivity, especially for AI. In the case of RQ.2 "Which digital technologies are more positively associated with labor productivity??" the results show that AI is the digital technology more positively associated with labor productivity.

Tab. X – The relationship between Digital technologies and labor productivity

Dependent variable: Labor prod

	(A)	(B)	(C)	(D)	(E)
Tech.all	0.122*** (0.004)				
Tech.int		0.093*** (0.004)			0.043*** (0.004)
Tech.ia			0.197*** (0.006)		0.137*** (0.006)
Tech.other				0.162*** (0.004)	0.125** (0.004)
+ *controls*					
Obs.	91.275	91.275	91.275	91.275	91.275

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In the table below, we report the results of the differences between the coefficients: a statistically significant test ($p < 0.10$) indicates that the difference between the two coefficients is statistically significant, leading us to reject the null hypothesis of coefficient equality. The results show that the difference in the coefficients between *Tech.int* and *Tech.ia* as well as between *Tech.int* and *Tech.other* are statistically significant. Instead, the difference between *Tech.ia* and *Tech.other* is not statistically significant. Therefore, we cannot conclude that the effect of AI technologies on labor productivity is greater than that of other digital technologies.

Table X.A Testing the statistical significance of coefficient differences.

Tech.int = Tech.ia	158.50***
Tech.int = Tech.other	167.53***
Tech.ia = Tech.other	2.0

The table reports the test statistic and its level of statistical significance.

*** p<0.01, ** p>0.05, * p>0.1

When we investigate possible heterogeneity by size class, we find that the relationship between digital technologies and labor productivity holds for small, medium and large firms: in all cases firms investing in digital technologies have a higher labor productivity than the others: the coefficients are always positive and statistically significant (in almost all cases at 1%). Particularly, if we find that in the case of AI the productivity premium rises for large firms (16.2% vs. 9.9% for medium firms, and 9.3% for small firms). While in the other cases the productivity premium does not consistently differ by size class. Thus, RQ.3. "Is there heterogeneity by size class in the relationship between digital technologies and labor productivity?" Our results show that there is no strong heterogeneity.

Tab. XI – The relationship between Digital technologies and labor productivity: heterogeneity effect by size class

Dependent variable: Labor prod

	Small **(A)**	Medium **(B)**	Large **(C)**
Tech.int	0.034***	0.037***	0.010*
	(0.004)	(0.009)	(0.027)
Tech.ia	0.093***	0.099***	0.162***
	(0.008)	(0.011)	(0.024)
Tech.other	0.099***	0.117***	0.115***
	(0.005)	(0.009)	(0.026)
+ *controls*			
Obs.	71.156	17.112	3.007

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Testing the differences between the coefficients, we find that the technology showing the most significant differences across firm size classes is Artificial Intelligence.

Table XI.A Testing the statistical significance of coefficient differences.

	Tech.int	*Tech.ia*	*Tech.other*
small = medium	0.12	0.17	3.21*
small = large	2.39	8.14***	0.42
medium = large	2.57	6.25**	0.01

The table reports the test statistic and its level of statistical significance.

*** p<0.01, ** p>0.05, * p>0.1

Since AI is the technology more associated to the labor productivity, investigating how the different AI technologies are related with labor productivity (Table XII) would be worthwhile. We find that big data and robots display the highest productivity premium: firms investing in big data have a higher labor productivity by 21.8% than the others (Model B), as well as by 19.7% in the case of robot (Model C), while the productivity premium decreases to 14.2% in the case of immersive technologies (Model A). These ranking holds when we consider simultaneously all the three types of AI technologies (Model D).

Tab. XII – The relationship between Digital technologies and labor productivity: deepening the AI technologies

Dependent variable: Labor prod

	(A)	**(B)**	**(C)**	**(D)**
Tech.ia.immersive	0.142*** (0.014)			0.010* (0.015)
Tech.ia.bigdata		0.218*** (0.008)		0.179*** (0.008)
Tech.ia.robot			0.197*** (0.008)	0.156*** (0.008)
+ controls				

Obs.	91.275	91.275	91.275	91.275

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The following table shows the results of the coefficient difference test among the different artificial intelligence technologies. The test rejects the null hypothesis of coefficient equality when immersive AI technologies are compared with big data and robots, indicating that the impact of immersive technologies on labor productivity differs significantly from that of the other two AI technologies. Furthermore, the difference between big data and robots is also statistically significant, although only at the 10% level, suggesting that the effects of these two technologies on productivity are relatively similar. Overall, the results highlight that not all AI technologies have the same impact, with immersive technologies showing the most distinctive effects.

Table XII.A Testing the statistical significance of coefficient differences.

Tech.ia.immersive = Tech.ia.bigdata	104.27***
Tech.ia.immersive = Tech.ia.robot	85.83***
Tech.ia.bigdata = Tech.ia.robot	3.32*

The table reports the test statistic and its level of statistical significance.

*** p<0.01, ** p>0.05, * p>0.1

Furthermore, besides the different types of AI technologies, to analyze if the AI technology intensity deserves attention. To achieve this objective, we constructed a variable (*Tech.ai.intensity*) ranging from 0 to 3 according to the number of AI technologies on which the firm invested. Table XIII reports the results. We find that, with respect to the firms that do not invest in any AI technologies, the ones investing in only one type of AI technology have a higher labor productivity of 18.0% than the others. This productivity premium rises to 25/26% when the firms invest in two or three types of AI technologies. Thus, concerning the research question RQ.4 "With regard to the digital technology most associated with labor productivity, does the technology intensity matter?", our results confirm the importance of the intensity by underlining that the step more impacting is from one to two AI technologies.

Tab. XIII – The relationship between Digital technologies and labor productivity: deepening the AI technologies

Dependent variable: Labor prod

	(A)
Tech.ia.zero	r.c.
Tech.ia.one	0.180***
	(0.007)
Tech.ia.two	0.267***
	(0.014)
Tech.ia.three	0.255***
	(0.022)
+ controls	
Obs.	91.275

r.c.: reference category. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, we investigated whether investments in human capital raise the productivity premium. In doing this, we analyzed the relationship between digital technologies and labor productivity across firms invested in training activities (high degree of investments) and across firms that did not invest in training activities. The results display in Table XIV shows that the productivity premium rises when the firms invested in training activities: in this case the firms invested in digital technologies have a higher labor productivity by 15.2% then the others ($p<0.01$) (Model A), while across the firms not invested in human capital the productivity premium diminishes at 11.7% (always $p<0.01$) (Model B). Thus, concerning the last research question RQ.5 "Does the relationship between digital technologies and labor productivity raise across firms investing in training activities?", our results provide a positive answer.

Tab. XVI– The relationship between Digital technologies and labor productivity: deepening the role of investments in training activities

Dependent variable: Labor prod

	(A)	(B)
Tech.all	0.152***	0.117***
	(0.017)	(0.004)
+ *controls*		
Obs.	7.547	83.728

Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

6)Policy Implications and Future Directions

The results of our analysis show that, within the broader process of digitalisation, artificial intelligence technologies generate the most significant impact on labour productivity. Our analysis also confirms the importance of intensity, highlighting that the adoption of a greater number of AI technologies leads to an increase in productivity, and the importance of the role of training activities. The positive effect we observed on productivity may stem from the prevalence of an augmenting effect, that is, an enhancement of human capabilities, over an automation effect, which replaces human tasks.

This evidence suggests that public and corporate policies should focus on promoting the adoption of digital technologies, particularly AI, by creating the conditions to maximise their effectiveness through investments in complementary technologies, skills development, and organisational adjustments. In the absence of such investments, the effects on productivity will be weaker.

Differences between high- and low-income countries confirm this dynamic: in less developed contexts, the impact of adopting generative AI technologies on productivity is lower, mainly due to the lack of reliable infrastructure. AI in fact depends on access to and the cost of broadband connectivity, as well as the availability of stable and secure electricity (International Labour Organization [ILO], 2023).

Policymakers should also focus both on the adoption of programmes aimed at developing digital skills necessary to close the AI-related skill gap and on strengthening complementary skills such as communication, creativity, and teamwork. Governments could introduce AI courses even at the school level, to prepare the future workforce and reduce the skills shortage. It is equally important to provide specific training programmes for workers at risk from the displacement effect, accompanied by subsidies and support measures to facilitate their reintegration into other sectors or new roles.

Although AI can be used to automate repetitive activities, freeing up time for more complex and engaging tasks, it can also reduce workers' decision-making power or intensify work rhythms. Companies using AI tools to monitor employees and evaluate performance based on data could create high-stress work environments, where employees feel constantly watched, under pressure, and with reduced decision-making autonomy. In some cases, this may lead them to sacrifice personal time and work-life balance. It is therefore essential for policymakers to consider AI's impact on job quality, promoting a use that safeguards well-being and dignity.

To ensure that technologies have a positive impact on working conditions, workers must be involved in the design, implementation, and use of technological solutions. Studies in the European context show that countries with stronger and more collaborative forms of workplace consultation, particularly the Nordic countries, followed by Germany, record greater openness among workers towards the adoption of new technologies (International Labour Organization [ILO], 2023).

Numerous scholars have also emphasised the importance of addressing ethical issues related to the use of these technologies, yet little attention has been paid to power imbalances in labour relations. AI tools can exacerbate such imbalances, especially if workers do not have access to the data used to monitor their activities, if there are no mechanisms to assess the technology's use *ex post* in the workplace, or if dismissal decisions are made without proper recourse to dispute resolution procedures (International Labour Organization [ILO], 2023).

It is therefore necessary for policymakers to introduce new laws to protect workers. The design and implementation of such regulations should take place through tripartite systems, ensuring equal decision-making power for representatives of employers, workers, and governments, and building on existing consultation mechanisms and structures as well as on current labour rights and standards.

To ensure trustworthy AI in the workplace, it is essential to establish a harmonised framework that combines soft law instruments and binding legal rules, covering all dimensions of trustworthiness. Since these dimensions are interconnected, public policies can be designed to pursue multiple objectives, thereby reducing the overall regulatory burden. Transparency, for instance, is essential for ensuring accountability, while explainability requirements for systems can help mitigate bias and discrimination. At the same time, the regulatory framework must strike a balance between flexibility and consistency, both nationally and internationally, to avoid hindering enforcement, stifling innovation, or creating unnecessary barriers to the adoption of trustworthy AI.

At the international level, the OECD AI Principles have played a central role in defining trustworthy AI, emphasising the importance of transparency, security, and system protection, as well as the accountability of all actors involved throughout the AI lifecycle. Individual countries, however, need to differ in their regulatory approaches, introducing various measures both to stimulate the adoption of digital technologies, particularly AI, and to regulate their use in an ethical and sustainable manner.

In summary, the results of this analysis confirm that digital technologies and mainly AI can have a positive impact on productivity, provided it is introduced in a context adequately supported by infrastructure investment, skills development, organisational restructuring, and solid regulatory protections. An integrated approach, based on cooperation between governments, businesses, and workers, is essential to transform AI from a potential source of risk into a strategic lever for sustainable economic growth and better job quality.

CONCLUSIONS

This thesis has analysed the transformative role of digital technologies, and in particular AI technologies, in revolutionizing business models, increasing productivity, and altering employment levels. The theoretical framework outlined highlights both the opportunities and challenges associated with the digital transformation process, examining the potential offered by Industry 4.0 and 5.0 as well as the critical issues raised in the ongoing debates on the productivity paradox and the digitalization paradox. The empirical analysis, focused on Italian firms, has provided robust evidence that investments in digital technologies, and especially in AI, are strongly associated with higher labor productivity. In particular, firms adopting AI technologies record a productivity premium of nearly 20% compared to non-adopters, with additional positive effects when multiple AI technologies are implemented and supported by adequate training.

At the same time, our results and the existing literature confirm that the benefits of digitalization are not automatic and may vary depending on firm size, sector, and organizational structure. Although digitalization can foster competitiveness, innovation, and even wage growth, its impact on employment depends on firms' ability to reorganize tasks, upgrade skills, and ensure an inclusive workforce transition.

Overall, the study shows the dual nature of digital transformation: it represents both a powerful engine of growth for individual firms and production sectors, and a potential source of inequality if not accompanied by strategic investments in skills and organizational capabilities. It is therefore essential that policy makers and business leaders act to create favourable contexts in which technological innovation translates into widespread productivity gains, sustainable competitiveness, and fair labor market outcomes.

APPENDIX A: Key enabling technologies of Industry 5.0.

Edge computing (EC) is a technology that enables data processing close to the source (e.g., in machinery or IoT devices) instead of sending it to a central server or the cloud. This system is essential for effective preventive analysis, making it easier to predict problems before they occur. EC also meets expectations regarding data protection and privacy, response time requirements, and reduces latency costs, which are the expenses incurred due to negative effects caused by transmission and processing delays. To manage the vast amounts of data generated by various software and machinery, companies are increasingly trying to access data through local servers. EC reduces the amount of information that needs to be collected in a centralized server. Thus, edge computing analyzes data locally, sending only the key information required for more complex analyses to a centralized server or the cloud. This helps detect failures or issues earlier while also enhancing data security, as large volumes of information are no longer transmitted to the cloud.

Digital Twin is a term used to refer to a digital replica of a physical object or system. Through IoT devices, data from physical objects is transmitted to digital systems, where simulations are created. This results in a digital mapping of the system, allowing for analysis, problem prevention, and the development of solutions before implementing them in the real world. Digital Twins enable the identification of elements that can be reconfigured to enhance productivity and improve forecasting. In Industry 5.0, they are also essential for product customization.

Cobots, or collaborative robots, are designed to work alongside humans, being equipped with numerous sensors that help prevent accidents. In the event of human error, the robot immediately stops its operations. This type of robot is functional for large-scale production while incorporating human critical thinking into the manufacturing process. In Industry 5.0, cobots help increase system productivity, facilitate product customization, and reduce costs. One of their main applications is in surgery, where the robot and the surgeon perform operations together.

The Internet of Everything (IoE) refers to the interconnection of processes, people, objects, and information. One of the main objectives of Industry 5.0 is to improve efficiency in the supply chain and logistics. These systems help reduce waste in supply chain management and facilitate product customization, ultimately enhancing customer loyalty and satisfaction.

Big Data is a central theme in both industry and academia. Every company must analyze large amounts of data to understand sales trends, consumer interests, and the efficiency of production processes. Big data analysis allows companies to make crucial forecasts regarding the key applications of Industry 5.0. In fact, data analysis improves mass customization processes by efficiently integrating resources while also uncovering new opportunities for innovation.

Blockchain, along with smart contracts, can offer significant advantages to Industry 5.0. Managing a large number of interconnected devices in a centralized manner is challenging. In this context, blockchain can be used to handle information in a decentralized way, ensuring operational transparency and accountability in the main applications of Industry 5.0. Smart contracts can play a key role in authentication, verifying the identity of an agent or device accessing a network or an industrial system. These contracts can also automate specific tasks, such as activating a machine under certain conditions or managing a production process. Blockchain is therefore crucial for creating digital identities for people and entities in Industry 5.0, managing access and authentication for all stakeholders involved, and, together with smart contracts, automating contract processes between different stakeholders.

6G represents an evolution of previous networks like 4G and 5G. The increasing use of automated machines and robots equipped with sensors heightens device interconnection, making information management more complex. In Industry 5.0, having extremely low latency is essential to ensure that devices respond almost in real time. 6G promises to drastically reduce latency, thereby improving the overall experience and making services more responsive and seamless. It will be crucial in supporting artificial intelligence, which can be used to optimize resources and processes. Ultimately, the importance of ultra-fast data transmission between various sensors and machines makes 6G fundamental to the revolution brought by Industry 5.0 (Maddikunta et al., 2022).

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