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***A PATH THROUGH KNOWLEDGE MANAGEMENT AND
ARTIFICIAL INTELLIGENCE MODELING:
a focus on Sustainability, Science Park's dynamics,
Backcasting on emerging technologies and the implementation of
TalTech Industrial Project***

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Abstract

***T**HE doctoral thesis examines how knowledge management strategically drives innovation, sustainability and competitiveness in the information and data analysis economy.*

The first chapter examines the fundamental principles and structures of knowledge management (KM) and how they fit into corporate decision-making, highlighting the shift from a static to a dynamic vision of knowledge as a fluid resource necessary for sustainable solutions.

The following section examines the challenges and opportunities of Science Parks as an ideal ecosystem for promoting the development and dissemination of knowledge, as well as the complex interaction between business intelligence, organizational learning, innovation and financial performance. This analysis has allowed the positive and non-positive critical relationships to emerge, on which it becomes strategic to focus, and to simulate such an ecosystem realistically, the application of an agent-based model is proposed.

Moving on to an innovative proposal for managing the R&D function, in the third chapter, a literature analysis procedure is presented through backcasting, replacing the traditional forecasting approach, within a blockchain system to classify and select emerging technologies, frontier and dominant ones to support the corporate decision-making process on the choice of investments to be made.

In the last chapter, the thesis discusses the relationship between KM, innovation, research, new technologies and organizational and economic performance, thanks to the development of the international research project "TalTech Industrial" and the analysis of Global Value Chains in emerging economies. This study and the reinterpretation of indicators such as the Catch-Up Performance Index show that knowledge-based policies have essential public and private economic implications to effectively reduce existing gaps and increase current company and sectoral performance.

In conclusion, the transformative capacity of KM as a bridge between theoretical and practical fields is crucial to support economic growth and competitiveness in the contemporary, constantly evolving socio-economic context. The findings contribute to the academic discourse and serve as a guiding framework for organizations aiming to leverage KM for strategic advantage in the ever-evolving business environment.

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Introduction

The Ph.D. thesis encompasses four unique elements, all interconnected by a central theme: the quest for knowledge as a catalyst for fostering innovation, sustainability, and competitiveness in the current information-based economy. This thesis is built upon the fundamental principles of knowledge, its management, and its strategic usage.

Proficiency knowledge administration has emerged as a pivotal determinant for firms' achievement and competitive advantage.

This Ph.D. thesis explores the complex domain of knowledge management, innovation, and sustainability solutions, specifically focusing on the significance of scientific parks and new technologies. The primary objective is to investigate how businesses can efficiently utilize information to facilitate innovation and achieve long-term, environmentally responsible expansion.

In the dynamic and constantly changing environment of modern enterprises, the acquisition and utilization of information have become crucial factors in determining competitiveness, fostering innovation, and ensuring long-term viability.

This study's initial section thoroughly investigates the complex dynamics of knowledge management within the contemporary knowledge-based economy. The aim is to fully understand knowledge management's fundamental concepts, frameworks, and operational mechanisms within organizational settings. The perception of knowledge has shifted from being a fixed entity to being seen as a fluid and crucial resource that forms the foundation of corporate decision-making processes. The primary focus of this chapter is to explore the various dimensions of knowledge management, examine the difficulties presented by the digital age, and clarify the significance of knowledge in building sustainable solutions. This analysis explores the conception of knowledge, its evolution within knowledge-intensive businesses, and its incorporation into strategic decision-making processes to influence the future economy.

Examining learning organizations is also conducted within the framework of dynamic environments, providing insight into organizations' adaptive and evolutionary processes.

Furthermore, this section elucidates the sophistication exhibited by knowledge management practices and their ability to adjust in the context of Industry 4.0.

It also highlights the pivotal function of business analytics in facilitating enhancements within organizations. Additionally, it scrutinizes the escalating significance of harmonizing knowledge management with sustainability efforts, specifically through initiatives such as B-Corporations and incorporating Environmental, Social, and Governance (ESG) considerations into corporate finance.

The primary purpose of the initial chapter is to provide a fundamental examination of the current difficulties and opportunities in knowledge management, thereby establishing a framework for a more comprehensive analysis of its various aspects.

Regarding the role of knowledge management as a catalyst for competitiveness and innovation in organizations, it sets the foundation for the examination in the subsequent chapter on enterprises functioning within Science Parks. These entities are frequently at the vanguard of innovation and have emerged as hubs for generating knowledge.

Science Parks facilitate a vibrant environment in which the exchange and generation of knowledge flourish, in line with the interconnectedness of business intelligence, organizational learning, innovation, and financial outcomes explored in chapter two.

Science parks facilitate an ecosystem that fosters the ongoing generation and dissemination of information among many stakeholders, such as enterprises, research institutes, and academic entities. These environments that promote innovation offer a distinctive context to analyze the extent to which well-managed knowledge, supported by solid business intelligence techniques and an organizational culture that values learning, leads to measurable financial achievements. Moreover, this chapter explores the complex connections between strategies for innovation and measurements for financial performance, providing a more profound comprehension of the mechanisms that propel enduring growth in the economy powered by knowledge.

The financial performance of these innovative enterprises is strongly correlated with their capacity to utilize their knowledge resources effectively. The outcomes presented in this section serve as compelling evidence of this connection.

The findings from this particular segment of the research have been previously disseminated in the esteemed scholarly publication *Information Processing and Management* (2021), as well as in the form of a chapter inside two Springer books titled: *Mathematical and Statistical Methods for Actuarial Sciences and Finance - MAF 2022* and *Applied Intelligence and Informatics - AII 2022*. Communications in Computer and Information Science.

In addition, the second chapter also directs its attention toward utilizing an Agent-Based Model (ABM), a computational modeling technique that replicates the behaviors and interactions of individual agents within a given system. This approach serves as a methodological link that will be employed to further analyze the dynamics between science parks and startups in future research endeavors.

This modeling approach expands our repertoire of analytical tools and presents a promising option for future research, enhancing our understanding of the complex dynamics within scientific parks and their influence on financial performance.

This chapter functions as a transitional link between the theoretical underpinnings of knowledge management discussed in the preceding chapter and the practical examination of how these ideas manifest in the context of science parks. It provides insights into the economic consequences of knowledge-focused strategies and introduces a modeling methodology for future research endeavors.

The transition from the second to the third chapter focuses on the theme of technology, specifically the exploration of emerging technologies and their implementation in research methodologies such as backcasting and the utilization of blockchain technology. This transition emphasizes the inherent connection between innovation, knowledge, and technology and the forward-looking approach of backcasting in utilizing developing technologies for inventive purposes. Furthermore, the blockchain, a decentralized ledger system, functions as a mechanism for scrutinizing current scholarly works, reinforcing the thematic connection with knowledge management and innovation, as discussed in the second chapter.

Therefore, the correlation between the second and third chapters highlights the role of knowledge and data in driving innovation and developing technologies. The third chapter further enhances our comprehension of the consequences of knowledge management by introducing innovative technical methods.

Within the rapidly advancing domain of technological progression, the third section of this doctoral dissertation delves into an investigation of an innovative research paradigm, which introduces the notion of backcasting. This strategic planning methodology entails commencing with a desired future state and subsequently tracing the necessary steps to achieve said future state. This method holds significant relevance in the contemporary context, characterized by a dynamic global landscape, wherein the swift advancement of nascent technologies carries substantial ramifications for various sectors, communities, and financial systems.

The chapter additionally presents a novel methodological aspect through the utilization of smart contracts, which are contracts that automatically execute based on pre-defined code, thereby automating different elements of transactions and decision-making. Furthermore, blockchain technology is employed to carry out a thorough literature review. The blockchain functions as a transparent and secure mechanism for registering, retaining, and examining enormous quantities of data, rendering it a well-suited instrument for investigating nascent technologies. This novel methodology enables a systematic and thorough analysis of the current knowledge base, facilitating the identification of patterns, deficiencies, and valuable insights that can guide strategic decision-making amidst swift technological advancements.

The third chapter of this study establishes the foundation for the ensuing analysis of how emerging technologies influence knowledge management and innovation in modern businesses.

In the last chapter, a pivotal point is reached where the many aspects of knowledge management, innovation, new technologies, and organizational performance intersect.

This chapter expands upon the principles established in the preceding sections, integrating the complex research and innovation (R&I) subject within the framework of the PNRR era, the goals and anticipated effects of the TalTech Industrial Project, in which the writing Ph.D. student collaborates at Bocconi University in conjunction with the coordinator Tallinn University of Technology, and the intricate examination of Global Value Chains (GVCs) in developing economies.

The preceding chapters highlight the relationships' significance, emphasizing that knowledge is not an independent entity but rather a dynamic influence that infiltrates all aspects of contemporary organizations and industries.

The TalTech project offers a concrete example of how research and innovation techniques can stimulate economic growth and enhance competitiveness. It establishes a clear connection between theoretical frameworks and their practical implementation. Building upon the ideas of knowledge management previously examined, this chapter provides a comprehensive analysis of how research and innovation (R&I) activities play a central role in augmenting the competitiveness of both enterprises and entire regions.

The complex interconnections of information, innovation, and value generation become prominent when analyzing the benchmarking of Global Value Chains (GVCs) regarding production efficiency and industrial performance.

The analysis presented in this study demonstrates a notable level of innovation, as it introduces indices such as the Catch-Up Performance Index. These indices serve to emphasize the dynamic nature of economic convergence. The above analysis reveals a precise alignment between the knowledge-driven strategies, business intelligence, and innovation discussed earlier in this thesis and their significant impact on emerging economies' Global Value Chains (GVCs).

The fourth part of this study represents the completion of the research journey, bringing together knowledge, innovation, technology, and strategic thinking to comprehensively comprehend the current dynamics inside companies and industries. The interconnection between research and innovation (R&I) endeavors, such as the TalTech project and Global Value Chain (GVC) analysis, highlights their inherent association with knowledge management, sustainability, and economic advancement.

Throughout this doctoral thesis, the critical connections established determine a comprehensive perspective on the transformative power of knowledge management, which emerges as the linchpin that connects theory to practice, innovation to sustainability, and competitiveness to growth in the ever-evolving socio-economic context thanks to cutting-edge research methodologies.

***FROM KNOWLEDGE MANAGEMENT
CHALLENGES TO
SCIENCE PARKS OPPORTUNITIES
&
A NEW R&D APPROACH
THROUGH BACKCASTING
AND BLOCKCHAIN SYSTEM***

CHAPTER 1

Knowledge Management: new research challenges through Innovation, Artificial Intelligence and Sustainable Strategies

1.1. Knowledge and strategies conceptualization

The prevalent perspective on knowledge, particularly in management, is "justified true belief" (Nonaka and Takeuchi, 1995). Although the origins of this definition can be traced back to earlier philosophical thought, it is essential to acknowledge that truth and its justification frequently involve a subjective element of interpretation.

On the other hand, in business, the term "strategy" is widely employed, yet its definition exhibits a certain degree of fluidity.

Initially, it is important to note that a strategy inherently pertains to an indeterminate future, a concept that has been widely acknowledged for a considerable period (Mintzberg and Waters, 1985). Furthermore, it is essential to recognize that individuals responsible for devising a strategy do not possess omniscience and are subject to certain limitations in their abilities.

So, a strategy can be characterized as a conceptualized vision of the future, prioritizing the desired outcomes rather than a strictly rational formulation outlining the steps to take. The concept of strategy has transformed the management field, as evidenced in the existing literature. These changes can be attributed to the evolving economic landscape and the progress made in theoretical discussions surrounding the fundamental aspects of strategic thinking.

In any event, one can contend that the notion of knowledge is closely interconnected with that of strategy. Knowledge is not solely a vital component for devising and contemplating the notion of a strategy, but it can also serve as the target of a strategy. There is a growing recognition that companies should consider the emerging concept of a knowledge strategy.

The concept of knowledge strategy has gained traction in the field of management literature relatively recently, primarily driven by the emergence of the knowledge economy and the widespread adoption of knowledge management

initiatives (Zack, 1999). Including knowledge in strategic formulation has long been acknowledged as a crucial component (as previously stated, a certain level of expertise is necessary for strategy development). However, knowledge strategy encompasses a broader scope; an organization should implement a strategic approach to effectively govern its knowledge assets. In addition to the coordination of production and distribution of goods and services, the establishment of profit and market objectives, and the formulation of competitive positioning goals, a knowledge strategy includes the deliberate planning of knowledge management activities and the overall organization of resources and processes within a company. These efforts aim to enhance the development of knowledge and competencies among individuals, foster learning processes, and facilitate knowledge storage, sharing, and reuse.

The above definition of "justified true belief" (Nonaka and Takeuchi, 1995) comprises three fundamental conditions, referred to by certain scholars as the tripartite account of knowledge. The conditions mentioned are as follows (Neta and Pritchard, 2009):

- The truth condition refers to the criteria determining whether a statement is true or false. It serves as the distinguishing factor between subjective opinions and objective knowledge.
- The belief condition necessitates that an individual, upon possessing knowledge of a proposition, also holds a corresponding belief in said proposition.
- The justification condition is crucial: it necessitates a pragmatic approach to substantiating the integrity of one's belief.

By synthesizing these criteria for knowledge, it can be inferred that the essential and complete prerequisites for possessing knowledge about a particular matter are as follows: firstly, the proposition that one claims to know must be factually accurate; secondly, one must have a high degree of certainty regarding the truth of the request; and thirdly, one must possess the entitlement to hold such certainty (Ayer, 2009).

The acquisition of certainty can be achieved through various means contingent upon cultural and contextual factors.

Nonaka and Takeuchi (1995) argue that traditional epistemology prioritizes knowledge as an absolute, unchanging concept detached from human involvement, often conveyed through propositions and formal logic. In contrast, they view knowledge as a dynamic, inherently human process involving the continuous justification of personal beliefs in pursuit of truth. The authors transform the philosophical discourse into a managerial approach, positing that the most effective form of validation occurs within the social framework in which novel knowledge is generated and disseminated, namely the organizational context. However, the authors demonstrate through this transition that, in practical terms, the development of novel knowledge should be assessed using a metric of

utility rather than one based solely on logic. In addition, they provide practical justifications for their assertions, such as cost, profit margin, and the extent to which a product can enhance the company's economic performance.

Nevertheless, through this mechanism, there was a fundamental alteration in the essence of justification, shifting it from a logical framework to an economic paradigm overseen by individuals in managerial positions. Senior executives seek alignment with the organization's strategic vision, whereas middle managers prioritize practical considerations.

According to Dombrowski et al. (2013), an integrated perspective on the nature of knowledge reveals the existence of three distinct types of knowledge.

Three key components contribute to an individual's understanding and expertise in a particular field: (a) experiential knowledge, (b) skills, and (c) knowledge claims. These entities exhibit interconnections yet possess distinct characteristics unique to each.

1. *Experiential knowledge* refers to the information acquired through direct interaction with the environment, facilitated by our sensory system, and subsequently processed by the brain. Experiential knowledge is inherently subjective as it is obtained exclusively through a potent interplay between emotional, rational, and spiritual knowledge, as it emerges from the comprehensive engagement of both the physical and mental faculties (Bratianu, 2015).
2. *Skills* refer to acquiring knowledge about the practical application of a particular task or activity. This knowledge is achieved through the iterative execution of a specific task, facilitating learning through direct experience. The process can be likened to developing knowledge or skills without conscious awareness, wherein one becomes proficient in executing a specific procedure or adhering to a prescribed algorithm. Thinking skills play a crucial role in the cognitive abilities of knowledge workers and decision-makers. Intuition is widely recognized as a critical skill in strategic design. As stated by Klein (2003), the utilization of intuition effectively is contingent upon one's experience, significant experiences that enable the recognition of patterns and the construction of mental models.
3. *Knowledge claims* refer to assertions or propositions based on what individuals perceive as their understanding or beliefs about a particular subject matter. The extent of our knowledge remains uncertain due to the encompassing nature of knowledge, including explicit and tacit knowledge. Ideas are subject to examination, discussion, questioning, evaluation, refutation, publication, and dissemination due to their expression in language. According to Dombrowski et al. (2013), knowledge claims facilitate the

process of acquiring knowledge from one another and constructing our collective knowledge.

1.2. Knowledge Economy for future firms

Peter Drucker's influential work, "The Age of Discontinuity: Guidelines to Our Changing Society," published in 1969, presents a comprehensive analysis of significant transformations occurring in four key sectors of the global economy, which have profound implications for society. According to Drucker (2008), the author refers to these significant changes as discontinuities that can alter the structure and significance of the economy, politics, and society, even though they may not yet be apparent. These discontinuities can serve as an "early warning system" for decision-makers across various sectors of contemporary society.

Drucker has identified significant discontinuities in various areas:

- The advent of novel technologies that can foster the creation of fresh industries and enterprises;
- the shift from the concept of an "international economy" to that of a "world economy" ultimately culminates in the establishment of a singular global market;
- the dynamic interplay between politics and the social and economic spheres is undergoing rapid transformation, resulting in the emergence of a novel sociopolitical landscape;
- the rise of a knowledge-based economy: in recent decades, knowledge has emerged as the primary form of capital, a significant cost center, and a critical economic resource.

According to Drucker (2008), these transformations have significant implications for labor forces, work dynamics, educational practices, and the conceptualization of knowledge and its associated politics.

Drucker's conceptualization of the "knowledge economy" was influenced by the work of economist Fritz Machlup, who introduced the term "knowledge industries" in his book "Production and distribution of knowledge" in the United States (1962).

According to Drucker (2008), statistics fail to disclose the crucial aspect: the central determinant in an advanced, developed economy is acquiring and utilizing knowledge, which has emerged as the primary "factor of production." As understood by intellectuals, the concept of "knowledge" is distinct from "knowledge" because it is associated with practical application. The knowledge possessed by intellectuals is primarily theoretical and is typically disseminated through books and scientific journals. In contrast, organizational knowledge is valuable and is actively utilized by knowledge workers in their professional endeavors.

According to Drucker, the advancement toward a knowledge economy can be attributed to Frederick W. Taylor's groundbreaking work in scientific management. Through the implementation of engineering methodologies to streamline and quantify the effectiveness of industrial operations, he achieved a significant and rapid escalation in work productivity. The achievement was not attributed to increased effort but to a more strategic approach. According to Drucker (2008), it can be argued that knowledge, rather than physical exertion, is a crucial factor in achieving productivity.

According to Powell and Snellman (2004), a knowledge economy refers to producing and providing goods and services that heavily rely on knowledge-intensive activities. These activities contribute to a heightened technological and scientific progress rate while also leading to rapid obsolescence.

This economy is characterized by the creation, acquisition, transformation, transfer, dissemination, and effective utilization of knowledge to promote economic development. A prominent characteristic of the knowledge economy is its heightened dependence on intangible resources and intellectual capabilities for their utilization, as opposed to physical ones.

The concept of the knowledge economy revolves around the abundance rather than scarcity of resources. All tangible resources that contribute to the attainment of a competitive advantage for a firm are limited in quantity and their utilization in the production process should be carried out with optimal efficiency. Conversely, intangible resources are abundant in numerous domains, such as data, information, and knowledge, thanks to their non-rivalrous nature. Simultaneous deployment across various applications is feasible, and their efficacy does not diminish through dissemination.

The current challenge lies not in the abundance of data, information, and knowledge but in the ability to analyze and interpret them effectively. Despite the advancements in Big Data technology and data mining algorithms, human cognitive abilities to solve and make decisions under uncertain circumstances remain significantly constrained (Davenport, 2005; North and Gueldenberg, 2011; Spender, 2014).

In the context of the industrial economy, growth can be achieved through the linear accumulation of tangible assets and their subsequent integration into the production process. In the context of the knowledge economy, it is argued that the linear collection of assets is not feasible due to the nonlinearity of intangible assets.

Instead, a distinct approach is required, emphasizing the integration of these intangible assets. As discussed by Bratianu (2009), the concept of nonlinearity necessitates the development of novel evaluation and reporting metrics for intellectual capital. In the context of the knowledge economy, various forms of intangible assets are encountered, each requiring distinct metrics and scales.

The contemporary business landscape is marked by the prominence of rapid change and innovation strategies as defining features of business models. While optimization is a crucial process in the knowledge economy, it cannot generate or

maximize value. In the knowledge economy, the adoption of innovation as the fundamental business process is the sole means of generating value. According to Al-Ali (2003), an organization's capacity to generate value is contingent upon its innovation process, intellectual resources, and the creative capabilities of its workforce, collectively referred to as its intellectual assets.

Information technology does not possess the ability to generate knowledge but rather serves as a fundamental framework for efficiently processing data and information at remarkable velocities, as well as facilitating their transmission within intricate networks. Additionally, the emergence of new information platforms facilitates the acquisition and dissemination of knowledge within and between organizations. Information technology facilitates the establishment of open innovation systems and virtual communities of practice (O'Dell and Hubert, 2011).

The effectiveness of utilizing information technology is contingent upon the managerial capabilities of individual firms and the implementation of essential structural modifications to align with the demands of said technology. To effectively utilize emerging information technologies and their applications, it is imperative to provide individuals with appropriate training and support to enhance their comprehension of the underlying principles and intelligent functioning of these technologies.

In the context of the knowledge economy, it is possible to generate novel interactions among social institutions to promote knowledge production, transfer, and application.

Leydesdorff (2006) analyzes the significance associated with establishing and cultivating a triple helix framework encompassing university-industry-government relations. The primary function of the government is to establish a comprehensive legislative framework that fosters the growth of novel scientific and technological structures and clusters. In this context, universities play a crucial role in generating and disseminating knowledge to the industry, which in turn utilizes this knowledge to create innovative goods and services.

According to Leydesdorff (2006), the development of university-industry-government relations can be understood in the context of institutional arrangements that involve the recombination of three critical functions within the socioeconomic system.

These functions include wealth generation and retention, novelty production, and control at the interfaces of these sub-dynamics.

Economic theories primarily focus on the behavior of firms within external markets. From an alternative standpoint, the firm's organizational theory examines the organization's internal framework and the interconnections between its various units and departments (Grant, 1996).

The knowledge-based theory of the firm is a theoretical framework that centers on the dynamics of knowledge within an organization (Grant, 1996, 1997; Nickerson and Zenger, 2004; Nonaka, 1994; Nonaka and Takeuchi, 1995; Spender, 1996; Sveiby, 2001; Tsoukas, 1996). Grant (1997) posits that the theory

elucidates the underlying reasoning behind the existence of a firm, the boundary of its limits, the characteristics of its organizational capability, the allocation of decision-making authority, and the factors influencing the formation of strategic alliances.

Grant's theory is based on several key assumptions, which include the following:

- in a strategic context, knowledge emerges as the paramount productive resource;
- explicit and tacit knowledge exhibit differences in terms of their transferability dimension. The transfer of explicit knowledge can be achieved through the utilization of either a natural or symbolic language, whereas tacit knowledge is inherently resistant to transfer;
- individuals play a pivotal role as the primary agents in the process of knowledge creation;
- the majority of knowledge is susceptible to the effects of economies of scale.

The firm is conceptualized as an institution that addresses the challenge of balancing knowledge specialization, which is essential for production, with knowledge integration. This is achieved through various mechanisms such as transfer, direction, sequencing, and routine. Grant (1997) argues that the primary management challenge lies in establishing tools that enable individuals to coordinate their activities and integrate their knowledge into productive endeavors.

According to Bratianu (2013), managers assume the role of organizational integrators.

The initial assumption posits that knowledge is the firm's primary and crucial productive resource. Consequently, the knowledge-based theory can be seen as an extension of the resource-based view theory of the firm, as proposed by Barney (1991) and further developed by Barney and Clark (2007).

The resource-based theory posits that a firm can be understood as a collection of distinct resources and capabilities. At the same time, management is viewed as the act of efficiently and effectively deploying these resources and capabilities to attain the firm's objectives.

Grant (1996, 1997) developed a theoretical framework known as the knowledge-based theory of the firm to highlight several critical properties of knowledge that form its core: transferability, capacity for aggregation, appropriability, and specialization in knowledge acquisition.

The main characteristic of explicit knowledge is its transferability, distinguishing it from tacit knowledge. Aggregation is a characteristic that arises from the accumulation of knowledge, similar to how a firm acquires other resources.

In this instance, Grant illustrates a linear logic of aggregation through the addition process. This logic is commonly employed when dealing with tangible

resources. However, as previously discussed, it does not suitably apply to intangible resources. When talking about knowledge, it is more advantageous to emphasize integration rather than linear aggregation.

Therefore, the fundamental characteristic of knowledge management is integrating knowledge at both individual and organizational levels. Organizational integrators utilize this characteristic when carrying out knowledge management tasks (Bratianu, 2013, 2015).

The knowledge-based theory of the firm posits that the entire organization functions as a knowledge-integrating institution, resulting in two primary outcomes: a hierarchical organizational structure and the dispersion of decision-making authority within the firm. The relationship between ownership and decision rights is a significant matter that warrants attention. In contrast to tangible assets wholly owned and controlled by shareholders, individuals generate and possess knowledge.

Only when a portion of this knowledge is transferred and integrated within an organization can we begin to discuss the concept of appropriability, which pertains to the capacity of resource owners to obtain a return commensurate with the value generated by said resource.

Given the inherent limitations of human capacity for storing and processing data, information, and knowledge, improving efficiency in the production and utilization of knowledge becomes imperative. This necessitates a focus on specialized knowledge acquisition and processing as the essential factor in generating value.

1.2.1. What are the characteristics that define a knowledge-intensive organization?

Organizations tend to evolve into knowledge-based entities when they encounter a situation where customer needs exhibit significant differentiation and necessitate the production of tailor-made goods. In response to a decline in the price of conventional or generic products and services, knowledge-based firms will provide intricate integrated solutions. This phenomenon, for example, is applicable to the supplier industry in terms of providing modules and systems rather than manufacturing individual parts or components. In consultancy, clients tend to place less value on implementing standard products than turnkey projects or comprehensive solution packages.

The latter options require higher expertise and consequently offer more lucrative compensation. Industries characterized by rapid innovation and short product life cycles necessitate expeditious generation and dissemination of related knowledge.

The significance of integrating knowledge from various business domains to foster innovation is increasingly recognized, as is the imperative to expedite the

creation of novel business sectors and enhance product development efficiency concerning competitors. Investors in knowledge-based firms exhibit a keen interest in achieving sustained growth in a company's value, particularly those enterprises involved in producing and distributing intangible goods.

The knowledge firm is primarily distinguished by its values, processes, and structures, which collectively form the organizational "ecology" that fosters the growth and success of knowledge within a company. In this context, referring to a "knowledge ecology" is also possible. The organization in question upholds fundamental principles such as trust, receptiveness to novel ideas, and authenticity.

The corporate vision and mission underscore the significance of knowledge in driving business success. The practical organization of leadership and incentives necessitates a structure that appropriately acknowledges and rewards both individual performance and the collective contribution to the company's overall success.

This phenomenon leads to a desire to achieve optimal performance within one's own organizational unit and to facilitate the enhancement of other teams, customers, and suppliers.

In contrast to traditional companies, knowledge firms place importance on measuring the creation and transfer of knowledge in alignment with their business objectives. In contrast, key performance indicators (KPIs) for these aspects are not typically utilized in traditional company settings. These indicators are essential components of the reporting system, as they demonstrate knowledge transformation into achieving business objectives. Non-financial indicators about customers, employees, and processes have garnered increased significance compared to conventional financial indicators.

The transition to a knowledge-based organization necessitates a shift in working methods and roles, as elucidated by prominent scholars in the field of organizational learning (Argyris and Schön, 1978; Senge, 1990; Flood, 2009).

In this novel corporate environment, employees must possess the capacity to engage in a continuous process of acquiring knowledge and skills, commonly referred to as "to learn learning".

In addition to possessing expertise in their respective fields, individuals must also have fundamental skills in navigating and utilizing emerging information and communication technologies. This proficiency is crucial for promptly accessing and transforming information into knowledge.

The responsibility for organizing the framework above conditions, specifically about "ecology," as well as determining goals and measuring goal attainment according to the expanded criteria of a knowledge-based organization, primarily lies with management. The management possesses expertise in various domains, including specialized subjects, coaching and mentoring, and effectively communicating organizational values and objectives.

1.3. Learning Organizations in a changeable environment

According to Bennet D. and Bennet A. (2003), a thorough examination of the development and progression of knowledge organization reveals that, from a strategic perspective, it is imperative for a knowledge organization to transform into a learning organization. This transformation enables the firm to acquire knowledge and adapt swiftly to market fluctuations and other environmental disruptions.

The subject matter pertains to the dynamics of organizational learning and organizational knowledge, as discussed by various scholars such as Argote (2013), Argyris (1999), Bratianu (2015), Garrat (2001), Nonaka and Takeuchi (1995), Ortenblad (2011), Senge (1999), and Wellman (2009).

According to Nonaka (1991), a company can be conceptualized as a living organism with a shared sense of identity and a core purpose. These factors subsequently impact individual members' dedication towards acquiring knowledge and facilitating knowledge exchange.

According to Argyris (1999), organizational learning involves adapting entire organizations or their constituent parts to dynamic environments by creating and selectively embracing organizational routines. Organizational learning refers to a dynamic process that facilitates the accumulation and enhancement of knowledge within a specific social structure. This process enables the organization to effectively address challenges, resolve problems, and adapt to a dynamic and evolving environment.

Nonaka and Takeuchi (1995) have conceptualized organizational learning as a knowledge spiral generation that occurs within the ontological dimension of an organization, progressing from individuals to groups and ultimately encompassing the entire organization. The spiral undergoes evolution as knowledge is transformed through the four primary processes of socialization, externalization, combination, and internalization, which collectively constitute the SECI dynamics model. From an alternative standpoint, Crossan et al. (1999) explain organizational learning as a sequential progression encompassing four distinct stages: intuiting, interpreting, integrating, and institutionalizing. Intuition functions at the individual level as a problem-solving mechanism that relies on personal experience. The unconscious region of the brain is responsible for analyzing individual experiences to generate solutions for novel and intricate problems that lack sufficient information and knowledge. The procedure's outcome is commonly referred to as intuition (Gladwell, 2005; Kahneman, 2011; Klein, 2014). The subsequent phase in the process of knowledge acquisition involves the act of interpretation.

This process facilitates the conversion of individual knowledge into collective knowledge through collective sense-making. This progression entails integrating knowledge and subsequent advancement to the organizational level. The integration of knowledge catalyzes decision-making and subsequent action. The institutionalizing stage is characterized by the implementation of new routines at

the corporate level. The organization should possess the capability to attain a competitive advantage by generating knowledge and exerting influence on its surrounding dynamic environment.

1.4. Knowledge Process and Value Chain

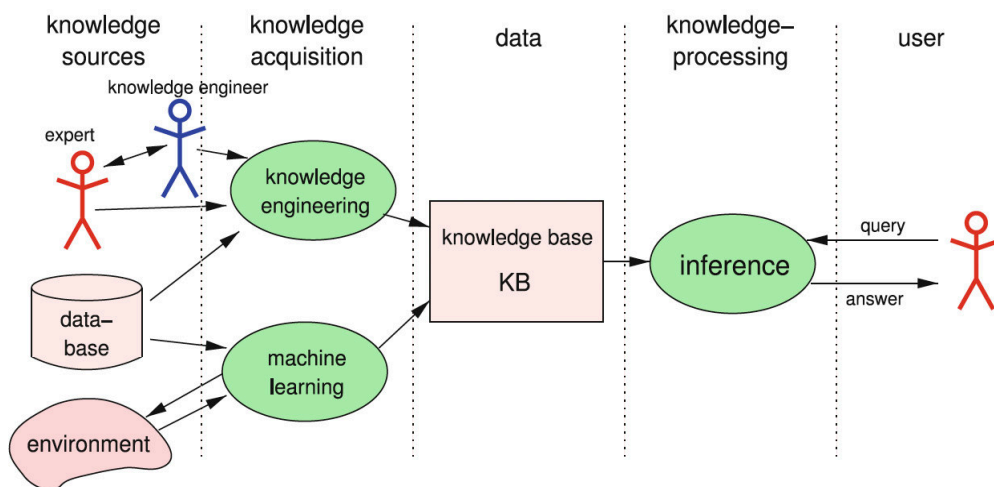
Knowledge management facilitates the collaborative and systematic creation, sharing, and application of knowledge among individuals, teams, organizations, networks, regions, and nations. This process is instrumental in helping them achieve their strategic and operational goals.

As explained above, knowledge management plays a significant role in enhancing operational efficiency and effectiveness, as well as transforming the competitive landscape through fostering innovation, achieved by cultivating a learning organization.

The process (Fig. 1) involves extracting knowledge from a given system or program, wherein the knowledge is subsequently utilized to accomplish tasks such as drawing inferences, responding to inquiries, or formulating strategies.

The aforementioned system is commonly referred to as the inference mechanism. Knowledge acquisition and retention is facilitated by utilizing a knowledge base (KB). The process of acquiring knowledge within the knowledge base is called Knowledge Engineering. This process relies on multiple sources of knowledge, including human experts, the knowledge engineer, and databases. Active learning systems can acquire knowledge by actively exploring the surrounding environment.

Figure 1: General architecture of knowledge-based systems



Source: Ertel, W., 2017

A comprehensive understanding of knowledge management necessitates identifying the principal knowledge processes operating within an organization, namely knowledge creation, knowledge acquisition, knowledge sharing and distribution, knowledge transformation, knowledge storing and retrieving, knowledge losing, and knowledge using.

The process of knowledge creation and knowledge acquisition plays a significant role in the accumulation of knowledge within an organization, whereas knowledge loss leads to a decline in knowledge levels. The act of sharing and distributing knowledge plays a significant role in the reorganization of organizational knowledge, ultimately leading to an overall increase in its average level. The knowledge transformation process holds considerable importance in knowledge creation and decision-making, as it encompasses the conversion of tacit knowledge into explicit knowledge, as well as the interplay between rational, emotional, and spiritual knowledge domains.

Knowledge storage and retrieval functions are specifically designed to facilitate organizational memory and the management of databases. Knowledge attrition occurs when individuals possessing substantial experience and expertise retire or transition to alternative employment opportunities.

Knowledge utilization refers to the amalgamation of various processes and serves as the ultimate objective of knowledge management.

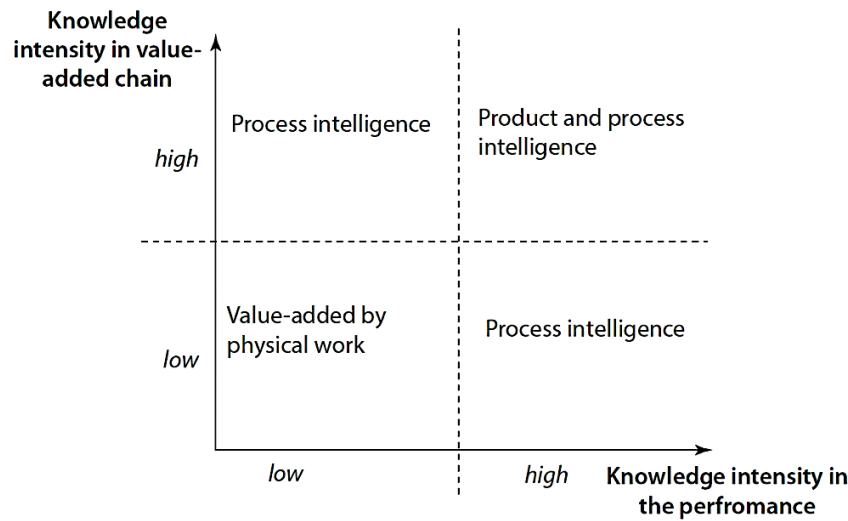
The sequential process through which knowledge is created, captured, organized, shared, and applied within an organization or a specific context is also known as the “knowledge value chain,” assuming that acquiring knowledge is crucial for comprehending the internal mechanisms through which companies generate value.

Porter's (1985) value chain is a widely recognized framework that conceptualizes the value creation process within organizations. This model identifies and analyzes the core activities undertaken by a company to comprehend their distinct contributions to the generation of economic value.

Porter and Millar (1985) propose that knowledge intensity can be characterized by two distinct dimensions: the knowledge intensity of the process and the knowledge intensity of the product or service.

In the knowledge intensity portfolio, four different fields are identified and categorized (Fig. 2).

Figure 2: The knowledge intensity matrix



Source: Adapted from Porter and Millar, 1985

The level of knowledge incorporated within products and services can vary. One metric that indicates "product intelligence" is the proportion of research and development (R&D) expenditure about total cost or sales. The level of product intelligence is notably elevated in various domains, such as software products, machine tools equipped with self-error detection capabilities, and pharmaceutical products, among others.

Process intelligence pertains to the intricacy of processes and the inherent knowledge within them. Process intelligence can be assessed by examining two key factors: the level of research and development (R&D) investments dedicated to process development and improvement and the qualification level of individuals employed in production. Sophisticated algorithms are increasingly prominent in governing various processes, such as those observed in the financial industry, commonly called "FinTechs."

As stated by Holsapple and Singh (2003), the Knowledge Chain Model (KCM) encompasses five core activities that directly contribute to the creation of value, along with four secondary or supportive activities, as explained below:

1. *Knowledge acquisition* refers to the process of obtaining knowledge from the external business environment and subsequently adapting it to meet the specific needs of an organization.
2. *Knowledge selection* refers to the process of carefully choosing the necessary knowledge from various internal sources and organizing it in a manner that is appropriate for effective utilization within the value chain.
3. *Knowledge generation* involves the creation of knowledge at the individual level, which is then further enhanced and expanded upon at the organizational level.

4. *Knowledge internalization* involves distributing, sharing, transforming, and storing information and knowledge within organizational knowledge bases.
5. *Knowledge externalization* refers to the process of incorporating knowledge into an organization's outputs, intending to make it available and applicable in the external business environment.

The following four secondary activities complement the aforementioned primary activities:

1. *Knowledge leadership* is considered the most crucial activity from a strategic standpoint. The absence of effective leadership results in a lack of vision and a deficiency in long-term managerial strategizing.
2. *Knowledge coordination* is a fundamental aspect of operational management that entails the integration of all knowledge-related activities within an organization.
3. *Knowledge control* ensures that the necessary knowledge processors and resources are readily accessible upon request. This control encompasses considerations of both quality and quantity.
4. *Knowledge assessment* comprehensively evaluates knowledge resources, capabilities, processes, and their implementation.

The KCM illustrates the essential activities related to knowledge management, highlighting the central aspects of organizational knowledge dynamics from a strategic standpoint. Therefore, the model offers a theoretical framework for understanding the knowledge value chain and its impact on attaining competitiveness instead of providing an exhaustive analysis of all knowledge management activities.

The ability of top management to develop and execute knowledge strategies is crucial for attaining a competitive advantage in a knowledge-based organization.

1.5. How can knowledge be an ingredient of strategy formulation?

The generation of economic value is widely recognized as a crucial prerequisite for attaining success. Consequently, this notion inevitably leads us to contemplate the concept of strategy, as aptly articulated by Grant (2016), who asserts that "strategy is concerned with achieving success." Therefore, when discussing the role of knowledge in the generation of value, it is imperative to address the interrelationship between knowledge and strategy. The literature has

previously demonstrated the strategic significance of knowledge as a vital resource in the contemporary economy.

The term "strategy" was initially employed in the field of economics, particularly in the context of *Game Theory*.

In this framework, a strategy is commonly understood as either "one of the available actions that a player can take" or "a comprehensive plan encompassing a set of choices" (Turocy and von Stengel, 2001). One could argue that the term has a limited connotation, yet it underscores a significant aspect: the ability of an economic entity to assess and select from various courses of action or alternatives.

The emphasis on strategies in management studies began to emerge during the 1940s and 1950s, coinciding with the expansion of large corporations. One frequently referenced definition is provided by Chandler (1962), who defines strategy as the process of identifying the fundamental long-term objectives of an organization, and subsequently formulating and implementing the necessary plans and resource allocation to achieve these objectives.

During the initial phases of economic competition, strategies primarily relied on managerial planning techniques that were predominantly driven by a deterministic logic. In light of intensifying competition and the unpredictable nature of the business landscape, the conventional approach of exclusively relying on rational strategic planning has diminished in its attractiveness.

Consequently, alternative concepts such as emergent strategy have gained prominence. The concept of strategy-as-practice has emerged as a novel approach to understanding the complexities of the dynamic business environment and effectively leveraging the insights gained by managers through their firsthand business encounters.

The objects of interest in this context pertain to the knowledge or cognitive resources possessed by a company. These resources comprehend the collective understanding and awareness of employees and managers, as well as the information stored in files, documents, procedures, routines, projects, artifacts, and the intellectual property represented by patents, licenses, and similar assets. Furthermore, a knowledge strategy pertains to the principles and practical implementation of procedures, with the aim of optimizing the utilization of current or emerging knowledge domains.

Consequently, a knowledge strategy should encompass strategies for effectively managing existing knowledge assets as well as methods for generating new knowledge. The overarching objective is to attain strategic or competitive advantage by utilizing these knowledge resources. Furthermore, the development and execution of knowledge strategies encompass not only the recognition of knowledge as a valuable strategic asset but also the cultivation of appropriate competencies to effectively manage and utilize information and knowledge in alignment with overarching strategic goals.

The relationship between knowledge strategy and company strategy can be observed from various perspectives. For instance, when considering the business performances or evaluating the competitive positioning.

The alignment between knowledge strategy and company strategy is crucial for enhancing the overall performance of a company. Failure to establish a harmonious relationship between these two strategies may jeopardize the attainment of the company's objectives (Greiner et al., 2007; Hofer-Alfeis, 2003).

Hence, it can be posited that a company's choices regarding its knowledge strategy are intertwined with the organization's competitive positioning (Zack, 1999). Specifically, the strategic context of an organization aids in identifying knowledge management endeavors that align with its purpose or mission, bolster its competitive stance, and generate value for shareholders. From an intuitive standpoint, it is logical to assume that a firm with extensive knowledge about its customers, products, technologies, markets, and their interconnections would achieve superior performance.

Conversely, traditional strategic management models have typically defined a firm's strategy about its product/market positioning, focusing on the specific products it produces and the markets it serves. However, a resource-based view and subsequently a knowledge-based approach propose that firms should strategically position themselves based on their distinctive, valuable, and difficult-to-replicate resources and capabilities rather than solely relying on the products and services derived from those capabilities.

To clarify, a company's strategy typically encompasses its envisioned future in relation to its product, market, and technology positioning compared to its competitors. On the other hand, a knowledge strategy pertains to the company's relative standing in terms of the knowledge it possesses, acquires, shares, and/or leverages compared to its competitors (Zack, 1999).

Formulating a knowledge strategy involves identifying and defining key elements, many of which align with the conceptualization of the knowledge strategy itself (Kim et al., 2003; Bolisani et al., 2014). These elements encompass the overarching objectives of cognitive and learning processes, as well as the design and implementation of knowledge management (KM) initiatives, including the determination of what knowledge should be accessed, processed, and leveraged, the potential value that can be derived from knowledge, and other pertinent considerations.

Additionally, the knowledge strategy entails the identification of the specific types of knowledge that are to be addressed within the organization, the methodologies and tools employed to achieve KM-related objectives, and the allocation of resources necessary for the successful execution of KM programs. Furthermore, the implementation of a knowledge strategy entails the integration of the company's perception of knowledge, thereby establishing a correlation with the overarching strategic objectives and organizational framework.

The inclusion of measurement is a crucial component in the process of strategy formulation, as highlighted by Simons (2013).

These indicators encompass factors such as demand, market shares of competitors, and demographic indices, among others. Industrial and financial accounting indexes, along with other internal measures that depict the condition

of the organization and its different components, are crucial elements. Forecasting techniques commonly incorporate quantitative extrapolations of indices that anticipate future measurements of pertinent external or internal factors.

When formulating strategic alternatives, it is common to express the objectives of a strategy in quantitative terms that pertain to metrics of significance to stakeholders and executives, such as profits, costs, and market shares. Likewise, the plans and resources include various indicators of investments, with both tangible and intangible assets that are either acquired or developed. It is important to note that financial planning and evaluation continue to be a significant component of strategy formulation (Hussey, 1998). It is widely recognized that these processes heavily rely on financial measures and other indicators of investment appraisal. In the process of strategy formulation, measures serve a crucial role in effectively communicating the primary objectives and priorities to both external stakeholders and the internal organization responsible for implementing the strategy in a practical manner (Micheli and Manzoni, 2010).

In the context of monitoring and controlling strategy implementation, the measures utilized to establish objectives, plans, and resources are also employed to evaluate the "success" of a strategy. This evaluation includes assessing the level of satisfaction with the budgeting plans and considering potential revisions and adjustments. The authors (Neely et al., 2005) argue that a strategy's effectiveness can be gauged by the positive outcomes it generates for a business.

According to Micheli and Manzoni (2010), the introduction of a greater number of performance indicators in organizations has been facilitated by advancements in data collection automation and improvements in data analysis. The emergence of the phenomenon known as "big data" has instilled a newfound confidence in our ability to make informed decisions. This confidence stems from the rational and systematic measurement of a wide range of data that is now accessible to companies through internal information systems and the Web (Provost and Fawcett, 2013).

Sveiby (2010) provides a classification of various methods, which can be categorized into four distinct groups due to their significant heterogeneity:

1. *Direct Intellectual Capital Methods (DICM)* are utilized to assess the financial worth of intangible assets associated with knowledge and its different elements.
2. *Market Capitalization Methods (MCM)* involve the computation of the disparity between a company's market capitalization and its stockholders' equity. Specifically, it is believed that as a company's knowledge capital increases in value, investors will correspondingly acknowledge its growth potential, thereby influencing the company's valuation in financial markets.
3. *Return on Assets (ROA)* methods are derived from comparable principles to those employed in financial analysis techniques. The measurement of returns

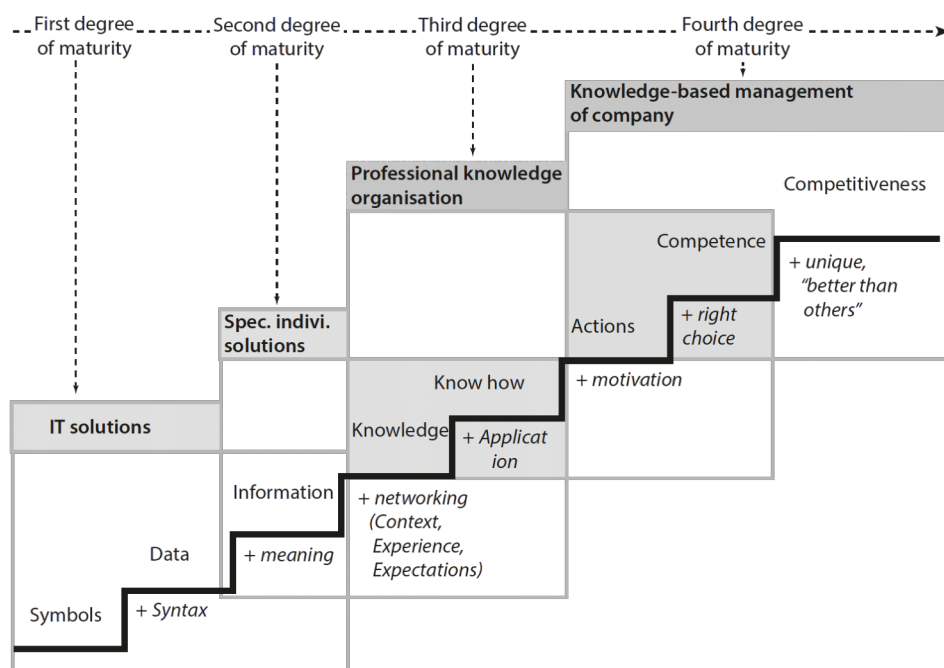
pertaining to the quantity of knowledge and intellectual capital held by a company, or the level of investments made in knowledge, is undertaken.

4. *Scorecard Methods (SC)*, designed to replicate the approaches by Kaplan and Norton (1996) in their work on the Balanced Scorecard, are composite indexes utilized to isolate and quantify the different components of intellectual capital (IC) and knowledge-related assets or activities.

1.6. Knowledge Management Maturity Assessment

Organizations vary in the degree of maturity of their knowledge-based management (Fig. 3):

Figure 3: Degree of maturity of knowledge-based management of a company



Source: North, K., and Kumta, G., 2018

Awareness about the importance to manage knowledge resources is a learning process and depends on the "maturity" of organizations. The change towards an "intelligent" knowledge-based organization is a progressive endeavor involving some "trial and error". A knowledge management maturity model can be considered as a structured approach to knowledge management implementation and it can also provide a common understanding to various stakeholders.

According to North and Kumta (2018), there are four levels of maturity in the way organizations manage their knowledge:

1. *Information Management*: companies implement an information and communication infrastructure to enable specific access to databases and documents. Accompanying organizational measures for promoting exchange of knowledge are not yet established or are established only to a certain extent. At this level, organizations achieve an increase in process transparency and speed, avoid double work and shorten training periods for new entrants, which result in an overall increase in the quality of products and services.
2. *"Island" Solutions*: organizations that intentionally implement knowledge management initiatives in specific areas or business units. At this stage, ICT is not enough for knowledge-based management; a "business case" is needed to demonstrate that knowledge management yields clear benefits. These solutions contribute to process accelerations, increase in reuse of internal knowledge as well as improved teamwork and increase in quality (ex. CRM systems integrated into sales management).
3. *Professional Knowledge Organization*: a professional knowledge organization across departments and business units where ICT guarantees easy availability of relevant information; employees are motivated and rewarded for sharing knowledge; knowledge management integrates business goals, processes and project organization; the exchange of knowledge is supported through Communities of Practice (CoPs) and competence centers; benefits of knowledge management are measured.
A balanced distribution of benefits resulting in improved processes, higher employee motivation and customer satisfaction is a typical feature of the professional knowledge organization thanks to the establishment of KM roles and responsibilities at centralized/decentralised levels of organization.
4. *Knowledge Culture*: an ideal condition achieved only by a few organizations until now. This level of maturity is characterized by deeply shared values, teamwork, active exchange of knowledge beyond the boundaries of departments and beyond the firm, active search for innovation as well as an open and trustworthy culture that is filled with and lived by management and employees consistently. An important component of this culture is learning from the outside (e.g. markets, technologies, rivals, suppliers, customers etc.) and from the inside. The company culture is supported by a mature information and communication system and media such as CoPs, competence centers and work-outs. Collaboration, knowledge sharing and continuous search for innovation is part of such a knowledge culture. Shared values, not tools, drive knowledge creation, transfer and protection.

1.7. Opportunities and challenges for Knowledge Management in Industry

4.0 context

The concept of Industry 4.0, also referred to as the fourth industrial revolution, has garnered significant attention in various professional and academic domains (Liao et al., 2017). The advent of Industry 4.0 has emerged as a transformative phenomenon that is fundamentally altering the dynamics of competition, enabling organizations to leverage advancements in diverse business processes. The impact of digital transformation is observed in various aspects of firms' operations, including their overall strategy, organizational mindset, business models, value creation process, supply chain activities, production processes, products, skills, and stakeholder relationships (Reinhard et al., 2016).

The concept of Industry 4.0 incorporates various dimensions, including the implementation of industrial automation systems that facilitate the management of production and value creation processes, as well as supply chain activities and their associated processes (Reischauer, 2018; Yin et al., 2017). In a broader sense, Industry 4.0 can be defined as a novel business strategy that involves the utilization of real-time data analysis and the facilitation of individualized product customization to effectively manage production processes (Kohler and Weisz, 2016).

Undoubtedly, integration and interoperability emerge as the pivotal elements for the successful implementation of Industry 4.0. The process of integration has a significant impact on the networking dynamics with stakeholders, involving both horizontal and vertical dimensions. Interoperability plays a crucial role in enhancing production processes, both within and outside the organizational boundaries, by facilitating the integration of systems and the exchange of knowledge and skills (Lu, 2017). In order to effectively adopt the Industry 4.0 paradigm, companies must demonstrate a willingness to embrace organizational changes (Arnold et al., 2016).

The introduction of digitalization compels companies to undergo structural changes and embrace governance models prioritizing knowledge-based, dynamic, and collaborative learning. This transformation necessitates the adoption of new technologies, which require a significant amount of knowledge and expertise (Ghobakhloo, 2018).

Regarding knowledge management, this shift involves replacing jobs that involve routine tasks with new positions that allow workers to assume broader roles, embracing interdisciplinary approaches in addition to specialization (Pfeiffer, 2016).

The evolution observed in factories is increasingly intertwined with environmental sustainability in production. This is evident in the adoption of circular economy principles, which emphasize the need for enhanced comprehension and assessment of resource utilization (Tseng et al., 2018). According to Bonilla et al. (2018), the factory possesses intelligence and has the

potential to adopt environmentally friendly practices through advanced technologies. Academics and professionals are currently investigating using digital technologies as a strategy for attaining enhanced environmental objectives, specifically within the context of the circular economy framework (Lacy and Rutqvist, 2016; Webster and MacArthur, 2017). The necessity for novel circular-focused innovation and the collaborative aspect of eco-innovation (Brown et al. 2019; De Marchi, 2012) compels companies to engage in knowledge sharing throughout the value chain, encompassing both upstream and downstream activities.

Implementing Industry 4.0 technologies presents intriguing prospects for managing resource utilization and facilitating knowledge sharing among relevant stakeholders (Tseng et al., 2018).

Furthermore, considerable focus was given by scholars and managers to the fields of big data and artificial intelligence, in addition to the aforementioned technologies. These technologies have the potential to bring about a significant transformation in the manner in which companies gather and handle data, as well as oversee learning processes and create business scenarios (Boden, 2016; Kaplan and Haenlein, 2019; Ransbotham et al., 2019). The discourse surrounding the correlation between knowledge management and artificial intelligence (AI) is a topic that has been previously discussed (Wiig, 1999). However, in the current context, these cognitive processes are not only automated but also enhanced, as described by Davenport (2018a) in the definition of Analytics 4.0.

From a knowledge management standpoint, the initial opportunity associated with Industry 4.0 technologies pertains to the availability of new processes and tools for acquiring and processing distributed knowledge. According to the McKinsey Global Institute (2015), the firm is able to acquire an expanding and continuous stream of detailed and personalized data through the utilization of the Internet of Things (IoT). This data is derived from both internal sources, such as smart machines equipped with sensors, and external sources, including smart products used by customers. The integration of data within Enterprise Resource Planning (ERP) systems, as well as other information systems utilized by firms, can be subjected to comprehensive analysis using advanced techniques such as big data analytics and artificial intelligence (Liebowitz, 2001). From this standpoint, the organization possesses a comprehensive understanding of its processes and products from various angles, including marketing, innovation, operations, and administration (Paschen et al., 2019).

The ability of a firm to convert data into knowledge, commonly known as a big challenge, is not a straightforward process. It involves the learning dynamics that an organization can cultivate through the utilization of big data (Pauleen, 2017; Tian, 2017). To derive solutions from problem-solving scenarios and make informed decisions and subsequent actions, organizations employ analytics on large-scale databases to extract valuable information and uncover novel insights. This process is complemented by the integration and alignment of contextual knowledge inputs (Pauleen and Wang, 2017).

By leveraging artificial intelligence and conducting extensive analysis of big data, the organization has the potential to enhance its strategic outlook by accessing novel resources that can fortify its competitive edge (Davenport, 2018b). Similar to the situation with automation, the introduction of artificial intelligence (AI) raises new unresolved inquiries regarding the specific skills and capabilities that organizations need to effectively utilize these technologies. (Daugherty and Wilson, 2018).

Additionally, Iansiti and Lakhani (2014) argue that the widespread availability of digital technology enables firms to have a constant presence and gather extensive knowledge about their customers. This approach seeks explicit knowledge management strategies to be implemented in the emerging digital landscape, as the significance of a substantial influx of new knowledge and how to safeguard the firm's competitive advantage in relation to it remains uncertain (Hagiu and Wright, 2020).

The inclusion of machines themselves as knowledge sources warrants consideration in the realm of actors in this context. According to Boden (2016), research on artificial intelligence suggests that machines can be regarded as novel digital agents capable of autonomous action, separate from human input. Artificial intelligence (AI) enables the generation of supplementary knowledge through machine learning techniques, which can be utilized to inform strategic advancements.

The current situation in the field of artificial intelligence (AI) and information technology (IT), as well as knowledge management, is characterized by the presence of significant advancements. These advancements include the abundance of big data, enhanced computational capabilities, and a network of interconnected technologies that facilitate the generation of "autonomous" knowledge for utilization within organizations (Yao et al., 2017; Zhuang et al., 2017). This scenario is associated with the issue of regulating and verifying the newly generated knowledge derived from AI outputs in relation to emerging processes like AI-driven design processes, specifically generative design.

Knowledge-based engineering (KBE) enhances the process of product development by integrating various perspectives and tools. This approach leverages technology to autonomously handle repetitive and non-creative design tasks, while also facilitating multidisciplinary design optimization (Rocca, 2012).

The Industry 4.0 scenario presents a potential issue of reduced exploration, as highlighted by March (1991). This issue is mitigated by technological solutions that integrate big data and advanced analytics, enabling more efficient data collection and knowledge generation. Furthermore, these solutions have the potential to overcome geographical limitations. However, the emergence of issues related to the control over such knowledge is also evident. The emergence of the platform economy (Parker et al., 2016) and the unequal distribution of power between large corporations and small and medium-sized enterprises (SMEs) (Wu and Gereffi, 2018) can potentially limit the ability of SMEs to engage in knowledge creation and utilization. Simultaneously, companies that have made

previous investments in IT and have experience navigating past industrial revolutions are likely to derive greater advantages from the fourth industrial revolution compared to firms lacking a well-defined digital strategy and prior experience in effectively implementing technologies within their organizational framework, regardless of their size.

The selection of Industry 4.0 technologies should not involve investing in all available options simultaneously (Reinhard et al., 2016). Instead, it is crucial to identify and adopt the appropriate technologies that align with the product, processes, and overall strategy of the firm (Bettiol et al., 2019; McAfee, 2004).

In a broader sense, the technological revolution contributes to the generation of novel knowledge that enhances the process of decision-making (Seetharaman et al., 2019) and has an impact on both organizational processes and business models (Jerman et al., 2019). The utilization of data derived from various technologies enables the enhancement of production systems and processes, the innovation of novel products and services, and the incorporation of customers and suppliers into the realm of product and service provision. (Kiel, Arnold, et al., 2017; Kiel, Müller, et al., 2017).

1.8. Business Analytics for companies improvement

Business analytics refers to the process of constructing and maintaining dynamic databases that encompass a wide range of information pertaining to consumer behavior. Additionally, it involves the creation of intelligent software systems designed to effectively process and analyze this vast amount of data. Furthermore, it entails the establishment of an internal capacity within an organization, enabling all employees to proficiently utilize these analytical applications. According to Davenport and Harris (2007), analytics refers to the comprehensive utilization of data, statistical and quantitative analysis, explanatory and predictive models, and evidence-based management in order to inform decision-making and guide subsequent actions. Nevertheless, this approach does not solely involve the utilization of "intelligent" systems for data processing, nor does it rely on the expertise of a specific group or department within the organization. Rather, it is a competence that ought to be possessed by all individuals engaged in knowledge-based tasks.

According to Davenport and Harris (2007), it is crucial for analytical competitors to engage in a wide range of experiments within various facets of their organizations and derive valuable insights from each of these endeavors. For the effective implementation of quantitative decisions, it is imperative that the analysis capability is widespread among employees, rather than being limited to a select few individuals who possess quantitative expertise. In essence, a knowledge strategy pertains to the organizational structure and employee management practices employed by a company to facilitate rapid learning and enhance the

ability to analyze information with greater efficacy, ultimately leading to the generation of valuable knowledge.

So, analytics can provide numerous advantages to various functions within a business like:

- *Customer analytics*: applications within the field of marketing, such as customer profiling, segmentation, social network analysis, brand reputation analysis, and marketing mix optimization. Additionally, it also pertains to the analysis of customer experience. Technologies known as SNAzzy (Social Network Analysis in Telecom) and VOCA (Voice-of-Customer Analytics) belong to this category.
- *Supply chain analytics*: aspects such as demand forecasting, inventory optimization, pricing optimization, scheduling optimization, transportation optimization, and storage optimization, all while mitigating and managing risks. The field of Human Capital Analytics, also referred to as Workforce Analytics, pertains to service industries in which human resources serve as the primary means of production.
- *Fraud and risk analytics*: evaluation of various forms of risk, such as market, operational, and credit risk, with a specific focus on the financial sector.
- *Analytics in Public Domain*: includes utilizing analytics to face natural resource constraints, for example, to identify water leakages in distribution systems, enhance the efficiency of energy grids and traffic systems, and enhance public safety.

The complexity of analytics can be deconstructed into three distinct layers. The first layer involves descriptive analytics, which can be executed through the utilization of spreadsheets or more robust and advanced software systems. Predictive analytics pertains to the anticipation of future events or outcomes, while prescriptive analytics focuses on determining the optimal course of action to attain the most favorable result.

Business analytics is centered around addressing five fundamental areas of customer requirements:

1. *Information access*: the primary objective is to cultivate a culture of informed and collaborative decision-making throughout the organization, wherein decision-makers possess a comprehensive understanding of the performance of their respective business domains, enabling them to make well-informed decisions.

2. *Insight*: the acquisition of a more profound comprehension of the underlying reasons for occurrences. For instance, it involves obtaining a comprehensive perspective of one's customers, encompassing their transaction history, segmentation, sentiment, and opinions, among other factors. This enhanced understanding facilitates improved decision-making and fosters the potential for profitable expansion.
3. *Foresight*: the strategic utilization of historical data to anticipate and forecast potential future scenarios. This proactive approach enables organizations to make informed decisions and take appropriate actions that align with their business objectives and meet the necessary requirements.
4. *Business agility*: the ability of an organization to make real-time decisions that optimize both people-centric and process/automated-centric processes.
5. *Strategic alignment*: the process of effectively aligning all stakeholders within an organization, encompassing the alignment of strategic objectives with operational execution. The focus is on facilitating enterprise and operational visibility. This pertains to the process of documenting the various preferences, priorities, objectives, and requirements that serve as the underlying factors influencing decision-making.

Organizations embarking on an exploration of business analytics applications must initiate their efforts with an information management agenda that regards data and information as a valuable strategic asset. When information is regarded as a valuable resource, it becomes possible to employ descriptive, predictive, and prescriptive analytics. Traditionally, a business or organization initiates this process by analyzing the data derived from its automation systems, such as enterprise resource planning, customer relationship management, time and attendance, e-commerce, warranty management, and similar systems. The business may also possess unstructured data, including contracts, customer grievances, internal correspondence, and, progressively, image data derived from facility monitoring systems. Additionally, unstructured data from diverse online sources, such as Facebook, Twitter, and blogs, may also be present.

The integration of structured and unstructured data enables a comprehensive and holistic understanding of information, facilitating enhanced decision-making processes. According to Akerkar (2013), numerous business analytic techniques that are commonly employed for structured data can also be effectively utilized for unstructured data:

- *Descriptive Analytics*: refers to the process of analyzing data in order to gain insights and understand patterns and trends. It involves summarizing and presenting data in a meaningful way. It consists of the preparation and analysis of historical data to identify patterns and trends through the examination of sample data.

Methods such as data modeling, visualization, and regression analysis are predominantly utilized within this domain. Business performance analysis is a comprehensive framework comprising various technologies and methodologies that leverage data to gain insights and evaluate the effectiveness of business operations.

Descriptive analytics is widely employed and comprehended as the predominant form of analytics because it involves the process of categorizing, characterizing, consolidating, and classifying data through a range of tools and techniques, such as dashboards, reports (such as those related to budget, sales, revenue, and costs), and various forms of queries. Standard features of these systems often encompass the ability to generate reports, distribute information, and provide data visualization capabilities. The application of descriptive analytics techniques is predominantly observed in structured data, although there have been several endeavors to expand their applicability to unstructured data. These efforts often involve the development of structured metadata and indices.

Numerous instances of descriptive analytics applications are commonly executed using pre-packaged business intelligence software solutions or spreadsheet tools.

One of the primary benefits of utilizing a descriptive analytics software platform, which includes business intelligence and information/data management software, is its capacity to establish a connection with the underlying trusted information management system. Additionally, this software platform enables users to analyze data from various perspectives, thereby facilitating the acquisition of valuable insights.

Gaining an understanding of current or past events can be valuable for informing future decision-making. However, descriptive analytics predominantly relies on human examination of data and lacks comprehensive methodologies for predicting future outcomes or offering prescriptive guidance for decision-making.

Furthermore, descriptive analytics offers valuable insights into business performance and empowers users to monitor and manage their business processes effectively.

- *Predictive Analytics*: refers to the practice of utilizing statistical models and algorithms to forecast future outcomes based on historical data patterns and trends. It leverages data to ascertain prospective outcomes. Naturally, the utilization of analytics is characterized by a greater level of sophistication and advanced application.

Predictive analytics, which falls under the umbrella of structured data analysis, employs data and mathematical methodologies to reveal explanatory and predictive models of business performance. These models capture the inherent connection between data inputs and outputs to forecast future probabilities and trends by uncovering relationships within data that may not

be readily discernible through traditional analytical approaches. Techniques such as data mining and predictive modeling are commonly employed within this domain leveraging historical knowledge to generate anticipatory insights regarding future events or outcomes.

Predictive analytics finds application in real-time scenarios, where it influences operational processes through actions such as retention measures or the immediate detection of suspicious transactions, or to enhance cross-selling and up-selling efforts, and predicts customer churn, among other applications.

Sophisticated techniques encompass the identification of cyclical patterns, the isolation of the influence of external factors such as weather, the characterization of inherent variability, and the detection of trends.

The objective is to establish causal relationships between multiple time series, specifically in the context of predicting the demand. The process of data mining is employed to extract patterns from extensive amounts of data in order to predict nonlinear behavior that may not be readily discernible using alternative methods.

- *Prescriptive Analytics*: refers to the branch of data analytics that utilizes various techniques and methodologies to provide recommendations and insights for optimal decision-making.

Prescriptive analytics leverages data in order to recommend the optimal course of action that maximizes the likelihood of achieving the most favorable outcome. Its methodology assesses and identifies novel approaches to business operations, with the aim of aligning them with organizational objectives and effectively managing various constraints. Methods such as optimization and simulation are commonly employed in this domain. Organizations, in their pursuit of enhanced analytical maturity, have expressed a desire to ascend the analytics hierarchy in order to optimize their business or operational procedures. The utilization of analytics in a prescriptive manner is perceived by companies as a distinctive element that will enable them to gain a competitive advantage and distance themselves from their rivals. However, it is evident that the process of optimization is contingent upon the analytics procedure.

The computational methods employed in this approach enable the determination of a collection of advantageous alternative actions or decisions, based on a multifaceted set of objectives, requirements, and constraints. The ultimate aim is to enhance the performance of a business entity.

Once a comprehensive understanding of the past has been attained, enabling the formulation of predictions regarding future occurrences, it becomes imperative to contemplate the optimal course of action or response, taking into account the finite resources available to the organization. Numerous predicaments often entail an excessive number of choices or alternatives,

thereby surpassing the cognitive capacity of human decision makers to adequately assess and prioritize.

In recent times, advancements in computer technology, including enhanced processing speed and expanded memory capacity, have facilitated rapid execution of computations that were previously time-consuming. Moreover, significant improvements in the efficiency of mathematical algorithms have further contributed to the remarkable reduction in computation time.

Contemporary assessments can now be conducted instantaneously to facilitate informed decisions regarding the modification of actions and allocation of resources, among other considerations.

1.9. A sustainable development perspective: SDGs, B-Corporation and ESG financial impact

The advent of artificial intelligence (AI) has brought about significant transformations in the processes of information generation and utilization for decision-making (Mikalef et al., 2017) as in the methods of conducting business (Schneider and Leyer, 2019). It has exerted a profound influence on trade and management practices across various sectors, leading to the emergence of increasingly competitive and sustainable products or services (Govindan et al., 2019; Kuo and Smith, 2018; Ding et al., 2019; Garbuio and Lin, 2019; Tuan et al., 2019; Wirtz and Müller, 2019). The integration of artificial technologies and human intelligence revolves around the utilization of algorithms to facilitate managerial decision-making processes. This integration has led to a cultural shift wherein organizations now incorporate a vast amount of data, connections, and interactions as part of their standard management practices (Schneider and Leyer, 2019). Mathematical models serve to streamline the tasks undertaken by managers. The information sets are meticulously catalogued and organized, to the extent that prior studies have demonstrated their superior efficiency compared to human decision-making (Kahneman et al., 2016). Sousa and Rocha (2019) put forth a theoretical framework that outlines the essential competencies required for disruptive business managers to enhance their skill set. These competencies encompass innovation, leadership, and management.

Knowledge Management Systems (KMS) play a significant role in facilitating the management of intelligent work (Johannessen et al., 1999) by integrating human, organizational, and technological elements to generate value through knowledge sharing (Tsui et al., 2000; Hlupic et al., 2002; Thomas et al., 2001).

Knowledge Management Systems (KMS) serve as a conduit for the establishment of a corporate culture (Liebowitz, 2001) that leverages artificial intelligence (AI) to enhance operational processes and business models (Hoeschl

and Barcellos, 2006) by fostering a mutually beneficial collaboration between humans and machines (Miller, 2018).

This integration of artificial intelligence (AI) into decision-making processes has been identified as a potential avenue for companies to explore the relationship between innovation and sustainability (Kuo and Smith, 2018). This trend also aligns with the objective of achieving the Sustainable Development Goals (SDGs) (Duan et al., 2019). The business sector plays a pivotal role in the pursuit of the United Nations Sustainable Development Goals for 2030 due to its significant contribution to economic growth. Indeed, enterprises of varying sizes and areas of expertise have the capacity to cultivate more socially and environmentally conscious business models.

This can significantly contribute to the advancement of Sustainable Development Goals (SDGs) by means of investing in technological advances and engaging in collaborative partnerships.

Innovation plays a crucial role in driving business growth, as it enables adopting sustainable production and consumption models that align with the objectives outlined in the United Nations 2030 Agenda. Specifically, it supports the achievement of Sustainable Development Goal n°12, which aims to promote responsible consumption and production by establishing sustainable patterns.

The integration of the company's standard with neoclassical economic theory (Brenner and Cochran, 1991; Key, 1999; Stormer, 2003), the protection of the ecosystem and individuals, as well as the promotion of social equity (Stubbs and Cocklin, 2008), are imperative in addressing emerging social and environmental needs.

The phenomenon above has resulted in the proliferation of sustainable business models, wherein sustainability is defined as the harmonious equilibrium of the economic, environmental, and social dimensions, which are inherently interconnected and mutually reliant (Bansal, 2002). Furthermore, several scholars have demonstrated that achieving Sustainable Development Goals (SDGs) is contingent upon the intricate interplay among human, technical, and natural systems (Nilsson et al., 2016).

The evaluation of the effects of AI on sustainable development is determined by the emergence of AI and its potential for growth across various sectors of society (Vinuesa et al., 2019). Companies are increasingly compelled to confront the imperative of sustainability as they endeavor to enhance the breadth of innovations to safeguard the integrity of the ecosystem and optimize the utilization of natural resources (Joyce and Paquin, 2016).

According to the Oxford Dictionary, sustainability is characterized as preventing the exhaustion of natural resources to uphold an ecological equilibrium. To attain sustainable development, it is imperative to establish a harmonious integration of three fundamental components: economic profitability, social welfare, and environmental stewardship. These elements exhibit an inherent interdependence as they collectively contribute to the maintenance of both individual and societal well-being.

The SDG objectives delineate the overarching global priorities for the year 2030 and establish a comprehensive action program to address the needs of individuals, the environment, economic well-being, and societal harmony (de Paula Arruda Filho, 2017).

The objectives comprehend diverse actors, including institutions, organizations, and civil society, and aim to stimulate the business sector. The advent of the Sustainable Development Goals (SDGs) has ushered in a novel framework for companies to adopt a sustainable development strategy. Establishing responsible organizations necessitates a robust and proactive strategy involving collaborative efforts with other companies to foster technological advancements. This collaborative approach aims to initiate a worldwide and all-encompassing progression towards sustainable development for all enterprises.

Moreover, innovation is a crucial factor in business, encompassing the final product and all operational procedures. This entails the utilization of innovative technologies and the adoption of novel sustainable approaches that align with the Sustainable Development Goals (SDGs).

Hence, *SDG#12* specifically targets businesses to ensure sustainable production and consumption patterns. It aims to advocate for an efficient and responsible utilization of natural resources, emphasizing the concept of achieving more excellent outcomes with reduced inputs. Within this context, AI assumes a crucial role by facilitating advancements in efficiency and productivity by implementing novel technologies (Vinuesa et al., 2019). These technological enhancements have the potential to overcome existing limitations.

Vinuesa et al. (2019) assert that AI has the potential to yield favorable outcomes across all Sustainable Development Goals (SDGs) using technological advancements that enhance performance in various sectors. This, in turn, facilitates progress in development and exerts substantial influence on both civil society and the environment.

However, it is essential to acknowledge that adverse consequences can also be associated with these effects. This is particularly relevant in the context of artificial intelligence, as certain aspects of AI, if left unattended, can impede the attainment of various goals.

Enterprises are confronted with additional concerns as they grapple with the absence of rigorous research methodologies to evaluate the enduring ramifications of artificial intelligence (AI). Furthermore, the intensity of AI application data gives rise to privacy concerns, as highlighted by Sachs et al. (2019). Governments should address several of these aspects before seeking the involvement of international organizations to safeguard progress while upholding the principles of equality and well-being for all individuals (Sachs et al., 2019).

1.9.1. From a theoretical framework to B-Corporation

Sustainable change can be fostered by renewing the corporate purpose and organization, guided by innovation strategies that aim to generate long-term value (Bocken et al., 2014). According to Morris et al. (2005), a business model (BM) concisely depicts how a collection of decision variables about business strategy, architecture, and economics are managed to establish a lasting competitive edge within specific markets.

A business model (BM) delineates the operational and physical framework of an organization (Osterwalder et al., 2005), anticipating the implications of corporate activities on the system architecture and promoting sustainable decision-making through inventive approaches to value creation (Zilahy, 2016). The business model (BM) is intricately linked to the corporate strategy, although it is essential to note that these two concepts are distinct. While the business model examines the company as a holistic system and describes its operations, the corporate strategy encompasses a broader framework for achieving organizational goals. On the other hand, the strategy covers the executive processes, execution, and implementation (Osterwalder et al., 2005).

The impact of technological advancements on business management can lead to cost-reduction and value enhancement while also promoting the integration of profitability and sustainability (Dirican, 2015).

According to Bocken et al. (2014), technological innovation has the potential to support a comprehensive approach directed to collaboration and education for sustainable business models (SBMs). Socially responsible business models (SBMs) aim to integrate economic, social, and environmental value through a multi-stakeholder approach. This approach is centered around maximizing the benefits of a company's operations for society and the environment (Lenssen et al., 2013).

As posited by the contingency theory, it is imperative to foster congruence between organizational management and the surrounding external context (Venkatraman and Prescott, 1990). This entails promoting digitalization strategies that prioritize machine learning and the effective handling of substantial volumes of data, thereby enabling the alignment of business models with sustainable objectives (Brenner, 2018). In this particular context, organizations are urged to adopt knowledge management systems that can effectively harness human resources to gain a competitive edge with the assistance of artificial intelligence (Tsui et al., 2000).

According to the innovation theory, scholars have proposed the utilization of Knowledge Management Systems (KMS) to manage intelligent work effectively (Johannessen et al., 1999). This is because KMS facilitates the collaborative acquisition of information and knowledge sharing (Tsui et al., 2000). KMS plays a crucial role in promoting the adjustment of companies to technological advancements. They serve as a platform that integrates various elements such as human resources, organizational structures, and technological components, all of

which contribute to the overall process of value generation (Hlupic et al., 2002; Thomas et al., 2001).

AI facilitates utilizing internal and external organizational knowledge, promoting novel approaches to acquiring and representing knowledge. This enhances managers' understanding that a KMS is the foundation of corporate identity and culture (Liebowitz, 2001). According to Hoeschl and Barcellos (2006), AI does not aim to replace human resources but instead seeks to emulate rational thinking by enhancing the efficiency of management and data processing by utilizing digital information systems. Furthermore, as stated by Miller (2018), there exists a need for a symbiotic relationship between humans and machines to enhance and augment their respective capabilities. This phenomenon has led to a cultural shift recognizing AI as a valuable tool for integrating human cognition and facilitating knowledge management (Duan et al., 2019).

The acquisition of Key Management Skills should primarily occur within the context of organizations and businesses.

The incorporation of AI into the strategic process has been explored by various researchers (Liao, 2003; Baskerville and Dulipovici, 2006; Strandhagen et al., 2017) as a means to enhance a company's sustainable performance and problem-solving capabilities (Haseeb et al., 2019).

This integration in sustainable business management can assist managers in their decision-making and management endeavors. By leveraging data-driven techniques, AI enables the generation of accurate forecasts and facilitates cost reduction in projection activities. Consequently, adopting AI in this context can foster a transformation in organizational culture and behavior, as highlighted by Duan et al. (2019).

Furthermore, according to Kuo and Smith (2018), many companies perceive creating sustainable products as advantageous opportunities in terms of competition. Nevertheless, many individuals faced challenges in independently scaling up these commodities. Thus, the organization successfully brought together all stakeholders within the supply chain to establish a viable and enduring business model. Determining a substantial improvement in management necessitates making decisions about product implementation and supply chains. Technological advancements facilitate the development of these optimized business models (de Sousa Jabbour et al., 2019).

One illustration of a notable sustainable business model that has surfaced in the previous decade is the B Corporation (Stubbs, 2014). The B Corp, which was established by B Lab, a non-profit organization based in the United States, in 2006, serves as a certification program that sets a benchmark for environmental and social performance, as well as transparency and accountability to achieve a balance between profit and purpose (Honeyman and Jana, 2019). It is witnessing significant global expansion (Paelman et al., 2021).

The B Corp model lacks legal instantiation and does not encompass a novel legal framework for businesses, thereby avoiding confinement to particular legal jurisdictions. According to *The B Corp Handbook: How to Use Business as a*

Force for Good, B Corp is compatible with various forms of corporate law. The handbook further elucidates that B Corp provides a universally applicable framework for companies worldwide, regardless of location or jurisdiction, to foster the development of more socially and environmentally responsible businesses. This framework is relevant across various business types, including B2B and B2C enterprises, local sole proprietorships and global brands, start-ups, third-generation family businesses, limited liability companies and partnerships, employee-owned companies and cooperatives, C and S corporations.

According to Honeyman (2014), B Corps must incorporate their obligations and social mission into their articles of association (or equivalent legal documents) to ensure legal backing for these commitments and safeguard against potential challenges. B Corps are granted a unique legal status as national legislation and judicial precedents permit. Certifications have been regarded as a mechanism in corporate governance to incorporate organizational purpose into for-profit corporations in conjunction with mission statements and share rights structures (Levillain et al., 2018). The B Corp model encompasses both the certification mechanism and mission statement, as it necessitates the amendment of its by-laws and articles of association. However, in contrast to formal legal status, the reliability of certifications and mission statements cannot be assumed, particularly during times of strain and pressure and in circumstances where shareholders possess divergent objectives or varying interests.

The certification is derived from a comprehensive analysis of leading approaches to corporate ethical responsibility, encompassing social, environmental, and governance factors, collectively known as the B Impact Assessment. Organizations aspiring to attain B Corp certification undergo an assessment process that evaluates their adherence to established guidelines. These guidelines serve as benchmarks for assessing the influence of a company's operations and business model on its stakeholders.

The evaluation comprises five significant impact areas: Workers, Community, Customers, Environment, and Governance. Each of these domains contains a set of inquiries with designated weights, and collectively, organizations are required to attain a minimum aggregate score of 80 out of 200 points to meet the eligibility criteria for the B Corp certification. To meet these criteria, companies must furnish supporting documentation to substantiate a representative set of inquiries. Subsequently, they must proceed to revise their articles of incorporation by a provision that demonstrates their dedication to their stakeholders, as evidenced by a purpose and directors' clause. The certification process also entails an annual fee, which varies depending on the firm's size, ranging from \$500 to \$50,000.

Additionally, firms must undergo recertification every three years, although initially, this requirement was set at every two years. Annually, B Lab US audits a subset of B Corps, amounting to 10% of the total, to verify their ongoing adherence to their stated commitments.

The B Corp movement underscores the importance for organizations to shift their focus towards being 'best for the world' rather than solely striving to be 'best in the world,' as advocated by the B Corp's motto.

The 'B' movement is operational in 60 countries, facilitated by B Lab US-affiliated organizations. While B Lab exclusively confers the certification, these partners actively advocate for the B Corp concept, encourage companies to pursue certification and foster regional B Corp communities.

In contrast to traditional enterprises, B Corps prioritize social and environmental objectives as fundamental components of their business operations while simultaneously striving for economic sustainability (Stubbs, 2017).

One approach companies employ involves the integration of externalities, such as social and environmental costs, into their evaluation of corporate performance (Marquis, 2020). B Corporations tend to allocate their profits towards expanding their positive effects and do not prioritize the interests of shareholders at the expense of other stakeholders (Stubbs, 2017). Additionally, research conducted by Paelman et al. (2021) indicates that B Corps exhibit higher turnover growth compared to enterprises that are not certified.

Additionally, B Lab advocates for cultivating sustainable entrepreneurial ecosystems to facilitate the establishment and growth of sustainable enterprises (Stubbs, 2018). Currently, most certified B Corporations are small and medium-sized enterprises (SMEs). However, notable industry leaders like Patagonia and Danone have also successfully obtained B Corp certification (B Lab, 2020).

The B Corp certification facilitates the establishment of "hybrid" enterprises that mitigate adverse effects and generate beneficial outcomes for society and the environment. This is accomplished by implementing legally binding agreements and governing documents (Dyllick and Muff, 2015; Schaltegger et al., 2012; Shevchenko et al., 2016; Stubbs, 2019; Wiek and Basile, 2019).

A limited amount of research has been conducted on the influence of B Corp certification on socially responsible behavior. According to Gamble et al. (2019), the study's findings indicate that the certificate of B Corps could potentially serve as a valuable mechanism for establishing legitimacy and building reputation.

A recent study by Winkler et al. (2018) examined the impact of the certification process on the engagement of small to medium-sized US B Corps with external stakeholders. The findings suggest that when these corporations offer their employees a certain level of control, such as ownership or other forms of encouragement to participate in decision-making actively, it enhances their engagement with external stakeholders. This highlights the importance of the founders' role in organizations that eventually become B Corps, especially since many are small and emerging social enterprises where the lines between management, governance, and operations are often unclear (Spear et al., 2009).

1.9.2. ESG impact on Corporate Finance

The Financial Times (2021) states that ESG is a widely employed term among investors for evaluating environmental, social, and governance corporate endeavors. ESG factors are commonly recognized as non-financial performance indicators that identify concerns about business ethics, corporate social responsibility, and corporate governance.

ESG integration stands as a pivotal concept within the realm of ESG investment. ESG integration, as defined by the United Nations Principles for Responsible Investing (2021), refers to the deliberate and systematic incorporation of environmental, social, and governance (ESG) factors into investment analysis and decision-making. ESG integration refers to the incorporation of environmental, social, and governance (ESG) factors into the conventional fundamental analysis within the realm of investment management.

There exists empirical evidence that substantiates the existence of a positive correlation between Environmental, Social, and Governance (ESG) factors and favorable investment performance.

The research conducted by Gompers et al. (2003) focused solely on examining the influence of corporate governance within the context of ESG components. The researchers studied the correlation between corporate governance and various aspects of corporate finance, such as enterprise value, profitability, sales, fixed asset purchases, and mergers and acquisitions (M&A). Utilizing their distinct governance index methodology for assessing shareholders' rights, the researchers found that companies with greater index values exhibited elevated firm value, increased profitability, accelerated sales growth, reduced capital expenditure outlays, and a diminished frequency of corporate acquisitions. The study conducted by Wang and Sarkis (2014) found that the successful implementation of corporate social responsibility (CSR) and corporate governance by companies has a positive impact on their financial performance, as evidenced by empirical research.

Corporate social responsibility (CSR) holds considerable importance in corporate finance, primarily driven by the increasing consciousness among consumers and investors. According to the study conducted by Reverte et al. (2015), there is a clear and positive correlation between the implementation of corporate social responsibility (CSR) practices and the overall performance of organizations, as observed across different types of companies.

Furthermore, Kim and Li (2021) developed a mathematical model to analyze the relationship between Environmental, Social, and Governance (ESG) sustainability factors and corporate financial performance. It uses multivariate regression to assess how independent variables such as ESG scores, debt/equity ratio, liquidity, natural logarithm of total assets, and Return on Invested Capital (ROIC) influence two critical financial performance indicators (dependent variables): Return on Assets (ROA) and credit rating. The model accounts for firm and time-fixed effects to mitigate endogeneity issues, and it applies a natural

logarithm to the total asset observations to address potential measurement and scaling challenges.

The model's general regression formulas for ROA and credit rating are as follows:

$$ROA = \alpha + \beta_1(ESG\ score_{i,t}) + \beta_2(Debt/Equity\ ratio_{i,t}) + \beta_3(Liquidity_{i,t}) + \beta_4(\ln(total\ assets)_{i,t}) + \beta_5(ROIC_{i,t})$$

$$Credit\ Rating = \alpha + \beta_1(ESG\ score_{i,t}) + \beta_2(Debt/Equity\ ratio_{i,t}) + \beta_3(Liquidity_{i,t}) + \beta_4(\ln(total\ assets)_{i,t}) + \beta_5(ROIC_{i,t})$$

Here, i represents the firm, t denotes the time period, and the coefficients (α , β_1 , β_2 , β_3 , β_4 , β_5) are estimated during the regression analysis.

Starting from this mathematical-statistical model, it is possible to develop a Python algorithm that not only automates this analysis process but can make it forecast. An effective forecasting model that analyzes the connection between ESG sustainability factors and financial performance can provide valuable insights into the financial impact of sustainable practices. By quantifying the influence of ESGs factors, this model empowers corporate decision-makers to make informed choices, guiding their investments toward sustainability initiatives that not only benefit society and the environment but also yield positive financial outcomes. Such a forecasting model is a strategic tool, fostering a virtuous cycle of sustainable decision-making, corporate responsibility, and long-term financial growth.

The Python model¹ (Fig. 4) aims to implement the mathematical model to analyze the impact of ESG sustainability factors on corporate financial performance using multivariate regression. It uses the “pandas” library to manage the data in tabular format and the “statsmodels” library to conduct regression analyses. The Python code incorporates firm-fixed effects and time-fixed effects as dummy variables, and it applies natural log transformations to the total asset observations.

¹ See Appendix A for mathematical notation of Python code.

Figure 4: Python code for training regression

```
import numpy as np
import pandas as pd
import statsmodels.api as sm

# Load historical data with ESG variables, financial indicators, and corporate financial performance
# Replace the following line with loading your actual historical data into the DataFrame 'df'
df = pd.DataFrame(...)

# Applying firm fixed effect and time fixed effect using dummy variables
df = pd.get_dummies(df, columns=['Year'], drop_first=True)

# Applying natural log transformation to total assets
df['ln_Total_Assets'] = np.log(df['Total_Assets'])

# Categorizing the dataset by asset size and total ESG score for further analysis
df['Asset_Size_Category'] = pd.cut(df['Total_Assets'], bins=[0, 1200, np.inf], labels=['Small', 'Large'])
df['ESG_Category'] = pd.cut(df['Total_ESG'], bins=[0, 2, np.inf], labels=['Low', 'High'])

# Preliminary regression analysis - profitability variable (Return on Assets, ROA)
ROA_models = {}
for esg_score in ['Environmental', 'Social', 'Governance', 'Total_ESG']:
    X_ROA = df[['Year_2018', 'Year_2019', 'Year_2020', 'Year_2021', 'Debt_Equity_Ratio', 'Liquidity', 'ln_Total_Assets', 'ROIC', esg_score]]
    X_ROA = sm.add_constant(X_ROA) # Adding constant for intercept term
    y_ROA = df['ROIC'] # Assuming 'ROIC' is the column for Return on Assets

    model_ROA = sm.OLS(y_ROA, X_ROA).fit() # Ordinary Least Squares (OLS) regression
    ROA_models[esg_score] = model_ROA

# Preliminary regression analysis - credit risk variable (credit rating)
credit_rating_models = {}
for esg_score in ['Environmental', 'Social', 'Governance', 'Total_ESG']:
    X_credit_rating = df[['Year_2018', 'Year_2019', 'Year_2020', 'Year_2021', 'Debt_Equity_Ratio', 'Liquidity', 'ln_Total_Assets', 'ROIC', esg_score]]
    X_credit_rating = sm.add_constant(X_credit_rating) # Adding constant for intercept term
    y_credit_rating = df['Credit_Rating'] # Assuming 'Credit_Rating' is the column for credit rating (categorical)

    model_credit_rating = sm.MNLogit(y_credit_rating, X_credit_rating).fit() # Multinomial Logit regression
    credit_rating_models[esg_score] = model_credit_rating

# The ROA_models and credit_rating_models dictionaries now contain the regression models for each ESG score.
# You can use these models to analyze the relationship between ESG and corporate financial performance
# and to identify potential patterns in the dataset.

# For example, to get the summary of the regression model for Total_ESG score and ROIC:
print(ROA_models['Total_ESG'].summary())

# To get the summary of the regression model for Total_ESG score and credit rating:
print(credit_rating_models['Total_ESG'].summary())
```

Source: own processing

This Python code performs a multivariate regression analysis to investigate the impact of Environmental, Social, and Governance (ESG) sustainability factors on corporate financial performance.

The dataset contains illustrative historical data for the specified variables over multiple years.

1. Data Preprocessing:

The dataset is first loaded into a pandas data frame ('df') to facilitate data management and analysis. The code applies firm fixed effect and time fixed effect using dummy variables by converting the 'Year' column into categorical variables using the one-hot encoding ('pd.get_dummies'). The 'Year_2017' column is dropped ('drop_first=True') to avoid multicollinearity.

2. Data Transformation:

To address potential issues related to measurement and scaling, the code applies a natural log transformation to the 'Total_Assets' column. This transformation can help normalize the data and improve the regression analysis. The code creates additional categorical columns ('Asset_Size_Category' and 'ESG_Category') by categorizing the dataset based on asset size and total ESG score. This categorization helps in further analysis and pattern identification.

3. *Regression Analysis - ROA:*

The code iterates through each ESG score ('Environmental,' 'Social,' 'Governance,' 'Total_ESG') and constructs separate regression models for the profitability variable (ROA). For each ESG score, the code selects the relevant independent variables ('Year_2018' to 'Year_2021', 'Debt_Equity_Ratio,' 'Liquidity,' 'ln_Total_Assets,' 'ROIC,' and the specific ESG score) and adds a constant term (intercept) to the independent variable matrix ('X_ROA'). The dependent variable ('y_ROA') is set as the 'ROIC' column. The Ordinary Least Squares (OLS) regression is performed using `sm.OLS(y_ROA, X_ROA).fit()`, and the resulting regression model is stored in the 'ROA_models' dictionary with the corresponding ESG score as the key.

4. *Regression Analysis - Credit Rating:*

Like the ROA analysis, the code performs regression analysis for the credit risk variable (credit rating). For each ESG score, it selects the relevant independent variables and adds a constant term. The dependent variable ('y_credit_rating') is set as the 'Credit_Rating' column, representing the categorical credit rating levels. The Multinomial Logit regression is performed using `sm.MNLogit(y_credit_rating, X_credit_rating).fit()`, and the resulting model is stored in the 'credit_rating_models' dictionary with the corresponding ESG score as the key.

5. *Results:*

The 'ROA_models' and 'credit_rating_models' dictionaries now contain the regression models for each ESG score. The code displays the summary of the regression model for the 'Total_ESG' score and the ROIC (profitability) as well as the credit rating. These summaries provide essential information such as regression coefficients, standard errors, p-values, R-squared, and more, enabling analysts to understand the relationship between ESG sustainability factors and corporate financial performance. They also aid in identifying significant predictors and assessing the overall model fit. The code can be further extended to explore other ESG scores and their impact on financial performance.

The second Python code (Fig. 5) focuses on predicting future corporate financial performance (ROA) and credit rating based on forecasted ESG sustainability factors and financial indicators. The future data is assumed to be available in a data frame named 'df_future', where each row represents a set of forecasted values for the corresponding variables.

Figure 5: Python code for making a prediction

```
import numpy as np
import pandas as pd
import statsmodels.api as sm

# Assume you have the future data in a DataFrame named df_future
# Replace the following line with loading your actual future data into the DataFrame 'df_future'
df_future = pd.DataFrame(...)

# Preparing independent variables for prediction for the future period
X_future = df_future[['Year_2018', 'Year_2019', 'Year_2020', 'Year_2021', 'Debt_Equity_Ratio', 'Liquidity', 'ln_Total_Assets', 'ROIC', 'Total_ESG']]
X_future = sm.add_constant(X_future) # Adding constant for intercept term

# Making predictions on future ROA
# Adding an additional year for the 'Year_2022' variable
X_ROA_pred = X_future.copy()
X_ROA_pred['Year_2022'] = 0 # Set 'Year_2022' to 0 to make the prediction
predicted_ROA = ROA_models['Total_ESG'].predict(X_ROA_pred)
print("Predicted Future Return on Assets (ROA):")
print(predicted_ROA)

# Making predictions on future credit rating
# Adding an additional year for the 'Year_2022' variable
X_credit_rating_pred = X_future.copy()
X_credit_rating_pred['Year_2022'] = 0 # Set 'Year_2022' to 0 to make the prediction
predicted_credit_rating = credit_rating_models['Total_ESG'].predict(X_credit_rating_pred)
print("Predicted Future Credit Rating:")
print(predicted_credit_rating)
```

Source: own processing

1. Loading Future Data:

The code creates a data frame named `df\_future` containing the future data. Each column corresponds to the independent variables used in the trained regression models, such as future ESG scores ('Year_2018' to 'Year_2021'), debt/equity ratio ('Debt_Equity_Ratio'), liquidity ('Liquidity'), natural log of total assets ('ln_Total_Assets'), and ROIC ('ROIC'). The 'Total_ESG' column represents the forecasted total ESG score.

2. Preparing Independent Variables for Prediction:

The code selects the relevant independent variables from the `df\_future` DataFrame and adds a constant term (intercept) using `sm.add\_constant(X\_future)`. This step is crucial as the regression models were trained with an intercept term, and it ensures consistent predictions.

3. Making Predictions - Future ROA:

The code creates a copy of the `X\_future` DataFrame named `X\_ROA\_pred`. To make predictions for future ROA, a new column, 'Year_2022' is added to `X\_ROA\_pred` and initialized to 0. This additional column represents the coming year (2022) for which the predictions are being made. The code then uses the trained regression model (`ROA\_models['Total\_ESG']`) for the 'Total_ESG' score and predicts the future ROA values using `ROA\_models['Total\_ESG'].predict(X\_ROA\_pred).`

4. Making Predictions - Future Credit Rating:

Like the ROA predictions, the code creates another copy of the `X\_future` DataFrame named `X\_credit\_rating\_pred`. The 'Year_2022' column is added and

set to 0 to indicate future predictions. The code then uses the trained regression model for credit rating (`credit_rating_models['Total_ESG']`) and predicts the future credit rating using `credit_rating_models['Total_ESG'].predict(X_credit_rating_pred)`.

5. *Displaying Results:*

The code prints the predicted future ROA values and the predicted future credit rating based on the provided forecasted ESG and financial data.

By combining the training and prediction codes, analysts can comprehensively analyze the relationship between ESG sustainability factors and corporate financial performance. The trained regression models provide insights into how changes in ESG scores impact financial indicators. At the same time, the predictions offer valuable information for decision-making and strategic planning, allowing companies to anticipate the potential financial performance and credit rating outcomes based on their sustainability initiatives and actions.

CHAPTER 2

The effect of Business Intelligence, Organizational Learning and Innovation on Financial Performance of innovative companies located in Science Park² & a new Agent-based approach

2.1. Introduction

The management mission and the primary goal of forming any company is to make a profit and increase shareholders' wealth (Katila et al., 2012; Lasi, 2013; Raghuvanshi et al., 2017). In line with this mission, it is essential to pay attention to the factors that can influence the company's financial performance because companies have limited resources and information (Villar et al., 2014).

More important than that is the success or failure and what guarantees the survival of an organization is how it works (Wanda and Stian, 2015). For this reason, there is a longstanding link between management and performance issues (O'Leary, 2011; Moss and Atre, 2003; Strohmeier, 2021).

Among companies, innovative/startup companies, generally based on one idea, are weaker companies that may not survive and fail in changing political, economic, and social conditions (Man et al., 2002; Prugsamatz, 2010). This failure hurts the economic sector of society, entrepreneurship and reduces the unemployment rate (Chen and Lin, 2021; Hawking and Sellitto, 2010; Sjarif et al., 2021).

² **Published paper:** Mallamaci V. et al.: «The effect of Business Intelligence, Organizational Learning and Innovation on the financial performance of innovative companies located in Science Park», *Information Processing and Management*, (IF. 6.222), 2021

Published chapter book: Mallamaci V. et al.: «Business Intelligence modelling for studying Science Parks externalities», in *Mathematical and Statistical Methods for Actuarial Sciences and Finance - MAF 2022*, Springer.

Mallamaci V. et al. : «Science Parks externalities on financial performance of small firms through business intelligence tools», in Mahmud, M., Ieracitano, C., Kaiser, M.S., Mammone, N., Morabito, F.C. (eds) *Applied Intelligence and Informatics. AII 2022. Communications in Computer and Information Science*, vol 1724. Springer.

Therefore, managers of these companies, in addition to paying attention to factors such as product quality, customer retention, maintaining liquidity, increasing the rate of return on investment, etc. that are necessary for sustainability in other companies, managers should pay attention to factors such as business intelligence, organizational learning, innovation, etc. Paying attention to these factors can increase the efficiency, effectiveness, and durability of innovative companies (Nithya and Kiruthika, 2021; Nuseir et al., 2021; Yiu et al., 2021).

According to many economic experts, entrepreneurship as an economic driver plays various roles in society and is the basis of all human developments and progress. It should be noted that not every innovation will necessarily succeed, which necessitates examining the various factors of failure (Fashanu, 2021; Hamad et al., 2021; Muntean et al., 2021).

So, the leading corporate objective is to generate profit and increase the well-being of the shareholders and the various stakeholders interacting with the company.

Science parks are indeed complex institutions designed to be applied as policy tools to support the development of innovative startups and regional clusters.

They facilitate the exchange of knowledge between universities, research and development bodies, and companies. For the pursuit of an efficient interaction between the parties involved, companies and Science Parks, it is essential to examine the factors that influence the financial performance of the company, considering the limited availability of resources and information.

In the literature, the International Association of Science Parks provided the primary definition of Science Park as follows: a Science Park is a business support and technology transfer initiative that:

1. encourages and supports the startup and incubation of innovation led, high growth knowledge-based businesses;
2. provides an environment where more extensive and international businesses can develop specific and close interactions with a particular center of knowledge creation for their mutual benefit;
3. has formal and operational links with poles of knowledge creation such as universities, higher education institutes and research organizations. (Waddock and Graves, 1997; Ferrara and Mavilia, 2013).

According to Almeida et al. (2020), research and technology parks are often portrayed as a solution for nations seeking to expedite the expensive processes associated with structural transformations. Internationally, renowned instances such as Silicon Valley, Cambridge, and Grenoble have stimulated a surge throughout Europe using endorsing universities and regional development organizations. The inclusion of these factors has become a crucial aspect in the implementation of regional innovation policy, as highlighted by Vasquez-Urriago et al. (2016) and Guadix et al. (2016).

Nevertheless, investments in regions lacking adequate research and development (R&D) capacities have elicited significant controversy.

According to Watkins-Mathys and Foster (2006), to optimize the return on research and development (R&D), particularly in the context of public R&D, policy makers and managers must allocate greater focus towards the commercial aspect. Hence, it is imperative to underscore the potentialities centered on the capacity to recruit external enterprises. According to Hobbs et al. (2017), science parks significantly strengthen regional innovation systems and drive structural transformation.

To enhance the success of science parks, it is imperative to incorporate design features that facilitate the advancement of university goods. This can be achieved by recruiting and consolidating external research and development projects from transnational corporations and public/non-profit institutions (Almeida et al., 2020).

Given the increasing use of this instrument among policymakers, it became imperative to delineate their responsibilities and duties within Regional Innovation Systems (RIS). The regional approach is primarily stressed regarding the significance of geographical proximity and the optimization of synergies among players.

Simultaneously, it underscores the imperative of enhancing collaboration and establishing networks for creativity. Additionally, they play a role in facilitating strategic research and development endeavors, as well as fostering the generation of information and expertise. Furthermore, the region may also promote the formation of a collaborative network among various enterprises and organizations, hence facilitating their collective advancement (Glittová and Šipikal, 2022).

In recent years, an increasing number of empirical studies have examined the relationship between innovation and firms' performance, considering different types of models, estimation methods, measures of growth and innovation activity.

In particular, corporate performance, and therefore investments in innovation, are strictly connected to the financial performances that influence the entire management. These are usually measured in terms of profitability through three accounting variables: Return On Assets (ROA), Return On Equity (ROE) and Return On Sales (ROS) which provide a system of measurements complete enough for potential investors to optimally assess the company's financial performance (Waddock and Graves, 1997).

In the study on the relationship between corporate governance and financial performance firms by Kyere and Ausloos (2021), ROA and Tobin's Q were used as dependent variables. ROA indicates how best a company is assets are utilized to generate profit and is not affected by leverage or other extraordinary and discretionary items; it is calculated by dividing the annual earnings of the company by its total assets. Tobin's Q is usually used to capture existing assets, future growth potentials of the company and investors' expectations of future events, including evaluation of current business strategies; it is a ratio of the market value of the company outstanding stock and debt divided by replacement

cost of the company's assets ("book value"). Instead, the independent variables considered in the same study are related to corporate governance mechanisms: insider shareholding, board size, independent board, CEO duality, and audit committee meetings (Kyere and Ausloos, 2021).

As anticipated, technological innovation is also correlated to the business intelligence mechanisms introduced in the company to make all available data productive. Business intelligence methodologies, through an assortment of coordinated operations just as choice help applications and databases, convert raw data sets into information to support decision-making processes to optimize knowledge and make processes faster and more efficient. Therefore, the development of business intelligence is one of the fundamental elements of innovation within a company and determines the improvement of its overall performance (Nithya and Kiruthika, 2021).

In recent years, a growing body of research has focused on Business Intelligence (BI) and its role in facilitating decision management. This surge in research can be attributed to the increasing recognition of BI's significance within organizations, particularly in data management and information generation for various operational processes. The aim is to enhance decision-making efficiency, enabling organizations to gain a competitive edge in the evolving market landscape (Gamboa-Cruzado et al., 2023).

Alyan (2022) posits that business intelligence is a strategic approach that aims to optimize business performance by facilitating informed decision-making and providing access to relevant information. Corporate intelligence tools are technological solutions that enhance the efficiency of corporate operations by maximizing the value of data for optimal utilization. According to Alzghoul et al. (2022), business intelligence encompasses the systematic collection, analysis, and dissemination of information to mitigate uncertainty in the decision-making process. The phrase "business management" has been characterized by some scholars as a concept that encompasses the integration of applications and technology to effectively gather, access, and analyze data pertaining to a firm, hence facilitating informed decision-making processes.

Furthermore, Arefin et al. (2020) explained an essential attribute of business intelligence tools: their capacity to collect data from diverse sources. By employing sophisticated analytical techniques, these tools can fulfill users' requirements. Bach et al. (2018) categorized business intelligence technologies according to how information is conveyed, specifically through reporting, statistical analysis, ad-hoc analysis, and predictive analysis.

In contemporary times, business intelligence has transitioned from a novel technology to an integrated solution for organizations that prioritize their needs as a pivotal driver of technological innovation. Hence, the primary obstacle business intelligence systems face in achieving a significant impact on business lies in effectively identifying and addressing essential business challenges.

According to Maaitah (2023), business intelligence encompasses a combination of essential components, such as a proficient data warehouse and a

responsive element that supervises time-sensitive operations. This integration empowers tactical and operational decision-makers to adapt their actions in alignment with the company's strategy. Additionally, business intelligence encompasses a range of technical tools, including knowledge management, decision support systems, enterprise resource planning, and data mining.

The second aspect considered is organizational learning, which is determined by the set of organizational features, practices and issues that enable the learning processes. Thus, organizational learning translates into the ability to convert new and past ideas into actions that can improve business performance ahead of competitors to gain a sustainable competitive advantage. This occurs through the generation, acquisition, dissemination and integration of knowledge and the modification of its behavior. It is argued that firms better at learning get a better chance of increasing market share thanks to a responsive structure that can quickly react to new challenges (Hailekiros and Renyong, 2016).

The significance of the interaction between knowledge management, organizational learning, and innovative performances is heightened in the current paradigm shift, whereby knowledge has a central role.

The relationship between knowledge management, organizational learning, and innovation performance has been examined in technology parks, commonly referred to as high-tech and knowledge-based industrial markets (Castro, 2015). These technology parks are characterized by active university-industry cooperation (Kör, 2013).

In the dynamic and unpredictable business landscape, intelligent enterprises must engage in continuous learning to maintain their competitive advantage. Organizational learning, in turn, thrives when it is founded upon a well-organized knowledge structure within the organization. The organizational learning process is crucial for firms as it involves assimilating and adopting knowledge (Therin, 2003). The learning capacities of organizations exhibit significant dynamism, particularly when confronted with uncertainty and external challenges (Bennet and Bennet, 2004).

The last aspect considered is innovation, which is defined as the application of discoveries and inventions, involving the introduction of novel or enhanced practices by an organization to generate value (Sahin, 2022). This value creation might manifest in many results, such as products, systems, or processes (Gloet, 2004; Kör, 2013). Innovation refers to the creation, adoption, and execution of novel concepts, procedures, commodities, or offerings (Calantone et al., 2002; Caroline and Angel, 2011; Dickel and de Moura, 2016). According to Mardani et al. (2018), innovation arises through reorganizing preexisting conceptual and physical resources within firms. Based on the extensive body of literature on innovation, it is well-acknowledged that innovation aptitude holds paramount importance in the business industry (Calantone et al., 2002; Dickel and de Moura, 2016).

Furthermore, the ever-evolving demands of customers contribute to the increasing complexity of innovation, which is further exacerbated by the rapid

advancements in technology and the competitive landscape (Du Plessis, 2007). Innovation has been identified as a crucial determinant that significantly impacts organizations' operational efficiency, resilience, and competitive advantage (Kör, 2013; Liao and Wu, 2010).

Innovation pertains to the execution of ideas. The innovation process heavily relies on knowledge, particularly tacit knowledge, as opposed to explicit information (Mardani et al., 2018; Gloet, 2004; Caroline and Angel, 2011).

The knowledge creation process is contingent upon acquiring knowledge from both internal and external sources of learning. Companies' effectiveness is contingent upon managers' ability to effectively leverage their available knowledge resources and convert them into actions that generate value (Alavi and Leidner, 2001).

According to King (2009), knowledge and learning systems benefit the processes and results of innovation. Furthermore, it has been demonstrated through empirical research that the process of learning and the generation of knowledge favor the outcomes of innovation (Alegre et al., 2013).

In organizational contexts characterized by challenging environments or job nature, knowledge management and organizational learning are crucial elements for long-term survival is emphasized (Bennet and Bennet, 2004). Scholars have concluded that organizational learning is linked to the acquisition of novel knowledge, a critical factor in enhancing a firm's capacity for innovation and overall performance (Calantone et al., 2002).

Finally, despite constituting a pioneering analysis, Ferrara and Mavilia (2014) have shown many interesting features of TP/SP's effects on both regional economic growth and associated (or incubated) firms' growth in terms of revenues. In particular, they found that TP/SP impacts are different if analyzed by geographic location and that their effects are still evident even in the aggregate model. The number of TP/SP per region seems to display a positive role in sustaining the economic growth of corresponding areas. In addition, the patenting activity and the creation of research centers foster the development of affiliated firms, affecting regional economy parameters. On the contrary, the distance between the TP/SP and related firms reduces the growing potential of the latter. In addition, firms within a TP/SP outperform (largely) the regional average and more recent structures tend to be more prone to both patenting activity and high-level growth. Younger systems are also characterized by higher dispersion rates (Ferrara and Mavilia, 2014).

This study aims to investigate the impression of business intelligence, organizational learning and innovation on the financial efficacy of start-up companies located in the Science Park.

The main objectives are likewise to explore the influence of business intelligence on the financial efficacy of start-ups, of organizational learning on the financial effectiveness of start-ups, and of innovation on the financial efficacy of start-ups.

The sub-objectives of the research include checking the significance of business intelligence on organizational learning, examining the influence of business intelligence on innovation, and examining the impact of organizational learning on innovation.

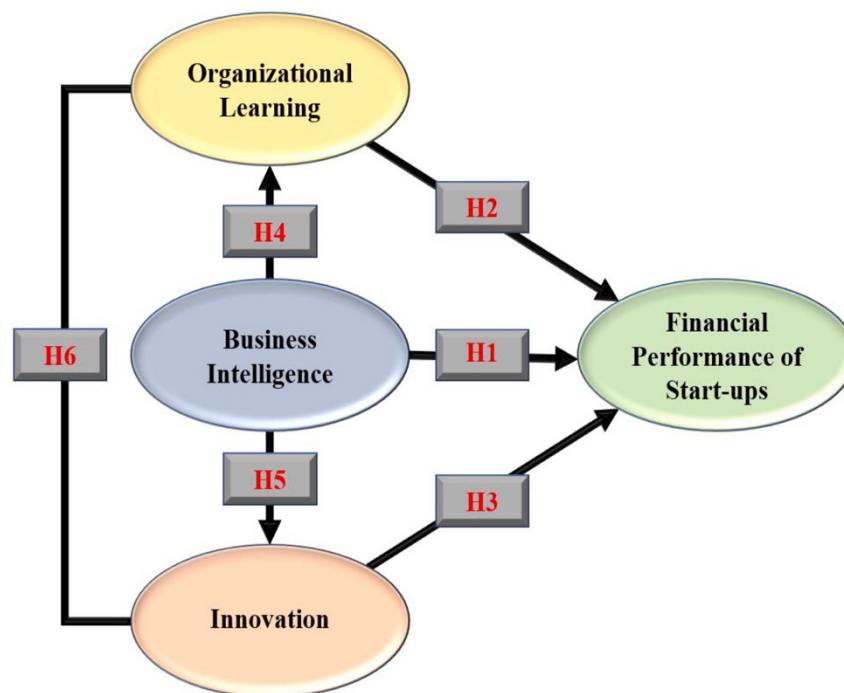
2.2. Problem statement and methods

2.2.1. Research method

The research is defined as applied research in purpose because it examines theoretical structures in scientific and real contexts and situations and seeks a solution to increase financial performance (Cochran and Wood, 1984; Kyere and Ausloos, 2021; Waddock and Graves, 1997) of startups. Also, regarding how to obtain scientific data, it is among the survey research because a questionnaire tool has been used to examine each of the criteria and variables. Due to measuring the relationships between variables, the research is descriptive-correlational. It is also a field study.

Fig. 6 shows the research conceptual model (Sakhvidi et al., 2019).

Figure 6: Conceptual model of research



Source: Yang, M., Mallamaci et al., 2022

2.2.2. Statistical population of the study and sample size

The statistical population of the research is made up of the start-up companies located in the Shanghai Zizhu Science-based Industrial Park, in the southeast of Minhang District, Shanghai.

The sampling of this research is simply random. Morgan's table was employed to demonstrate the sample size, as shown in Table 1.

It was found that the number of executives of start-up companies located in Science Park is 400; therefore, the required number of samples is 196 people, and 280 questionnaires were distributed to compensate for any statistical bias due to the choice of sample.

Table 1: Krejcie and Morgan Table (1970) for determining the sample size of a known population³

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	346
25	24	130	97	320	175	950	274	4000	351
30	28	140	103	340	181	1000	278	4500	354
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	191	1200	291	6000	361
45	40	170	118	400	196	1300	297	7000	364
50	44	180	123	420	201	1400	302	8000	367
55	48	190	127	440	205	1500	306	9000	368
60	52	200	132	460	210	1600	310	10000	370
65	56	210	136	480	214	1700	313	15000	375
70	59	220	140	500	217	1800	317	20000	377
75	63	230	144	550	226	1900	320	30000	379
80	66	240	148	600	234	2000	322	40000	380
85	70	250	152	650	242	2200	327	50000	381
90	73	260	155	700	248	2400	331	75000	382
95	76	270	159	750	254	2600	335	1000000	384

2.2.3. Research data collection tool

A critical phase in research is data collection, which demands the use of convenient tools. Reliable results cannot be expected from inaccurate data. Instrument design has requirements that failure to comply with, the accuracy of the data collected and ultimately distorts the research, so to design or select the instrument, it is essential to pay attention to its psychometric quality.

³ N is the population size; S is the sample size.

The present research questionnaire includes demographic information and 47 questions of research variables: financial performance – 12 questions; business intelligence – 12 questions; innovation – 12 questions; organizational learning – 11 questions (Sakhvidi et al., 2019).

The questionnaire was distributed online (according to the Corona pandemic). Attempts were made to collect information carefully and then, by analyzing them, the research hypotheses were tested.

2.2.4. Validity and reliability of the questionnaire

Due to the fact that in this study the tool for collecting information and measuring variables is a questionnaire, validity is of particular importance. The validity of the research indicates the degree of coordination of the questionnaire with the purpose of the study. In other words, content validity aims to ensure the tools for measuring the concept it claims to measure.

The first step is for the designers to identify the target tool clearly; it must be clear whether the tool is Predictive, Evaluative, or Discriminative. The second step is to specify the target group.

In the third step, selecting and reducing items is considered.

Two methods can be used to calculate the validity: qualitative (expert opinion) and quantitative (calculating CVI and CVR). Content Validity Index (CVI) is a process to compute value validity measurably. CVR sizes the importance of the part that is between 1 and -1.

Reliability is one of the technical features of measuring tools. To calculate the reliability coefficient, the re-execution method, the parallel method, the composition method, and the Cronbach's alpha mode are used.

In this study, Cronbach's alpha approach was used. The approach is employed to compute the internal consistency of the measuring instrument. The questionnaire has agreeable reliability if the alpha coefficient is larger than 0.7.

Table 2 presents Cronbach's alpha. The case has agreeable dependability because Cronbach's alpha of whole variables is bigger than 0.7 (0.913 for the whole questionnaire).

Table 2: Calculate the dependability of questionnaire.

Variable	Questionnaire questions	Number of questions	Cronbach's alpha
Financial performance	1 to 12	12	0,852
Business Intelligence	13 to 24	12	0,866
Innovation	25 to 36	12	0,888
Organizational Learning	37 to 47	11	0,894
Whole Questionnaire	-	47	0,913

2.2.5. Research data analysis method and structural equation modeling

In the study, the demographic data of the research were described employing descriptive statistics, frequency tables and pie charts and the data were analyzed employing SPSS software. Affirmation of the relationships between factors - variables was done through PLS modeling/confirmatory factor analysis employing Smart software, a divergence path design method that allows the study of theory and metrics.

Structural equation modeling (SEM) is a comprehensive statistical approach to testing hypotheses about relations among observed and latent variables (Hoyle, 1995); a methodology for representing, estimating, and testing a theoretical network of (mostly) linear relations between variables (Rigdon, 1998); it tests hypothesized patterns of directional and nondirectional relationships among a set of observed (measured) and unobserved (latent) variables (MacCallum and Austin, 2000).

Two goals in SEM are:

1. to understand the patterns of correlation/covariance among a set of variables;
2. to explain as much of their variance as possible with the model specified (Kline, 1998).

There are two critical issues in measuring behavioral and cognitive sciences variables: Measurements and Cause-and-effect relationships between variables.

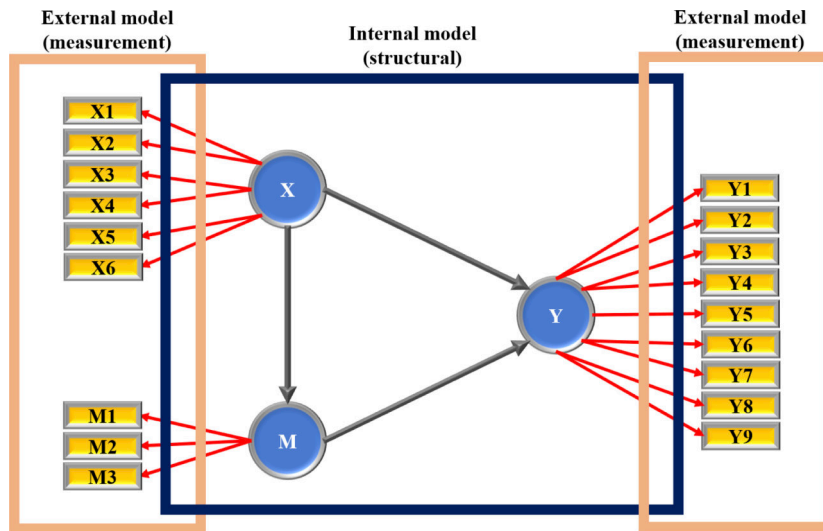
Structural equation models contain two parts, the measurement model and the structural function model (Fig. 7). Structural Equation Models, by integrating the two models of confirmatory factor analysis and structural function analysis, solve many problems and difficulties in measuring latent variables and inferring causal relationships between these latent variables.

One of the most robust and appropriate analysis methods is multivariate analysis, which means the analysis of different variables that, in a theory-based structure, demonstrates the simultaneous influences of variables on each other. The default partial least squares method does not require the type of distribution of the measurement variables. Therefore, it is suitable and practical for data with abnormal or unknown distribution.

Goodness of Fit (GOF) index is defined as:

$$GOF = \left(\frac{\sqrt{\bar{R}^2 * \overline{communalities}}}{1} \right)$$

Figure 7: Internal and external model



Source: Yang, M., Mallamaci et al., 2022

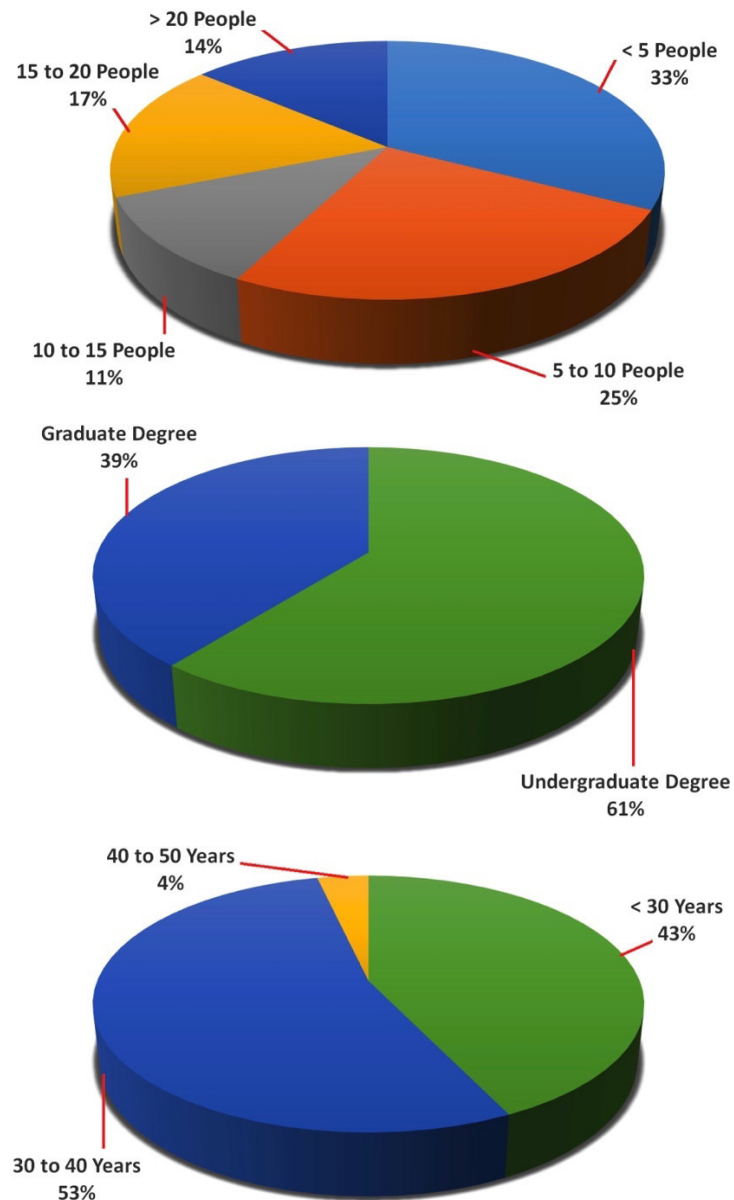
2.3. Results and Discussion

2.3.1. Data analysis

Fig. 8 examines how statistical samples are distributed in terms of variables such as age, level of education, and number of staff.

According to statistics, of the 196 sample respondents, 75 were male, and 121 were female. Also, 41% were single, and 59% were married.

Figure 8: Frequency distribution of respondents



Source: Yang, M., Mallamaci et al., 2022

In the research, structural equation design by support of Partial Least Squares pattern and Smart software has been employed to question hypotheses and accuracy of the main model. The approach is used in cases where the distribution of variables is not normal or the sample size is small.

In PLS patterns, two plans are evaluated: External plan or the measurement plan and Internal plan or the structural plan in structural equation patterns.

The external plan exemplifies the load factors of the observed variables.

External (measurement) model: in the fundamental equation design procedure method, it is first inevitable to study the validity of the structure to demonstrate that the picked parts have the vital veracity to size their desired variables.

Confirmatory Factor Analysis is employed for this aim. In such a way, that load factor of every part by its variable has a rate of "t" larger than 1.96. In this case, this part has essential veracity to measure that latent variable/structure.

Tables 3 to 6 show the amount of load factor for the parts of every latent variable.

The entire parts had a "t" statistic larger than 1.96, so none were detached from the design. Therefore, we continue with entire items (questions) and examine the model.

Table 3: CFA (load factor and "t" rates) for Financial Performance variable

Variable	Item	Load factor	Standard error	"t" statistics
FP	Q1	0.492193	0.076127	6.465460
	Q2	0.622708	0.077793	8.004666
	Q3	0.548894	0.065956	8.322162
	Q4	0.835878	0.025181	33.195080
	Q5	0.696886	0.038736	17.990588
	Q6	0.661032	0.035280	18.736782
	Q7	0.548635	0.070582	7.772977
	Q8	0.721561	0.040424	17.849916
	Q9	0.586031	0.070443	8.319190
	Q10	0.570061	0.075692	7.531324
	Q11	0.564791	0.065290	8.650437
	Q12	0.517017	0.076489	6.759327

Table 4: CFA (load factor and "t" rates) for Business Intelligence variable

Variable	Item	Load factor	Standard error	"t" statistics
BI	Q13	0.730557	0.052138	14.012104
	Q14	0.589276	0.053926	10.927565
	Q15	0.597998	0.071622	8.349338
	Q16	0.732724	0.033726	21.725707
	Q17	0.733823	0.040780	17.994480
	Q18	0.770443	0.042191	18.261021
	Q19	0.616846	0.065166	9.465827
	Q20	0.475452	0.072934	6.518901
	Q21	0.559210	0.062195	8.991300
	Q22	0.615476	0.055440	11.101713
	Q23	0.673410	0.066497	10.126864
	Q24	0.517431	0.087247	5.930674

Table 5: CFA (load factor and "t" rates) for Innovation variable

Variable	Item	Load factor	Standard error	"t" statistics
I	Q25	0.622802	0.054736	11.378342
	Q26	0.790376	0.031716	24.920124
	Q27	0.718456	0.036542	19.661024
	Q28	0.689335	0.046446	14.841744
	Q29	0.682036	0.047572	14.336778
	Q30	0.578895	0.065543	8.832352
	Q31	0.663431	0.044736	14.829967
	Q32	0.646462	0.050920	12.695741
	Q33	0.764198	0.034131	22.390061
	Q34	0.726147	0.047207	15.382209
	Q35	0.672393	0.049779	13.507435
	Q36	0.476731	0.062602	7.615214

Table 6: CFA (load factor and "t" rates) for Organizational Learning variable

Variable	Item	Load factor	Standard error	"t" statistics
OL	Q37	0.759524	0.030754	24.696623
	Q38	0.691761	0.040261	17.181810
	Q39	0.546217	0.058348	9.361329
	Q40	0.680557	0.039109	17.401759
	Q41	0.706696	0.034220	20.651710
	Q42	0.661237	0.053347	12.395095
	Q43	0.733164	0.040780	17.978481
	Q44	0.674948	0.042602	15.843247
	Q45	0.727473	0.048557	14.981751
	Q46	0.656604	0.065271	10.059716
	Q47	0.804510	0.024279	33.136036

2.3.2. Evaluation of external model fit

Convergent reliability and validity: in the structural equation model, aside from the construct validity that is employed to evaluate the significance of the picked items for measuring variables, diagnostic validity is also deliberated, meaning that the items of each variable ultimately have a good separation in terms of measurement relative to other variables provide the model. In other words, each item measures only its variable and combines them so that entire variables are well disconnected from each other. The approach is determined by the extracted mean-variance index (AVE).

AVE coefficients demonstrate what percentage of the structure or model variable variance is defined by a severe item.

The structures or variables of the model have a more considerable mean-variance, higher than the standard index of 0.5. Therefore, it can be concluded that the items can adequately explain the variance of the research model variables.

In measurement patterns, the internal consistency of the pattern or the degree of reliability is measured by calculating the composite reliability.

The reliability coefficients are exhibited in Table 7. In the model, all model structures have great composite reliability and are larger than the standard index of 0.6. Composite reliability indicates the great internal reliability of research data.

Also, a Cronbach's alpha value higher than 0.7 expresses agreeable reliability.

Table 7: AVE values and reliability indicators

Variable	AVE	Composite Reliability	Cronbach's Alpha	Redundancy
BI	0.585747	0.891225	0.866388	–
FP	0.610568	0.880388	0.851707	0.152961
I	0.654413	0.907851	0.888437	0.196221
OL	0.686749	0.911863	0.893956	0.119509

Divergent validity: it is measured in two ways. One is the cross-factor loading method, which compares the degree of correlation between the indices of a structure and their correlation with other structures; the other method has been used in this research. The AVE square root of the latent variables in the present study, located in the cells placed in the main diameter of the matrix (Table 8), is greater than the correlation value between them, which are arranged in the lower and left cells of the main diameter. The power of this criterion was considered acceptable and confirmed the appropriate divergent validity.

Table 8: AVE values and the rate of divergence validity indices

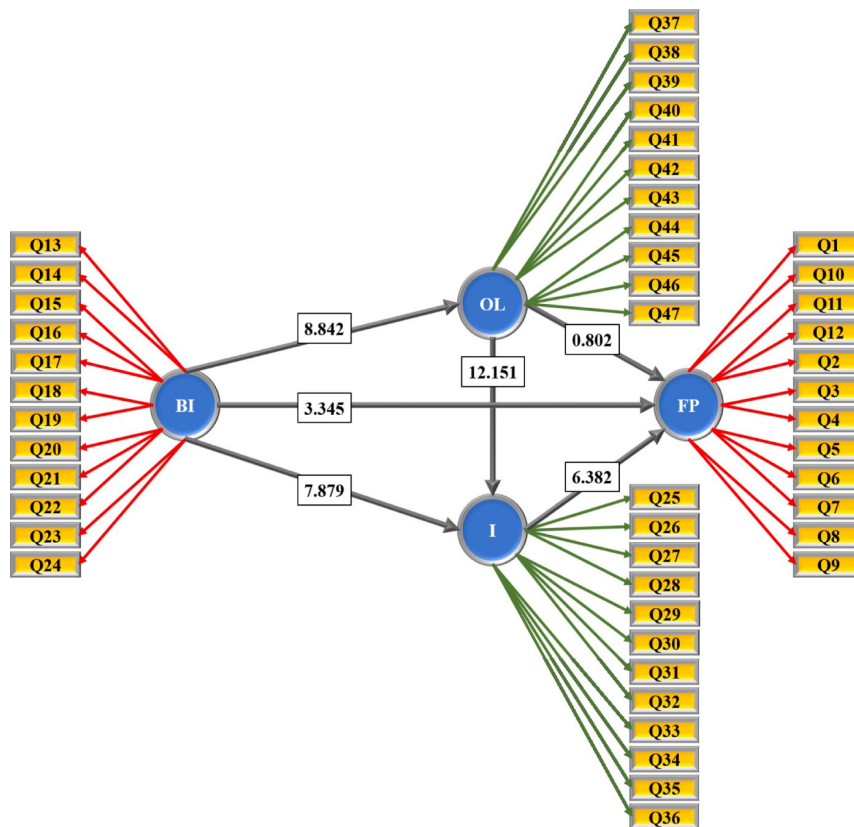
Variable	BI	FP	I	OL
BI	1.000000	–	–	–
FP	0.638575	1.000000	–	–
I	0.658450	0.667040	1.000000	–
OL	0.519122	0.608079	0.750602	1.000000

2.3.3. Main model outputs (path coefficients and "t" statistics)

Employing the internal model, hypotheses could be inspected. We could confirm or reject the research hypothesis by correlating the value of "t" computed for the coefficient of every path. Therefore, if the specific rate of the "t" statistic is more significant than 1.96, it is meaningful at the 95% trust level, and if the statistical rate is more significant than 2.58, the path coefficient is at the 99% trust level.

In analysis, "t" statistics value for all paths except the path of organizational learning (Bilan et al., 2020; Haseeb et al., 2019; Wiewiora et al., 2020) to financial performance, is more significant than 1.96 and as a result are meaningful at the 95% confidence level (Fig. 9).

Figure 9: The main model in the mode of critical numbers (t-value)



Source: Yang, M., Mallamaci et al., 2022

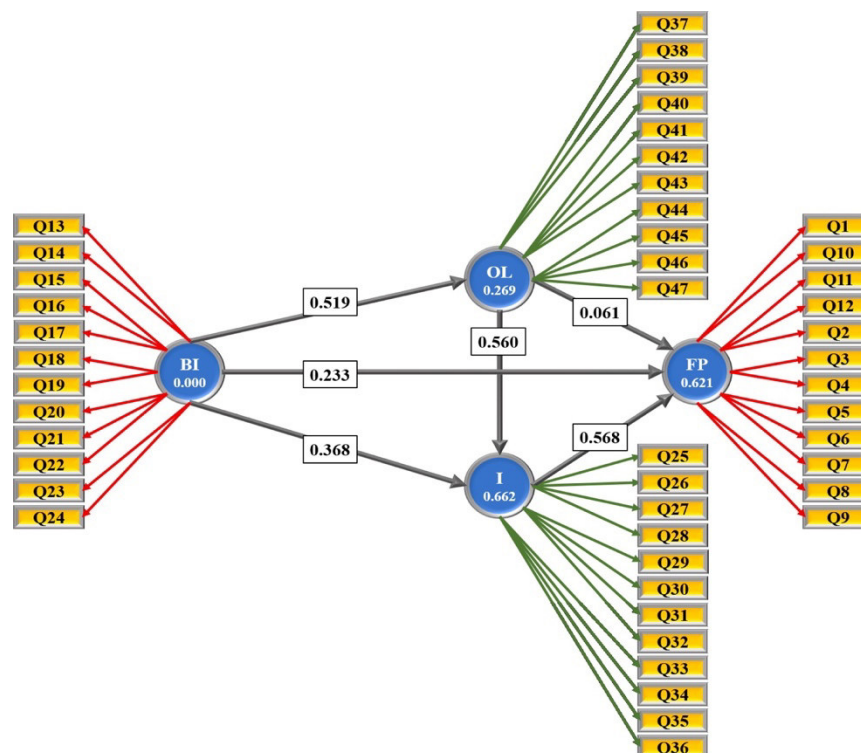
Numbers on routes express a value of "t-value" for every path. To check the importance of path coefficients, every path's "t" value must be bigger than 1.96. In the assay, the value of "t" statistics for whole paths other than the path of organizational learning to financial performance is larger than 1.96 and, as a result, paths are meaningful at the 95% trust level.

The line numbers are beta coefficients from the regression equation between the changeable, which is the path coefficient. Circle numbers indicate the R² rate whose prediction changeable was entered into a circle aside from an arrow. The coefficient of perception for the financial performance variable is estimated to be 0.62. It shows that the variables of organizational learning, business intelligence and innovation, together, could explain 62% of the changes in financial performance. According to the value of standard coefficient and "t" statistics, variables of innovation (0.568) and business intelligence (0.233) had the topmost impact on the financial performance variable, respectively, and the organizational learning variable did not have a significant effect. (Fig. 10).

Similarly, the variables of organizational learning and business intelligence explain a total of 0.66 of the changes in innovation. According to the value of the standard coefficient and "t" statistics, the organizational learning variable has a more significant impact on the innovation variable than the business intelligence variable.

According to the number of coefficients of determination, it can be said that the business intelligence variable explains 27% of the changes in the organizational learning variable.

Figure 10: The main model in the mode of path coefficients.



Source: Yang, M., Mallamaci et al., 2022

2.3.4. Internal model (structural model)

In internal pattern mode, hypotheses were investigated and the structural pattern path was checked out. Every path correlates to model hypotheses. Examining every hypothesis by inspecting the size, sign, and statistical significance of the path coefficient (beta) between every latent/dependent changeable. The bigger the path coefficient, the more significant predictor influence of latent changeable than dependent changeable. Forasmuch as outcomes of examining relationships between dependent-independent variables employing relevant co-efficient, it is possible to study the influences between the research variables. To confirm the weight of the path coefficient or beta, the weight of the "t-value" rate for every path coefficient should be thought out, so the Bootstrapping approach was employed. To the aim, sampling was simulated in 500 and 800 samples. The outcomes exhibit that there is no change in the importance or non-significance of the parameter in both cases and the outcomes have strong validity.

The value of the "t" statistic for all paths except the organizational learning path to financial performance is more significant than 1.96, which exhibits a 95% confidence level for all paths except the organizational learning path to financial performance (Table 9).

Table 9: Direct linear influence of the role of research changeable in primary pattern

Path	Beta	Standard error	t-sampling statistics 200	500	800
BI – OL	0.519122	0.058709	8.842305	8.925968	9.356432
OL – I	0.559588	0.046051	12.151371	10.658339	11.241002
BI – I	0.367955	0.046702	7.878725	7.083970	7.421153
OL – FP	0.060781	0.075778	0.802095	0.835589	0.841795
BI – FP	0.233042	0.069670	3.344942	3.413065	3.370821
I – FP	0.567971	0.088996	6.382017	6.758262	6.721716

2.3.5. Evaluation of internal model fit

According to Table 10, the effect of business intelligence on organizational learning and organizational learning pathway on strong innovation, repercussion of BI on innovation and innovation path to moderate financial performance and other paths are weak.

As shown in Table 11, the predictive power of the endogenous variables of innovation and financial performance has a medium level of predictive power, indicating a good fit for the structural model.

Table 10: Effect size of f^2

Path	R^2_y (X excluded)	R^2_y (X included)	f^2
BI – OL	0	0.269	0.367989
OL – I	0.444	0.662	0.644970
BI – I	0.566	0.662	0.284024
OL – FP	0.621	0.621	0
BI – FP	0.593	0.621	0.073879
I – FP	0.514	0.621	0.282322

Table 11: Predictive Quality (Q^2)

Structure	Q^2
FP	0.246701
I	0.271567
OL	0.118110

2.3.6. Evaluation of overall fit of the main model (quality indicators)

PLS-path modeling absences a general optimization criterion, i.e., there is no general function to evaluate the model fit, so in PLS-path modeling there are three different indicators for model fit: Goodness of Fit (GOF) index, Redundancy (Red) index, and Communality index.

The communality index shows how much of the variability of the indicators (questions) is explained by the related structure and the average of this index is used to determine the convergent validity (Table 12).

A suitable criterion for measuring the fit of the structural part of structural equation models is the redundancy mean value corresponding to interior structures in the model. The value is a good indicator of the fit of the structural model and is also used in calculating the overall fit of the model. The value of Red for the research model is 0.16, which indicates a relatively good value (Table 13).

Using the R^2 geometric mean and the mean communality index, the value of Goodness of Fit (GOF) index (Table 14) for the whole model was calculated to be 0.573, indicating that the pattern's overall fit is firm.

Table 12: Evaluation of quality indicators

Variables	Communality Index
BI	0.610568
FP	0.585747
I	0.654413
OL	0.686749

Table 13: Evaluation of quality indicators

Variables	Redundancy Index
FP	0.152961
I	0.196221
OL	0.119509

Table 14: Path coefficients, designation coefficients, "t" statistics and outcome of the primary pattern hypothesis

Main model assumptions	Path coefficient	t-statistics	Coefficient of determination	Result
BI – OL	0.519122	8.842305	0.269	Approved
OL – I	0.559588	12.151371	0.662	Approved
BI – I	0.367955	7.878725	–	Approved
OL – FP	0.060781	0.802095	0.621	Disapproval
BI – FP	0.233042	3.344942	–	Approved
I – FP	0.567971	6.382017	–	Approved

2.3.7. Testing research hypotheses

By inspecting and confirming the original model, the hypotheses of the research pattern have been confirmed. If certain rate of the t-statistic is fewer than 1.96, the hypothesis-zero is settled, and if the specific t-statistic value is larger than 1.96. Assumption zero is rejected.

Hypothesis 1: Business intelligence affects organizational learning.

H0: BI has no meaningful impact on organizational learning.

H1: BI has a meaningful impact on organizational learning.

The specific t-statistic value is 8.84 and larger than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, BI has a meaningful

impact on the organizational learning of start-up companies and the impact value is 0.52 and positive (direct). That is, with an increasing level of business intelligence, the amount of organizational learning also increases.

Hypothesis 2: Organizational learning influences innovation.

H0: Organizational learning does not have a meaningful impact on innovation.

H1: Organizational learning has a meaningful impact on innovation.

The specific t-statistic value is 12.15 and greater than 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, organizational learning has a critical influence on the innovation of start-up companies and the impact value is 0.56 and positive (direct). As the level of organizational learning increases, so does the level of innovation.

Hypothesis 3: Business intelligence has an impact on innovation.

H0: Business intelligence does not have a critical influence on innovation.

H1: Business intelligence has a crucial impact on innovation.

The specific t-statistic value is 7.88 and greater than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% trust level, BI has a critical influence on the innovation of start-up companies and the magnitude of the impact is 0.37 and positive (direct). As the level of business intelligence increases, so does innovation.

Hypothesis 4: Organizational learning affects the financial performance of innovative companies.

H0: Organizational learning does not have a significant effect on financial performance.

H1: Organizational learning has a significant effect on financial performance.

The specific t-statistic value is 0.8 and less than 1.96, so the hypothesis-zero is not rejected, i.e., at 95% confidence level, organizational learning has no critical influence on the financial performance of start-up companies.

Hypothesis 5: BI impresses the financial efficacy of innovative companies.

H0: BI does not have a significant effect on financial performance.

H1: BI has a substantial impact on financial performance.

The specific t-statistic value is 3.34 and greater than the value of 1.96, so the null hypothesis is rejected, i.e., at the 95% confidence level, BI has a critical influence on the financial efficacy of start-up companies and the effect value is 0.23 and positive (direct). With an increasing level of BI, financial effectiveness also increases.

Hypothesis 6: Innovation affects the financial performance of innovative companies.

H0: Innovation does not have a critical influence on financial efficacy.

H1: Innovation has a crucial impact on financial efficacy.

The specific t-statistic value is 6.38 and greater than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, innovation has a critical influence on the financial efficacy of start-up companies and the impact value is 0.57 and positive (direct). That is, as the level of innovation increases, so does financial performance.

2.4. Conclusion

The present study investigates the influence of business intelligence, organizational learning, and innovation on the financial efficacy of innovative companies. The study is a descriptive survey in terms of method, a survey in terms of purpose, applied to aim, and finally, research in terms of data collection is field research. The objectives of this paper are to answer the question of whether operationalization of Business Intelligence, Organizational Learning and Innovation and utilization of their applications can provide financial performance enhancement for these organizations.

Also, in this research, a questionnaire that is made according to previous research and the opinions of elites has been used to collect information. The questionnaire used in this research consists of two parts. The first part includes the characteristics of people (age, gender, education, and level of work experience). The next section of the questionnaire consists of questions related to financial performance, business intelligence, organizational learning, and innovation, which has 47 questions on a five-point Likert scale and was distributed among 250 staff working in start-up companies located in the science park; finally, the sample of 196 people was achieved.

In this study, descriptive and inferential methods have been used to analyze the data. Based on the analysis, out of six hypotheses, five hypotheses were confirmed and one hypothesis was rejected in the study population.

Results are:

- Business intelligence has a positive and critical influence on organizational learning. Particularly, improving business intelligence can enhance organizational learning.
- Organizational learning has a positive and critical influence on innovation. Mainly, organizational learning can increase innovation.
- Business intelligence has a positive and critical influence on innovation. Mainly, business intelligence can increase innovation.

- Following the existence of a relationship between organizational learning and the financial performance of innovative companies, the results showed a lack of connection between these two variables in the study's statistical population and this hypothesis was rejected. One of the reasons is the discrepancy between organizational maturity formed in start-up companies versus large companies.
- Business intelligence has a positive and critical influence on financial efficacy. Particularly, business intelligence can improve financial performance. This path coefficient is significant at the error level of 0.05.
- Innovation has a positive and critical influence on financial efficacy. Particularly, innovation can improve financial performance.

Despite other possible effects on "return on investment", companies with higher innovation rates are more likely to be profitable because there is innovation at work to improve business capacity to create a culture of value-added products. Better quality than competitors is critical to gaining and maintaining superior performance.

Finally, business intelligence plays a crucial role in enabling precise and well-informed decision-making, serving as a valuable instrument for gaining a competitive edge. According to Maaitah (2023), the utilization of business intelligence proactively and efficiently enables the formulation of advantageous decisions, with the primary objective being the enhancement of both the promptness and the caliber of the generated information.

The capability of business intelligence can be perceived as a source of data and information that offers a knowledge infrastructure and capabilities for knowledge processes. These capabilities include integrating, synchronizing, analyzing, disseminating, and codifying data and information (Božič and Dimovski, 2019). Organizations utilize these capabilities to enhance their internal and external business environment comprehension.

Organizations that possess business intelligence capabilities have the potential to acquire distinct, scarce, and highly valued business insights. These insights can enhance decision-making procedures and attain a competitive edge (Alzghoul et al., 2022).

There is a probable positive correlation between organizational learning and innovation. Suppose a corporation is proficient in integrating novel information and effectively communicating pre-existing knowledge. In that case, it is likely to possess a strong capacity for generating innovative outcomes, whether in the form of new products or improved processes. In addition, it has been argued that a more effective organizational learning process is positively correlated with the ability to generate significant innovations, whether they are related to products or processes (Therin, 2003).

Establishing and managing a prosperous Science Park incur significant expenses, encompassing financial investment, human resources, time allocation, and effective administration. Research infrastructures of this nature play a crucial role in facilitating integration by consolidating diverse research capabilities, including international collaboration, inside a single location.

It is posited by McCarthy et al. (2018) that there exists an assumption regarding the heterogeneity of techniques employed by parks, leading to variations in their operations within the region.

Nevertheless, the attainment of success is significantly influenced by robust collaboration, clustering, and networking among corporations, governmental bodies, municipalities, and other institutions. Establishing sustainable solutions for scientific parks necessitates a comprehensive elucidation of strategies aimed at augmenting and fortifying investments in research infrastructures, ensuring their long-term viability.

2.5. Further research proposal on the Agent-Based Model to analyze the interaction between Science Parks and start-ups

Contemporary markets and organizations exhibit intricate structures comprising diverse components that interact with one another and the surrounding environment. These interactions give rise to interdependencies across various spatial and temporal dimensions, posing challenges in comprehending, forecasting, and managing them effectively (Boisot and Child, 1999). The environment in which they operate is marked by dynamic and rapid changes across various domains, rendering them susceptible to uncertainty, systemic risks, and networked impacts (Helbing, 2013). To effectively manage challenging situations, companies must establish processes that facilitate learning, adaptation, and coevolution.

To comprehend and effectively handle the inherent intricacy within companies, it is necessary to employ solutions that surpass reliance on intuition and conventional analytical approaches (Andriani and Mckelvey, 2007). Hence, there is a requirement for novel theoretical and methodological frameworks.

In organizational theory, agent-based simulation (ABS) has gained prominence as a novel study and management approach over the last twenty years (Wall, 2016).

Nevertheless, the use of ABS in management has not been as extensive as in other fields, resulting in its potential to manage businesses remaining largely untapped effectively. It is posited that this phenomenon can be attributed, at least in part, to a deficiency of understanding regarding prior advancements in the discipline and the most promising avenues for prospective implementation.

Agent-Based Simulation (ABS) enables researchers to replicate and analyze the interactions between individuals within an organization or between companies

within a market. This allows for evaluating the collective outcomes resulting from their behavior (Fioretti, 2012). The ABS framework offers a comprehensive structure that facilitates detailed descriptions, explanations, predictions, and theories regarding organizations and their activities (Fioretti, 2012). Additionally, it promotes the advancement of tools that facilitate strategic and operational decision-making and problem-solving (North and Macal, 2007).

2.5.1. What is Agent-Based Model (ABM): main characteristics and advantages

Agent-based modeling (ABM) is a versatile simulation model comprised of autonomous agents that interact with their environment and other agents through a range of behaviors to accomplish their experimental goals (Onggo and Foramitti, 2021).

A model is a simplified depiction of a "target" system that aims to illustrate the operational mechanisms of said system accurately.

Computational methodologies, such as agent-based modeling, encompass constructing computer programs that serve as models. The program represents the processes believed to be present inside the social realm (Macy and Willer, 2002).

Agents are individual components within a program that represent social actors, such as individuals, companies, or even nation-states. The programmed entities exhibit responsive behavior within the computational environment in which they are situated, wherein this environment represents the actual context in which social actors function.

Agent-based modeling (ABM) distinguishes itself from other analytical tools due to its ability to independently simulate agent interactions (Macal, 2016). The approach employed does not build direct connections between fundamental variables; instead, it focuses on modeling interacting agents that mutually affect one another.

One possible explanation for the current surge in interest could be the growing recognition that conventional modeling methodologies are inadequate in addressing the intricate intricacies and nuances inherent in contemporary market dynamics. The concept of Agent-Based Modeling (ABM) encompasses the underlying principles of emergence, as discussed by Wilensky and Rand (2015). ABM demonstrates the manifestation of global patterns that arise from the interactions among its constituent micro-components. However, these emergent patterns cannot be readily deduced, reduced, or predicted only based on the properties of these micro-components, as highlighted by Gómez-Cruz (2017).

Agent-based modeling (ABM) possesses numerous inherent benefits when applied to the modeling of business scenarios, enabling the analysis and prediction of emergent behaviors, as well as the modeling of the underlying mechanisms that generate such behaviors. One key advantage is its ability to handle multiscale and

complex interaction structures. In many business applications, interactions occur between multiple businesses of different scales, between companies and consumers, or among individuals occupying various hierarchical levels within an organization. Furthermore, in situations where the agents are uniformly sized, it is typical for the interactions inside a model to take place on an intricate interaction structure, such as a social network. Agent-based modeling (ABM) can incorporate many levels of agency and network-based interactions within a single model.

Heterogeneity is a crucial factor in numerous commercial applications, particularly in consumer market models, where many persons with diverse characteristics are necessary. These topics may exhibit variations in personal wealth status, innovation thresholds, or product preferences. While recent advancements in equation-based and mathematical modeling have enabled the inclusion of greater levels of heterogeneity in models, agent-based modeling (ABM) continues to offer the highest degree of potential heterogeneity.

Adaptive agents refer to entities inside companies and consumer groups that exhibit non-linear behavior over time. These entities, characterized by their ability to learn and be influenced by past experiences, deviate from a consistent set of rules and instead modify their behavior based on prior acts and resulting consequences. This assertion holds particular validity when substantial incentives exist for individuals to engage in actions that maximize their outcomes. Agent-based modeling (ABM) is a distinctive methodology that enables modelers to create agents that can adjust the parameters of their governing rules and fundamentally modify the rules themselves.

Furthermore, there is an interaction between the behaviors observed at the individual agent level, also known as the micro level, and the behaviors observed at the population level, also known as the macro level. This phenomenon occurs when an individual agent's actions are impacted by a population's collective behavior, such as social norms. In turn, the population's behavior is gradually molded by the actions of the individual agents. Therefore, comprehending the actions of an agent necessitates an examination of the social context within which these agents function.

Numerous business applications are often deployed over a physical place. Agent-based modeling (ABM) facilitates the straightforward incorporation of physical geography as an operational environment for agents. Previous studies have demonstrated the efficacy of ABM in comprehending intricate phenomena associated with geography and urban development (Benenson and Torrens, 2004; Batty, 2005).

An agent is an entity capable of autonomously making decisions to accomplish its goals. These decisions can manifest as observable actions that involve sharing information and utilizing shared resources from the environment. Alternatively, decisions can also affect modifying internal attributes of an agent, such as altering the level of trust in another agent or adjusting the level of satisfaction with a particular service. The behaviors above are not readily perceivable by external entities. Agents possess autonomy, retaining a memory to

store past states and activities, as well as a collection of rules, heuristics, or strategies. These components enable agents to select their subsequent course of action based on their current circumstances and historical data. Therefore, an agent-based model (ABM) lacks a centralized controller responsible for coordinating the actions of individual agents. Every individual agent can autonomously make decisions. The interactions among agents can give rise to a distinct pattern that manifests at the collective level, commonly referred to as emergent behavior.

The second element within an Agent-Based Model (ABM) encompasses the virtual world where agents reside, which may take the form of either a spatial or relational structure. The spatial environment pertains to the geographical setting where an agent resides, whereas the relational environment encompasses the interconnections among agents, such as social networks or supply chain networks. The environment holds significant relevance inside an Agent-Based Model (ABM) due to its potential to influence the agents and their corresponding actions.

Moreover, the environment can serve as a conduit for the interactions among agents, explicitly referring to the indirect interactions between individuals. In this scenario, one agent has the potential to modify the environment, hence exerting an influence on other agents. The alterations will impact the decision-making processes of other individuals residing in both the previous and current communities.

NetLogo is widely regarded as the leading agent-based simulation environment at now.

The objective is widely considered the most crucial element, as any inaccuracies in its formulation might result in a significant misallocation of resources towards solving an incorrect problem within the context of simulation modeling. The aims in the context of ABMS can be categorized into two distinct groups.

In this particular category, the aim is to investigate the potential outcomes at the macro level by utilizing existing knowledge of micro-level behaviors exhibited by interacting entities. Therefore, we are exploring the consequences of established mechanisms and behavior at the individual level on the behavior of a larger, unidentified population. Thus, agents are programmed to exhibit specific experimentation behaviors within the context of Agent-Based Modeling (ABM). These agents are then allowed to interact with other agents, and the resulting emergent behavior at the population level is observed and analyzed. The utilization of deductive reasoning characterizes this particular category.

This study aims to investigate the relationship between micro-level behaviors of individual agents and macro-level phenomena to explain a known population behavior. The hypothesis being tested is that the observed behavior at the macro level may be attributed to specific behaviors shown by the individual agents. Put simply, our objective is to comprehend the individual-level mechanisms or behaviors that account for a recognized behavior or occurrence at the population

level. This particular category presents a more significant difficulty due to the utilization of abductive reasoning.

The outputs are intricately connected to the target, as they estimate key performance indicators (KPIs) that facilitate the attainment of our objective.

The inputs refer to the experimental factors that can be manipulated to get insight into their impact on the outcomes. The inputs in this context can consist of decision variables, which represent designs or policies that are within the decision maker's control.

They can also include uncontrollable variables, representing external circumstances that are usually beyond the decision-maker's control.

AgentPy is a freely available software library designed to develop agent-based models (ABMs) using the Python programming.

The software is designed to be very efficient for interactive computing using Jupyter Notebooks. It provides a range of capabilities that cater to diverse scientific applications, such as parameter sampling, conducting experiments across numerous runs, facilitating interactive simulations, analyzing stochastic processes, and doing sensitivity analysis (Foramitti, 2021).

2.5.2. Agent-Based Model (ABM) evaluation process: calibration, verification and validation

Agent-based complexity models necessitate meticulous and comprehensive assessment, encompassing the processes of calibration, verification, and validation (Manson, 2003). Calibration refers to the process of optimizing the parameters and specifications of a model to align with specific theories or empirical facts. The verification process is crucial in assessing the alignment between the model's execution and its intended design. Agent-based models (ABMs) rely heavily on computer code, inherently prone to programming errors. Model verification often involves executing the model using simulated data and conducting sensitivity testing to assess whether the resulting output aligns with anticipated outcomes. Validation entails assessing the accuracy and reliability of model outputs by comparing them to real-world observations or the outcomes generated by alternative models. This evaluation is frequently conducted through statistical techniques and geo-visualization analysis.

Verification refers to the assessment of whether a program is functioning by the researcher's expectations. On the other hand, validation pertains to the evaluation of whether a simulation adequately represents the natural system, sometimes referred to as the 'target'. A model that can accurately represent the target's behavior is said to be "valid." One prevalent approach to model validation is the juxtaposition of simulated outputs with empirical data obtained from the target system.

Regarding calibration, there exists a variety of optimization methods (Fletcher, 2000). However, the genetic algorithm (GA) is a particularly suitable approach for this task due to its unique characteristics, such as the ability to conduct a parallel search across a vast solution space (Holland, 1992). A genetic algorithm (GA) utilizes the concept of "survival of the fittest" from the domain of genetics to a group of individuals or solutions that are in competition with each other inside a specified environment known as the search space (Soman et al., 2008).

In the context of the Genetic Algorithm (GA), the Root Mean Square Error (RMSE) is widely employed as a fitness or error metric (Chatfield, 1992). This choice is primarily attributed to its ability to quantify the amount of mistake instead of relative error percentages (Armstrong and Collopy, 1992).

This statistical measure quantifies the squared discrepancies between the simulated or predicted values and the observed or reference values as follow:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_{1,i} - x_{2,i})^2}{n}}$$

The expression $(x_{1,i} - x_{2,i})$ represents the discrepancy between variable i obtained from data source 1 (the simulated result) and data source 2 (the reference or actual data). The variable n denotes the total count of variables. The root mean square error (RMSE) is a comprehensive metric for evaluating performance by consolidating all individual discrepancies into a singular indicator of predictive capability.

2.5.3. Simulation of an Agent-Based Model (ABM) application to Science Parks and start-ups interactions

Agent-based models (ABMs) offer a flexible and dynamic framework for conducting a complete analysis of the complex and diverse interactions between Science Parks and start-up enterprises and the subsequent effects that arise from these interactions. Science parks are intricate ecosystems that facilitate innovation development, the interchange of knowledge, and entrepreneurial endeavors.

Agent-based models (ABMs) can encompass the intricacy of the situation by simulating various actors, including start-ups, researchers, and investors. Each agent is endowed with its unique qualities, strategies, and ambitions.

The functioning of these models is based on establishing rules, behaviors, and decision-making processes that govern the interactions between agents inside the Science Park environment.

For example, start-up companies may actively pursue partnerships with researchers, avail themselves of shared research facilities, or compete to secure financial support from potential investors.

ABMs can be utilized by researchers to investigate diverse scenarios by manipulating parameters to examine distinct results, including the formation of prosperous clusters, the developmental paths of start-ups, and the impact of particular policies on the dynamics of innovation and regional economic advancement. Agent-based models (ABMs) allow researchers to simulate and conduct experiments on the intricate and non-linear connections between different agents and elements. This allows for the acquisition of valuable insights into the operations of Science Parks and their contribution to the promotion of innovation and entrepreneurship within a broader regional framework.

Agent-based models (ABMs) contribute to comprehend the dynamic characteristics of Science Park ecosystems by offering a versatile and adjustable methodology. Consequently, ABMs assist policymakers and scholars in making well-informed decisions and undertaking thorough evaluations of the effects of these ecosystems.

So, in the context of Science Parks, Agent-Based Models (ABMs) can play a crucial role in facilitating an in-depth comprehension of the operations of start-ups and other players within these ecosystems.

In this analysis, we will delve into an examination of how Agent-Based Models (ABMs) might be effectively employed in the context of this particular case:

- 1. Modeling the ecosystem:** a Science Park is characterized by an extensive range of participants, such as start-ups, researchers, financiers, companies, and support organizations. Agent-based models (ABMs) can represent many entities as agents, each possessing unique properties, actions, and aims.

Start-up enterprises typically pursue various resources, collaborations, and opportunities for expansion, whereas investors tend to seek out prospective ventures. Researchers' primary objective is to enhance the acquisition and dissemination of knowledge and facilitate the transfer of technology.

To achieve this goal, park management plays a crucial role by providing necessary infrastructure and support services. Agent-based models (ABMs) can effectively represent and simulate the many functions and interactions exhibited by agents within the Science Park.

- 2. Dynamic Interactions:** Science Parks exhibit distinctive features including ongoing interactions, feedback mechanisms, and changing partnerships. Agent-based models (ABMs) demonstrate a high level of proficiency in capturing dynamic processes of interest.

The agents within the model can independently make decisions according to their aims and adjust their methods accordingly in light of evolving circumstances.

This capability allows for the modeling of intricate scenarios, such as the impact of rivalry on the innovation paths of start-ups or the emergence and evolution of collaborative networks over some time.

3. **Policy experiments:** frequently implemented within the context of Science Parks, which are characterized by the presence of diverse policy frameworks and incentives. Agent-based models (ABMs) provide a platform for conducting experiments to explore various policy interventions and assess their possible implications.

Researchers can modify parameters to replicate the impacts of multiple policies, such as tax incentives aimed at promoting start-ups, research funding, or initiatives that facilitate cooperation across different sectors. These experiments can provide policymakers with valuable insights into the potential consequences and trade-offs linked to various policy alternatives.

4. **Spatial considerations:** these play a significant role in establishing Science Parks, as their geographical location and the spatial distribution of resources and agents are of utmost importance.

Agent-based models (ABMs) can integrate spatial components, enabling the simulation of the park's physical arrangement, infrastructure accessibility, and the impact of geographic proximity on patterns of collaboration. Understanding how Science Parks contribute to regional development and innovation clusters necessitates a thorough awareness of the geographical dimension involved.

5. **Data-Driven Modeling:** Agent-Based Models (ABMs) can incorporate empirical data, enabling the integration of real-world information to inform agent behaviors and parameterization.

Academic researchers can utilize historical data pertaining to the success rates for start-up ventures, patterns of funding, and networks of collaboration to construct more accurate models and verify their findings through empirical observations.

6. **Scenario Analysis:** Agent-based models (ABMs) facilitate the conduct of scenario analysis, providing researchers with the opportunity to investigate hypothetical inquiries. Consider the scenario where a Science Park transitions in its strategic orientation, shifting its primary emphasis from biotechnology to clean energy.

What potential effects could this have on the composition of start-ups that choose to establish themselves within the park and the overall innovation ecosystem of the region?

7. **Stakeholder interaction:** Agent-based models (ABMs) have the potential to enhance stakeholder interaction and provide decision assistance.

By actively engaging essential stakeholders in developing the model, researchers can obtain valuable insights into their viewpoints and apprehensions, improving the efficacy of Science Park management and the design of policies.

Thus, agent-based models (ABMs) present a robust and adaptable methodology for simulating Science Parks and their dynamics with start-ups. These models can comprehend the intricacy of these ecosystems, facilitate policy analysis, and enable stakeholders to make well-informed selections regarding the management and advancement of Science Parks as drivers of innovation and economic prosperity.

In the following analysis, the given Python code (Fig. 11) that applies the AgentPy library will be examined to present a prototype agent-based model (ABM) for examining the interaction dynamics between, for example, an Italian Science Park and start-ups. This model considers budget indices, employment rates, innovation rates, and their influence on the surrounding region.

Figure 11: Prototype Agent-Based Model (ABM) for Science Park and start-ups interaction

```

import agentpy as ap
import numpy as np
import matplotlib.pyplot as plt

# Define model parameters
parameters = {
    'num_startups': 50,
    'initial_budget_mean': 500000,
    'initial_budget_std': 100000,
    'innovation_rate': 0.1,
    'num_runs': 10 # Number of model runs for comparative analysis
}

# Define the agent behavior
class StartupAgent(ap.Agent):
    def setup(self):
        # Initialize startup attributes
        self.budget = np.random.normal(parameters['initial_budget_mean'],
                                       parameters['initial_budget_std'])

        self.innovation = False
        self.roe = self.random.uniform(0.1, 0.3) # Random ROE for demonstration
        self.roa = self.random.uniform(0.05, 0.15) # Random ROA for demonstration
        self.ros = self.random.uniform(0.08, 0.2) # Random ROS for demonstration
        self.tobins_q = self.random.uniform(0.5, 2.0) # Random Tobin's Q for demonstration
        self.patents = 0 # Number of patents

    def step(self):
        # Simulate the behavior of startup agents
        if self.random.uniform() < parameters['innovation_rate']:
            self.innovation = True # Start-ups may introduce innovation
            self.patents += 1 # Increase the number of patents when innovation occurs

# Create the model
class ScienceParkModel(ap.Model):
    def setup(self):
        # Initialize the agent population
        self.agents = ap.AgentList(self, parameters['num_startups'], StartupAgent)
        self.park_members = ap.AgentList(self) # List to track start-ups in the Science Park

    def step(self):
        # Calculate aggregate statistics
        total_budget = self.agents.sum('budget')
        employment_rate = len(self.park_members) / parameters['num_startups']
        innovation_rate = self.park_members.mean('innovation')
        impact_on_territory = total_budget * innovation_rate
        total_patents = self.park_members.sum('patents') # Sum of all patents produced

        # Record statistics for each time step
        self.record('Total Budget', total_budget)
        self.record('Employment Rate', employment_rate)
        self.record('Innovation Rate', innovation_rate)
        self.record('Impact on Territory', impact_on_territory)
        self.record('Total Patents', total_patents) # Record the total number of patents

        # Record financial indicators for each time step
        avg_roe = self.agents.mean('roe')
        avg_roa = self.agents.mean('roa')
        avg_ros = self.agents.mean('ros')
        avg_tobins_q = self.agents.mean('tobins_q')
        self.record('Average ROE', avg_roe)
        self.record('Average ROA', avg_roa)
        self.record('Average ROS', avg_ros)
        self.record("Average Tobin's Q", avg_tobins_q)

# Perform multiple model runs and store results
results = []
for run in range(parameters['num_runs']):
    model = ScienceParkModel(parameters)
    results.append(model.run())

# Extract and analyze results over time
time_series_data = {} # Dictionary to store time series data for each run

for run, result in enumerate(results):
    time_series_data[run] = {}
    for variable in ['Total Budget', 'Employment Rate', 'Innovation Rate', 'Impact on Territory',
                    'Total Patents', 'Average ROE', 'Average ROA', 'Average ROS', "Average Tobin's Q"]:
        time_series_data[run][variable] = result.record(variable)

# Plot comparative analysis over time for all variables
variables_of_interest = ['Total Budget', 'Employment Rate', 'Innovation Rate', 'Impact on Territory',
                        'Total Patents', 'Average ROE', 'Average ROA', 'Average ROS', "Average Tobin's Q"]

for variable in variables_of_interest:
    plt.figure(figsize=(10, 6))
    for run in range(parameters['num_runs']):
        plt.plot(time_series_data[run]['Time'], time_series_data[run][variable], label=f'Run {run + 1}')
    plt.title(f'Comparative Analysis of {variable} Over Time')
    plt.xlabel('Time')
    plt.ylabel(variable)
    plt.legend()
    plt.grid(True)
    plt.show()

```

Source: own processing

This Python code is a simulation model using the Agent-Based Modeling (ABM) framework to study a kind of interaction between start-up companies and a Science Park, considering some example hypothetical variables to have an exemplary representation of how this model works.

1. **Model Parameters:** it starts by defining various parameters for the simulation, such as the number of start-up companies, their initial budget distribution (mean and standard deviation), the innovation rate, and the number of simulation runs.
 - “**num_startups**”: Number of start-up companies in the simulation.
 - “**initial_budget_mean**”: Mean value for the initial budget of start-up companies.
 - “**initial_budget_std**”: Standard deviation of the initial budget.
 - “**innovation_rate**”: Probability of a start-up introducing innovation in each time step.
 - “**num_runs**”: Number of simulation runs for comparative analysis.
2. **Startup Agent Behavior:** Each start-up company is represented as an agent with specific attributes. In the “**StartupAgent**” class, agents are initialized with budgets drawn from a normal distribution, and they have a chance to introduce innovation during each time step based on the specified innovation rate. Additionally, random values for financial indicators like ROE, ROA, ROS, and Tobin’s Q are generated for each startup agent. There’s also a new attribute, “**patents**”, to keep track of the number of patents produced by each start-up.
 - “**setup()**”: Initializes the agent’s attributes.
 - “**step()**”: Defines the agent’s behavior during each time step, including the increase in the number of patents when innovation occurs.
3. **Science Park Model Setup:** The model is set up in the “**ScienceParkModel**” class. It includes creating a population of startup agents (“**self.agents**”) and an empty list (“**park_members**”) to track the start-ups that join the Science Park.
 - “**setup()**”: Initializes the agent population and the list to track park members.
 - “**step()**”: Defines the model’s behavior during each time step, including the calculation of the total number of patents produced.
4. **Model Simulation:** During each time step in the simulation, the model calculates aggregate statistics such as the total budget, employment rate (percentage of start-ups in the park), innovation rate (percentage of start-ups introducing innovation), impact on the territory (a function of the total budget

and innovation rate) and the total number of patents produced. These statistics are recorded over time.

- **“step()”**: Calculates and records aggregate statistics, including the total number of patents produced, and financial indicators for each time step.
5. **Recorded Variables**: The code records various variables over time, including financial indicators like ROE, ROA, ROS, and Tobin’s Q, as well as the aggregate statistics mentioned earlier and the total number of patents produced.
 6. **Multiple Model Runs**: The code then performs various runs of the model (as specified by **“num_runs”**) to capture variation and uncertainty. The results of each run are stored in the **“results”** list.
 7. **Time Series Data**: The recorded data from each run, including the aggregate statistics, financial indicators and the total number of patents produced are organized into a **“time_series_data”** dictionary for further analysis.
 8. **Plotting Comparative Analysis**: Finally, the code plots comparative analyses for all recorded variables over time for each run. This allows for a visual examination of how these variables evolve during the simulation, providing insights into the interaction between start-ups and the Science Park, the impact on financial and non-financial metrics, and innovation in terms of patents produced.

Potential results and interpretations of this agent-based simulation model on the dynamics of start-up companies and Science Parks over time are the following:

1. **Total Budget**: Over time, the total budget of all start-up companies may fluctuate, reflecting financial changes within the ecosystem. A growth trend might indicate the park's success in attracting and nurturing start-ups.
2. **Employment Rate**: The employment rate (percentage of start-ups in the park) can indicate how attractive the science park is to start-ups. An increasing employment rate suggests that more start-ups are joining the park.
3. **Innovation Rate**: Tracking the innovation rate (percentage of start-ups introducing innovation) can provide insights into the park's role in fostering innovation within start-ups. An increasing innovation rate may positively impact the park's resources and environment.
4. **Impact on Territory**: The impact on the territory, calculated as the product of the total budget and innovation rate, measures the economic influence of

the science park on the surrounding area. A higher impact indicates a more substantial economic contribution.

5. **Financial Indicators:** The simulation also considers financial indicators like ROE, ROA, ROS, and Tobin's Q for start-ups. Comparing these indicators before and after joining Science Park can reveal the impact of park membership on start-up financial performance. After entering the park, improved financial indicators may suggest the park's value in enhancing start-up profitability and efficiency.
6. **Total Patents:** Tracking the total number of patents produced over time can help assess the science park's impact on innovation within start-up companies. An increasing trend in total patents suggests that the park fosters a culture of innovation among its members.

By visualizing these variables and conducting comparative analyses, the model can help stakeholders, policymakers, and researchers better understand the dynamics and potential outcomes of start-ups and Science Parks interactions. It provides a valuable tool for exploring different scenarios and strategies to optimize the performance of Science Parks in fostering innovation and economic development, considering both financial and innovation-related variables.

Hence, it can be concluded from the exemplification provided in the simulation that agent-based models (ABMs) provide a simulated laboratory environment that facilitates the integration of theoretical and empirical investigations for researchers. Although agent-based modeling (ABM) encounters various obstacles in terms of calibration, verification, and validation, it presents novel perspectives on the interplay between data and theory, as well as the relationship between pattern and process.

The advancement of complexity and agent-based models (ABMs), both alone and in conjunction, is contributing to the development of our understanding of scale in various complex systems. This progress includes sensitivity, nonlinearity, resilience, equilibrium, and change considerations. ABMs, in conjunction with other methodologies, exhibit significant potential as a strategy for the modeling and comprehension of decision-making processes.

CHAPTER 3

Backcasting and new research challenges: a study on emerging technologies by using literature reviewing in a blockchain system

3.1. Introduction

Procedures and methods that consistently monitor and identify emerging trends from scientific publications are required, given the quickly evolving nature of scientific research.

Because of their significant potential for socio-economic effects, emerging technologies have recently attracted more attention from research and development departments, academic publishing organizations, and policymakers. The planning of scientific dissemination activities is another area where early trend detection is essential.

Conference planners must comprehensively understand emerging trends to find hot themes for calls for papers and hire knowledgeable reviewers.

However, new technologies are characterized by uncertainty and ambiguity because their future influence is unknown and little agreement exists about their potential.

According to Kishita et al. (2017), backcasting scenarios can be used to imagine desirable futures with discontinuous change from the present in mind, with particular attention to the concept of resilience, which is crucial for creating visions of desirable futures designed to withstand the widest variety of shocks external to the system.

The authors proposed a method to design backcasting scenarios to allow a systematic process of predicting resilient futures; however, they also point out that there are still several open challenges concerning the practical application of the proposed method.

By extending the backcasting approach in the design of desirable future scenarios in different sectors (including primarily the choice of investment in certain emerging technologies), the sharing of knowledge between experts and

other stakeholders (as the industries themselves) would significantly increase the value of this decision-making process support tool to the point of being able to influence the most functional choices concerning what is identified as a desirable future.

Moreover, the emergence of new technologies is a significant and intensively studied area. The research by Park et al. (2022) identifies the characteristics of the early stage of technological emergence by analyzing the early patents in five different technologies.

The research's primary finding is that technological and scientific knowledge are strongly intertwined in the emerging stage, as early patents in all five technologies cite scientific papers more frequently than patents that support the continued development of technologies.

Furthermore, most of the patents are granted to firms. In contrast, the proportion of non-firm patents in the early stage of the technological domain is relatively higher than that of the other periods, consistent with the more significant role of scientific knowledge in the emerging scene.

Their results reveal crucial theories concerning the link between scientific accomplishments and technical innovation that were not previously offered and can be studied further as data sources improve.

Considering the limitations expressed by the authors of that research, the methodology exposed in the present work could, instead, provide a suitable tool for the upstream selection of the optimal scientific material for the subsequent scanning of the patent connections and their next technological evolution in companies concerning the literature considered and suitably filtered in advance.

Therefore, in the present research, we will suggest a new method that combines the backcasting approach for identifying the desirable future of emerging technologies as a systematic tool to support the related decision-making process and the analysis of the scientific literature corresponding to the emerging technologies under investigation, through Natural Language Processing (NLP) algorithms to analyze large amounts of linguistic data, cluster them and obtain a ranking (among emerging, frontier and dominant technologies) within a blockchain that guarantees transparency and correctness of the process.

Existing solutions based on citation analysis are less suitable for contemporary analysis of emerging trends because citation analysis cannot be applied until documents have sufficient circulation to be cited, i.e., not in the immediate time frame, which is a relevant aspect for companies since the timeliness of innovation in the market is a fundamental variable.

This is why it is preferable to resort to an analysis of the narrative and systematic literature, appropriately filtered as will be illustrated in the methodology, to identify the best path from a backcasting point of view that the company can adopt to implement the technology that will be more effective and sustainable.

Furthermore, to guarantee the desired sharing of scientific knowledge and that the network thus generated is valid and unalterable, it is proposed to introduce a blockchain system in the company that integrates the intra-muros R&D function.

3.2. Literature Review as Research Methodology

Before this, relevant literature should be considered for all research fields and projects. When reading an article, regardless of discipline, the author discusses past research to map and appraise the research area to motivate the study's goal and justify the research question and hypotheses.

To become a proper research methodology, like any other research, necessary procedures must be performed and action must be taken to ensure the review is exact, precise, and trustworthy.

The researcher can employ a variety of methodologies, standards, and guidelines designed specifically for performing a literature review, depending on the review's goal. (Snyder, 2019)

To develop the procedures and to achieve the results of this paper, we examine two reviews of the literature:

- Systematic review
- Narrative review

3.2.1. Systematic Review

Systematic reviews may answer research questions, summarize issues and assess topic knowledge, set research goals, find gaps and discuss a topic. (Tranfield et al., 2003).

Systematic reviews can also analyze data from an alternate present to various plausible bifurcation sites and routes and findings from an alternative present. A systematic review could create a new theoretical model and track a study problem in these cases.

We can determine if an effect is consistent and if more research is needed. Techniques can also reveal which study-level or sample characteristics affect the issue, such as whether study in one sociocultural environment gives statistically diverse results from those in others (Davis et al., 2014).

A publishable review requires multiple steps and decisions (for specific considerations with respect to each phase):

1. Audience interest determines the review topic: it's best to scan the case first to evaluate previous literature reviews, estimate the number of research papers to be assessed, and define the review's objective, scope, and study

issue. Create a literature search plan after choosing the study question and general review technique.

2. Review the aim, research questions, and procedure: pre-evaluate search phrases and inclusion criteria. Evaluation type and scope determine sample selection.
3. Analyzing the review: article evaluation is crucial after systematic review and sample selection. Select a sample and consistently extract meaningful information from each article. The review's purpose and topic determine this.
4. Writing up the review: justify the assessment first. The technique may require varied facts and depth in the review piece. PRISMA was developed for systematic literature reviews and meta-analyses; RAMSES was designed for systematic narrative reviews (Wong et al., 2013); and guidelines for integrative reviews were developed by Torraco (2005).

These guidelines cover literature review reporting and structure. Then, discussing review progress and literature collection is crucial. Authors must describe how they found, studied, and created literature.

3.2.2. Narrative Review

Most articles reporting empirical research, grant applications, and, of course, many articles and book chapters are devoted mainly to reviewing the literature on a particular topic. Therefore, narrative reviews are an essential component of all these types of writing.

Narrative reviews offer a conceptual overview of the topic. Such reports may be better suitable for specific questions and may give short, useful guidance. This paragraph discusses the contemporary significance of narrative reviews. Narrative reviews are written from the narrator's perspective, capable of providing an explanatory review of the current literature in the topic.

According to Sarkar and Bhatia, the advantages of narrative reviews are (Sarkar and Bhatia, 2021):

- Gives an expert's perspective on the subject, preventing information overload and focusing attention on the most important facts and topics.
- The proof is presented understandably. Such assessments try to convey the information in an accessible way, emphasizing the valuable discoveries.
- It is useful to present a summary of the literature when the evidence is scarce, scattered, or clear objectives for the topic are difficult to formulate.

The following are the disadvantages, according to the same authors:

- may influence (bias) the selection of material.
- may miss out some relevant findings.

Literature reviews help when evidence is scant, fragmented, or issue objectives are unclear. So, experts can assess the evidence and point out flaws and clarifies results.

A narrative review, like a systematic review, requires multiple steps to complete and, on the other hand, allows for far greater flexibility.

In this paper, we consider two standards while producing a narrative review:

- the simple collation of the selected articles (handout of selected research papers);
- the synthesis of the evidence that has been selected in a structured manner.

First, decide what questions the review will address, the criteria for the literature search, and the flexibility in choosing databases, search terms and combinations, identification criteria and thresholds, information extraction procedures, and data synthesis and implication methods.

Instead of summarizing literary findings, authors should highlight themes and compare and contrast. A trusted expert could review the manuscript. In-house evaluation and improvement may benefit.

Therefore, the process may lead to the following outcomes: a structured representation of the chosen articles or a simple collection of the chosen articles.

3.2.3. Past-Facing and Future-Facing Approaches

Long-term planning requires a dependable way to predict and change future events.

Operational environment dynamics and technology-induced changes—which are interrelated—present the biggest opportunities and threats to the organization's survival in both cases. Thus, a well-calibrated organization must be imagined.

Today's choices will last. Big decisions should regard the future and visionary states need future scenarios.

Forecasting optimizes organizational and labor policy. A forewarned plan permits proactive response to near-to medium-term opportunities and risks. Forecasting helps companies stay ahead by managing risk and it can somewhat enable this, however validation and replication methods are becoming insufficient to validate forecasts in the near future. This contributed to the creation of the backcasting process (Dortmans, 2005).

Bendor et al. (2021) assess several ways and depict the future of landscape as a two-dimensional interaction of activity concentration on goals or paths and stakes.

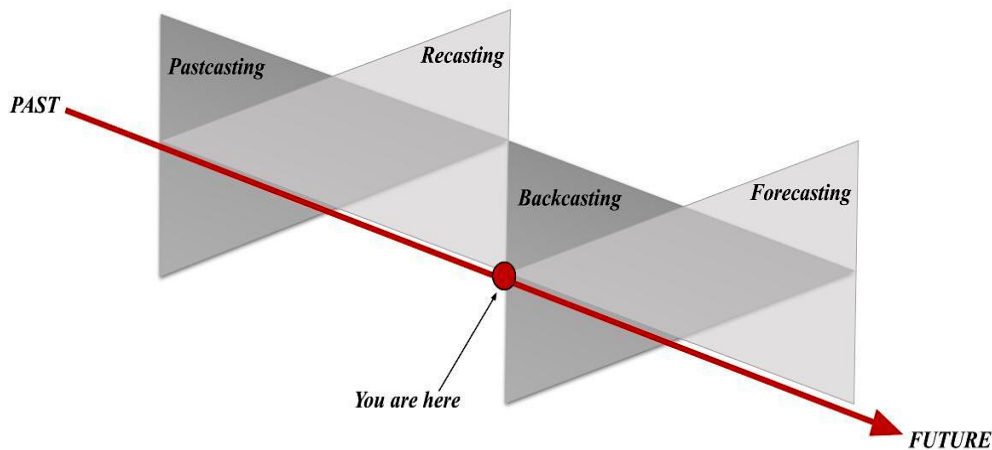
Future data—the building blocks of the future—comes from the past, making their task cliché. Few futuring procedures explicitly engage the past, but all do. Forecasting, backcasting, recasting, and pastcasting are foresight methods that shape futuring. Recasting imagines a new present, while forecasting predicts the future. Backcasting explores future possibilities to discover paths from the present to a preferred future, while pastcasting starts with a favored present and examines how past possibilities could have led to that present (Fig. 12).

These four futuring methodologies can examine the activity's results and stakes. Backcasting and pastcasting, the current study's symmetries, appear to be convergent and suited for examining numerous routes to a desirable future or present, pluralizing past and current stakeholders' voices.

Past and future methods have different stakes; prediction is riskier than recasting. The past is less changeable than the future, making it harder to modify.

So, while backcasting can help futures researchers and practitioners gain a better understanding of future change levers, pastcasting can help them uncover the conditions, assumptions, barriers, and opportunities that influenced the realization of past-futures, thereby informing, inspiring, and preparing future-facing actions (Bendor et al., 2021).

Figure 12: Schematic representation of Past-Facing and Future-Facing Approaches



Source: Bendor et al. 2021

3.2.4. First symmetry: Forecasting and Recasting

Forecasting: a typical forecast begins with a (near) current state and projects to a future state, which typically refers to land-use changes that may occur during a specific period. All futuring tactics that aim to “systematically explore the possibilities that lie ahead” use forecasting as an example (Whiston, 1979). Forecasting multiplies a predicted future into several feasible options. Forecasting has lost its promise of scientific impartiality due to ideological, organizational, methodological, and human biases after its popularity after the Second World War (Cole, 1979). In addition to this, there is a growing realization that forecasting influences not only the present, but also the very futures that it aims to unfold (van Lente, 2012; Mallard, 2011). Forecasting helps us see the future as a growing set of options to explore, assess, and navigate, guiding technological and policy innovation.

Recasting: it refers, in its most fundamental sense, to the process of reconstructing the present. It makes use of methodologies for forecasting that begin with a condition that was established in the past and projects to the current state, typically for the purpose of comparison (from a projected current state to the actual state).

This kind of analysis is helpful for calibrating instruments and acquiring a comprehension of a condition that was unknown in the past but has become apparent in the current state.

Recasting, unlike anticipating, finds “tracks not taken” that could have changed the present. It involves testing simulation models using historical datasets, interpreting their output in light of real events, and publishing the results. The use of recasting in some form has already been used by futurists in order to improve upon previously conducted exercises geared toward the future, but it has also been put to use in order to model and decrease risk (Woo, 2019). Recasting lets futuring activities explore hypothetical histories that (did not but could have) taken place to motivate them.

3.2.5. Second symmetry: Backcasting and Pastcasting

Backcasting: The backwards version of forecasting, in which the model begins from some point in the future and then plots a course of development leading up to the present status quo. This is helpful for mapping out a pathway that provides answers to questions such as “how do we get there?”.

Although projections are frequently used in scenario planning procedures, it is not necessary for analysis, modeling techniques, or mental processes to follow that timeline (moving forward in time) to design or effectively explain a scenario.

Backcasting, the method of beginning an analysis from a desired future state and examining the route to get there, has been proven to be very helpful.

The objective of forecasting is to identify a set of probable or possible futures; the aim of backcasting is to have a clearer understanding of the range of possible developmental paths leading to an ideal future. “Generating a desirable future and then looking backward from that future to the present to strategize and plan how it could be achieved” (Vergragt and Quist, 2011).

Whereas forecasting attempts to pluralize the future, backcasting tries to pluralize paths to the future. As a result, where forecasting appears to be divergent, backcasting seems to be convergent, giving the cone representing it its distinctive shape and orientation.

Then, it is possible to define backcasting as imagining a favorable future and then working backward from that future to the present to formulate a strategy and arrange a plan for how it might be attained.

Backcasting analyses are primarily characterized by their focus on achieving desirable futures rather than plausible futures. It involves “going backward” from a specific future end-point to the present to determine what measures would be necessary to achieve that future and is thus explicitly evaluative. Backcasting adds a focus on desirability to forecasting’s emphasis on plausibility (otherwise, it remains only fantasy or creative speculation). Concerns about probability are shifted away from the future and toward “the degree of freedom of action.” (Robinson, 1982).

Pastcasting: This study begins with a present time point (often a virtual, improved “now”) and traces a developmental path backward.

Pastcasting creates fictional paths, representing a non-factual historical bifurcation that could have transformed the present. Pastcasting, unlike forecasting and recasting, works backward from a chosen alternative present to various bifurcation points and trajectories.

Pastcasting, like recasting, enables planners to compare projected and actual spatial planning outcomes.

It evaluates implementation while recasting compares model predictions and results: “We journey from what planners envisioned for a present scenario to earlier time points to determine where the developmental pattern strayed from the planned path” (Deal et al., 2017). They found that pastcasting and recasting can assist planners and communities in avoiding mistakes. Reevaluating old goals can also help rank new tactics.

Backcasting is commonly used to forecast complicated long-term challenges encompassing many facets of society, technical advancements, and developments. The focus is on a perceived major social issue, such as technological advancement.

Given this starting point, the following characteristics favor backcasting:

- when the problem to be studied is complex, affecting many sectors and levels of society;
- when there is a need for significant change, i.e., when marginal differences within the existing order will not suffice;
- when dominant trends are part of the problem—these trends are often the cornerstones of forecasts;
- when the problem is essentially a matter of externalities which the market cannot control.

As a result, the backcasting approach aims to broaden perspectives of potential solutions among diverse players and emphasize the societal effects of strategic choices (the opening or closing of future options).

Each alternative must look cohesive, and the analysis of the implications must be convincing. The data might then be used as scientific material, allowing actors with varied values and purposes to establish an opinion and vision of the future. (Dreborg, 1996).

So, from a purely business point of view, backcasting allows companies to contain switching costs related to technological transitions and to maximize existing knowledge advantages and benefits by using all resources already integrated into companies.

Finally, Sanford (2019) distinguishes between the “instrumental future” which explores present untapped and abstract desires and the “lived future” which relies on society’s imagination future and social interactions’ material and dynamic features. This last picture of the future is like the backcasting approach we intend to use in this research. Sanford suggests it to develop future research that aims to have a positive social impact by engaging with the past through linked interests and values. To keep their earlier experiences relevant, future academics interested in understanding and developing care-related futures and context-specific interests should interact with these.

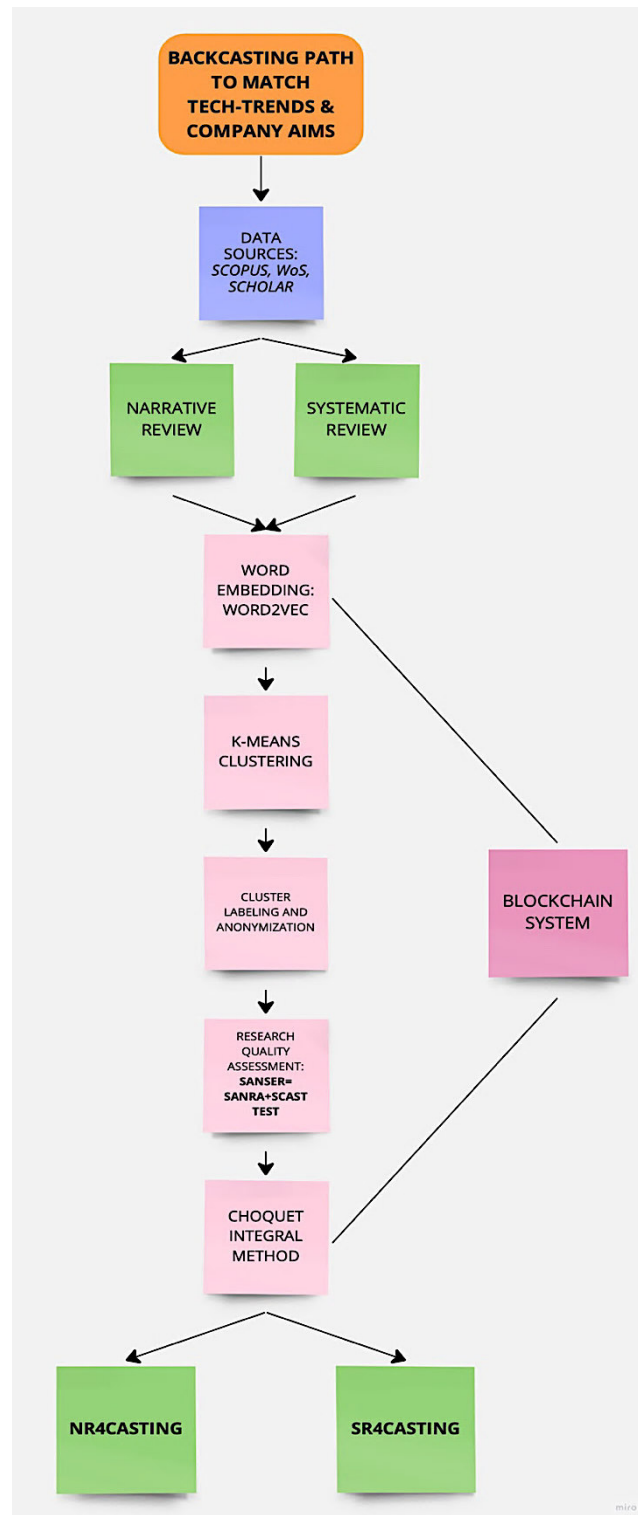
3.3. Methods And Tools

Here, the specific challenge is maximizing the validity (i.e., trustworthiness) of qualitative systematic reviews that provide new information and theories.

This viewpoint views literature searches as open-ended iterative processes that allow the topic or research question of interest to be refined over time as the nature of the evidence becomes more apparent. Most of the time, a select few pertinent documents are initially picked for inspection, and searching then begins with these critical documents.

The following diagram (Fig.13) illustrates all the steps of the new methodology proposed by this study.

Figure 13: Conceptual Model



Source: own processing

3.3.1. Search strategies and data sources

It is crucial to consider the general nature of qualitative investigations before conducting a knowledge-building or theory-generating qualitative systematic review. Generally speaking, context-related research questions are the primary driving force behind single qualitative studies. As a result, the contextual characteristics of the subject under research are carefully shaped into each qualitative study throughout the stages of problem identification, data gathering, and analysis. These characteristics include gender, culture, class, geography, and other topics.

Therefore, the goal is to provide qualitative findings that are firmly based on the opinions and experiences of the research subjects. Choosing a topic and a body of related research reports that support and justify a review is the responsibility of the R&D area of each company.

To adequately support analysis, interpretation, and synthesis across studies, there must be enough topic-specific and contextually rich qualitative research reports. Sometimes, there may not be enough studies to support a thorough analysis.

In other cases, several reports on the same issue might be accessible. Still, they might not contain enough in-depth explanation to develop concepts and their links with one another completely.

In conclusion, when data are being gathered for knowledge-building or theory-generating qualitative systematic reviews, there seem to be two significant risks to reliability.

The first entails a complex collection of research reports not cohesively linked by carefully formulated research questions and subjects. The best course of action in this case might be to refine the sample to align with the original research topic and questions.

The second issue, on the other hand, is when there aren't enough studies—or not enough descriptively rich studies—to produce saturated findings.

The process of searching the literature is a dynamic one that requires ongoing oversight and frequent recalibration. Bates described a broad technique for searching for literature consistent with thorough searching. As a result, the researcher browses as he or she catches glimpses, samples, evaluates, and obtains or discards information.

Casual surfing may halt as phenomena of interest emerge, populations of importance become evident, contextual components take shape, formative research questions are identified, and more focused searches may occur. Key search concepts arise as research questions become more logical, and foundational research reports begin to create the primary database for a systematic review. (Barroso et al., 2003; Bates, 2007, 1989; Boell and Cecez-Kecmanovic, 2010; Hannes and Lockwood, 2011; Hider, 2006; Johnson, 2009).

Searching the literature and building an impartial database provide several difficulties. Because publication procedures differ between the qualitative and

quantitative research paradigms, there are distinctions in the biases that qualitative and quantitative systematic reviewers must strive to reduce (Finfgeld-Connett, 2010; Wilson, 2009). Researchers who carry out quantitative studies typically seek out statistically significant outcomes. The likelihood that their findings will be published in prestigious and widely accessible publications declines if this is not the case. Multiple interrelated reasons contribute to this publication bias, including author dissatisfaction with or lack of interest in unfavorable findings, funding agency publication preferences, and editor and/or reviewer biases. As a result, Wilson (2009), Booth (2010), Song et al. (2010), and others have found that positive quantitative findings are typically easier to access for systematic review than negative ones. Qualitative researchers are more extensively interested in learning about a scenario's contextual aspects and establishing whether an intervention is beneficial. Due to this change in emphasis, qualitative findings are no longer typically viewed as good or negative, non-significant results are no longer penalized, and these associated publication biases are frequently avoided (Finfgeld-Connett, 2010).

Thus, to overcome these biases, it is advised that qualitative systematic reviewers carefully consider whether to conduct literature searches using expert-designed optimal search algorithms. Researchers may utilize such tactics at the beginning of a literature search. Still, if their findings are scant and data saturation seems unlikely, they may need to attempt alternative strategies. It could be essential to manually choose qualitative research reports from this initial batch after searching for topically pertinent papers.

When building knowledge and creating theories through qualitative systematic reviews, “the more, the better” isn’t always the best way to look at things from a methodological point of view. No matter what kind of systematic review is done, deciding when to stop the literature search is a matter of judgment since it is impossible to know what information has not been collected (Barroso et al., 2003; Booth, 2006). Nevertheless, every effort should be made to ensure that decisions to stop looking are well thought out and supported in the context of each review (Booth, 2010).

Therefore, to start the research process according to the logic of backcasting, necessary to identify the relevant literature in the technological field in which the company has in mind to invest, we propose the components of the R&D area to draw on the most extensive and most varied research databases, SCOPUS and Web of Science (WoS) but also Google Scholar, which is a free search tool that claims to index a large amount of scientific documentation of academic origin and even patents. Thanks to filters, it is possible to select the subject of interest and quickly identify existing scientific research in this regard. In addition, it is possible to further refine the research by choosing a specific period of publication (particularly useful in the case of research related to emerging technologies), the source (preferably open source to avoid problems related to copyright and material availability of the research work) and the level of citations to select from the beginning the research considered most relevant in the scientific panorama.

This first step allows, in fact to carry out an elementary clustering of all available resources by the same company without the need to incur additional costs for specialized human resources to match technology trends and the company's aims.

The identified resources can be classified into systematic and narrative reviews from the beginning of the analysis procedure.

3.3.2. Word-Embedding and Clustering

Word embedding is a crucial approach utilized in the field of Natural Language Processing (NLP), which holds significant importance in converting textual data into a numerical representation that machine learning algorithms may efficiently process. This technique enables the capturing of semantic links among words, hence facilitating the extraction of significant insights from textual data.

The discipline of NLP has been significantly impacted by the introduction of word embedding techniques, namely Word2Vec, GloVe, and FastText. These approaches have brought about a revolutionary change by enabling the representation of words as dense vectors inside a multi-dimensional space.

The vectors in question serve the purpose of representing the semantic significance of words, as well as their contextual associations, inside a specific body of text.

The word embeddings that are obtained possess several significant advantages:

- *Semantic Comprehension*: Word embeddings encapsulate the semantic significance of words. Words with comparable meanings are denoted by vectors that exhibit proximity to one another inside the embedding space. This facilitates the ability of algorithms to comprehend the contextual similarities among words.
- *Dimensionality Reduction*: Word embeddings reduce the inherent high dimensionality of text data, hence rendering it more amenable for utilization in machine learning models. The utilization of fixed-size vectors facilitates efficient computing and analysis to represent individual words.
- *Preservation of Contextual Information*: Word2Vec effectively maintains contextual information by considering the words that appear together in a given context. The comprehension of context plays a pivotal role in grasping language's intricacies and delicate aspects.

Thus, after collecting resources from the existing literature in the cited databases, in the second stage, the textual data will be preprocessed, which is an essential preliminary measure before the use of the Word2Vec algorithm.

The preprocessing step guarantees that the text data is subjected to cleaning, standardization and made suitable for the generation of word embeddings.

Using word embedding, it becomes possible to afterward conduct an analysis and grouping of our papers according to their semantic content. This capability allows us to reveal repeating themes and get valuable insights within our collection of literary data.

Pre-processing operations to perform are:

- *Remove punctuation and special characters*: use NLP libraries like “spaCy” to remove punctuation and special characters from the text.
- *Remove “Stop Words”*: stop words are common words like "is," "that," and "and" that often do not carry significant information so that we can remove them.
- *Tokenization*: split the text into words or tokens. For example, the phrase "My house is big" would be divided into ["My", "house", "is", "big"].
- *Lemmatization or Stemming*: reduce words to their base form. For example, "running," "ran," and "will run" can all be reduced to "run."
- *Lowercasing*: standardize all words to lowercase to avoid ambiguity between uppercase and lowercase words.

After pre-processing, it is possible to use the Word2Vec algorithm (Mikolov et al., 2013) to create vector embeddings of words (using the Gensim library in Python).

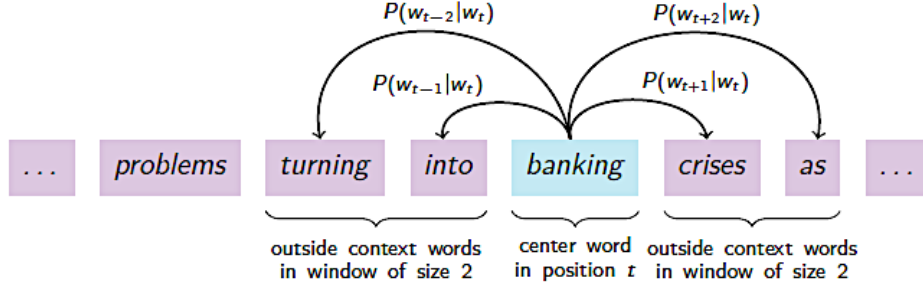
The Word2Vec technique has been chosen as the best method for word embedding because of its remarkable capability to capture semantic associations among words within a given corpus. One notable characteristic of the system is its ability to understand the contextual subtleties and connotations of words within an extensive text corpus. The Word2Vec algorithm functions by examining the occurrences of words. It employs the Skip-gram and Continuous Bag of Words (CBOW) models, which have exhibited exceptional efficacy in capturing contextual knowledge.

Word2Vec is highly appropriate for examining literary data due to its capacity to preserve contextual significance and semantic intricacies found within scholarly and scientific texts. The embeddings of the model accurately capture the semantic context in which words are used, enhancing its efficacy in comprehending the prominent underlying themes and topics within our literature sample.

Moreover, the utilization of Word2Vec (Fig. 14) leads to a reduction in dimensionality, resulting in vectors that are more computationally efficient and easier to handle. This is particularly important when dealing with a substantial amount of textual data. Therefore, Word2Vec emerges as a resilient and adaptable option, positioned to generate significant insights and enable the future categorization of documents according to their semantic substance.

Word2Vec is a supervised model that predicts context words $\mathbf{o}$ given center word $\mathbf{c}$ (and vice versa).

Figure 14: Word2Vec illustrative application



Source: Adapted from Mikolov et al., 2013

For each position t in the corpus, predict context words within a window of fixed size m . Given $\mathbf{w}_j = \mathbf{c}$

$$L(\theta) = \prod_{t=1}^T \prod_{-m \leq j \leq m} P(w_{t+j} | w_t; \theta)$$

Its methodology is based on the minimization of the following objective function $J(\theta)$, which is the average negative log-likelihood⁴

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m} \log P(w_{t+j} | w_t; \theta)$$

Optimizing the embedding matrices results in representing words in a high-quality vector space, capturing word semantics.

To train the Word2Vec Model (Fig. 15) using the preprocessed data, it is essential to configure model parameters like vector size (how many dimensions the word vectors will have) and window size (how many surrounding terms to consider).

Once the model is trained, it is possible to obtain word embeddings, as illustrated in the following example (Fig. 16):

⁴ See Appendix B for detailed objective function explaining.

Figure 15: Word2Vec training code

```
from gensim.models import Word2Vec  
  
model = Word2Vec(sentences=data, vector_size=100, window=5, min_count=1, sg=0)
```

Source: own processing

Figure 16: Word2Vec result example

```
vector = model.wv['word']
```

Source: own processing

The next step is the application of the K-means algorithm, a robust clustering methodology that complements our prior implementation of Word2Vec embeddings. The K-Means algorithm is a commonly utilized and flexible unsupervised machine learning technique employed to partition data into clusters based on similarity. The primary aim of this method is to categorize data points that demonstrate comparable characteristics, rendering it especially advantageous for our analysis.

The justification for utilizing the K-Means algorithm after Word2Vec is rooted in its capacity to leverage the intricate semantic representations of words derived from the Word2Vec embeddings. Word2Vec is a model that captures the semantic associations among words, whereas K-Means expands this concept to encompass entire documents or data points.

By clustering documents based on their Word2Vec embeddings, we can identify groups of documents that share underlying semantic themes or topics.

The K-Means algorithm functions iteratively, assigning data points to clusters to minimize the within-cluster variance. The clusters that emerge from the analysis offer valuable insights into the underlying structures inherent in our literature dataset. This step enables us to identify and analyze patterns, tendencies, or areas of research that appear repeatedly throughout the collection of texts, thus playing a vital role in extracting significant findings from the extensive literature.

Employing the K-Means algorithm with Word2Vec, researchers can effectively analyze the semantic associations among individual words and categorize documents based on their semantic context. Utilizing this sequential methodology enables a holistic comprehension of the overarching concepts and subjects prevalent throughout the literature, ultimately facilitating the examination and formulation of informed judgments and the decision-making process.

The objective function that K-Means minimizes is defined as:

$$J = \sum_{i=1}^n \|x_i - \mu_{j(i)}\|^2$$

Where J represents the total within-cluster variance (inertia), n is the number of data points, x_i is a data point, and $j(i)$ is the cluster index to which x_i is assigned.

The goal of K-Means is to find the cluster centroids $(\mu_1, \mu_2, \dots, \mu_k)$ and cluster assignments $j(i)$ that minimize this total within-cluster variance, effectively partitioning the data into compact, well-separated clusters.

Thus, it is possible to employ the K-Means algorithm to extract themes and clusters from pre-existing literature after acquiring word embeddings through the utilization of Word2Vec, as indicated in the following outline process:

1. *Data Pre-processing*: ensuring the availability of word embeddings for all the words included in the documents is essential. Words should be represented as a numerical vector. In addition, it is necessary to construct a matrix in which each row corresponds to a document and each column corresponds to the vector embeddings of the words contained inside the text. The matrix provided will serve as the input for the K-Means method.
2. *Determine the number of Clusters*: before implementing the K-Means algorithm, it is necessary to decide on the desired number of clusters to be obtained. The optimal number of clusters can be determined using techniques such as the elbow method⁵ or silhouette method⁶, which assist in identifying the most suitable clustering solution based on the available data.
3. *Apply K-Means*: use an implementation accessible in libraries such as “scikit-learn” in the Python programming language (Fig. 17) to execute the algorithm on the given dataset. Provide the matrix of document vectors as input and indicate the desired number of clusters.

⁵ *Elbow Method*: to find the optimal number of clusters by identifying a point on a plot where the rate of change in cluster sum of squares sharply decreases.

⁶ *Silhouette Method*: to determine the ideal number of clusters by quantifying the similarity of data points to their own clusters relative to other clusters using silhouette scores.

Figure 17: K-mean application Python code

```
from sklearn.cluster import KMeans  
  
kmeans = KMeans(n_clusters=num_clusters)  
clusters = kmeans.fit_predict(embeddings)
```

Source: own processing

4. *Analysis of Results:* following the implementation of the K-Means algorithm, clusters of documents will be obtained. Each cluster signifies a thematic category or a collection of comparable materials, determined by their semantic resemblance. Analyze each cluster's documents to gain insight into the emerging topics.
5. *Cluster Labeling:* to effectively ascertain the underlying themes associated with each cluster, it is possible to analyze the primary texts or the most representative words within each cluster (manually or using cluster analysis algorithms, such as calculating the most frequent keywords within each cluster). This approach will facilitate the assignment of appropriate labels to the clusters, thereby accurately reflecting the themes found.

Utilizing the K-Means algorithm for theme analysis is a prevalent methodology that has demonstrated efficacy, contingent upon the appropriateness of the data for clustering purposes. It is important to note that the outcomes of cluster analysis are contingent upon the caliber of word embeddings and the selection of K-Means parameters. Therefore, it is crucial to maintain a flexible approach and engage in experimentation to attain optimal findings.

3.3.3. Blind bias and introduction to the blockchain system

The next step involves anonymizing the selected scientific papers in each cluster to make the subsequent evaluation by the team of experts as objective as possible, avoiding any personal bias.

This procedure can be carried out by adopting specialized software based on the format of the search file.

In particular, considering the most popular formats, PDF Anonymizer is available for the automatic removal of identifiable information from PDF documents: by uploading the file into the software, you can select the desired anonymization options, such as removing author names, affiliations, addresses, contact information, etc. and start the anonymization process.

Alternatively, a LaTeX package called "anonymous" can be used to anonymize the document's content created by adopting this language. This package automatically replaces author names with generic placeholders, such as "Author 1", "Author 2", etc.; removes other identifiable information, such as affiliations and contact information; removes or replaces references to previous work by the authors themselves or other researchers that you do not want to identify; finally, you can identify and remove any further information, such as names of companies, organizations or places that may be related to the authors or their affiliations.

As analyzed by Goues et al. (2018), peer review is a cornerstone of the academic publication process but can be subject to the flaws of the humans who perform it. Evidence suggests subconscious biases influence one's ability to evaluate work objectively; these biases can affect anyone, regardless of the evaluator's race and gender therefore a double-blind review is usually adopted to mitigate these effects and reduce the perception of bias, both conscious and subconscious, making it a constructive step toward a review system that objectively evaluates papers based strictly on the quality of the work.

Any benefits attributed to double-blind peer review presuppose that the submitted paper has been successfully blinded and that reviewers cannot identify the authors or their institutions. Many have utilized the idea that an experienced referee may recognize the author of a specific piece in a specialized publication to debunk the alleged benefit of a double-blind review. Several research have explored the effectiveness of blinding. These interdisciplinary investigations found that blinding had success rates ranging from 53% to 79%. The practicality and success of blinding are contingent upon the amount of work invested in the blinding procedure and journal-specific criteria. It is a common interest that the system be fair: favoritism, prejudice, and condescension bring dishonor to the entire operation and eventually work against the discipline, despite the occasional short-term benefits that may accrue to individuals. (Snodgrass, 2006)

So, scientific judgment should be based primarily on the content of publications, not on name recognition or standing within institutions. Editors are, at their core, people. When people recognize the author's name, gender, country of origin, or institution, among other things, they may be subconsciously or intentionally predisposed in favor of or against an article. Like this, despite the possible quality of the provided content, an article may be rejected after the first screening without further review if the editor has a preconceived notion about the author's name, gender, past work, nation, or linked institution. Furthermore, well-known scientists with track records who work at "prestigious institutions" or in wealthy countries would have a significantly higher probability of having their papers approved for publication at the same level of content.

Thus, blind submission (submission without revealing the author's identity and contact information) would be a successful strategy to lessen biases in article rejection at the editorial levels and the initial assessment stage. Articles submitted

anonymously can be judged solely on their merit and content, free from personal or organizational bias.

Blind submission would improve the scientific rigor and objectivity along with blind peer review. To improve the impartiality of the publication evaluation, the blind review system was implemented (Kmietowicz, 2008).

Therefore, in identifying the most suitable literature review procedure to classify and select the emerging technologies that best meet business needs, we believe it is essential to provide a step that anonymizes the articles, as already discussed, before submitting them to expert analysis in the next step.

In addition, to further ensure the transparency and impartiality of this procedure, we introduce the application of the blockchain technique by carrying out a kind of research tokenization.

A “token” is the digital representation of an asset, a sort of security document, available on the blockchain (Weingärtner, 2019). The token is not necessarily related to a cryptocurrency like Bitcoin or Ether but refers more to a smart contract on a blockchain (Kondrateva et al., 2022).

The development of blockchain technology and tokens could give entrepreneurs and innovators new ways to raise funds to finance their growth and compensate their core developers (Lerner et al., 2000).

Depending on their actual function, tokens are categorized into three main categories: the first type consists of Payment tokens, also known as currencies, with Bitcoin and Ethereum serving as typical examples. Moreover, they are all non-unique and non-divisible, contrary to the concept of fungible tokens (FTs), also known as non-fungible tokens (NFTs). The second variety of tokens is utility tokens, extensively employed and designed to grant digital access to an application or service. The emergence of NFT has significantly expanded the scope of asset tokens, the final type.

A properly designed token offering could offer greater security, liquidity, and transparency than conventional financial instruments. Moreover, a tractable dynamic equilibrium model of token pricing and platform adoption has been developed, demonstrating that the introduction of tokens reduces the effective transport cost of undertaking platform transactions, thereby accelerating the adoption of productive platforms. (Bao and Roubaud, 2022)

Blockchain technology fosters network confidence by assuring the verifiability of each transaction. Due to the technology's decentralized nature, trust in a central authority is unnecessary (Ahluwalia et al., 2020).

In addition, tokenization can be utilized for intellectual property protection due to its function in transaction verification and its capacity to demonstrate the fluidity of the innovation process. Through tokenization, cost reductions, trust, and decentralization can be applied to all business functions (Ahluwalia et al., 2020).

Therefore, the methodology proposed in this study aims to apply blockchain technology for the advantages expressed considering scientific papers' second type tokens, utility tokens.

More specifically, the results obtained from the previous steps can be implemented in a blockchain as follows using the Python library "web3.py" (Fig. 18), which allows to interact with Ethereum blockchains:

Figure 18: Blockchain Python implementation

```
from web3 import Web3

# Connect to an Ethereum node or a testnet
web3 = Web3(Web3.HTTPProvider('http://localhost:8545'))

# Address of the smart contract on the blockchain
contract_address = "0x...123"

# Enable the account for sending transactions
web3.eth.defaultAccount = web3.eth.accounts[0]

# Load the smart contract
contract = web3.eth.contract(address=contract_address, abi=abi)

# The results to be recorded on the blockchain (e.g., cluster_labels)
results = [0, 1, 1, 0, 2, 1, ...]

# Send the transaction to register the results on the blockchain
transaction_hash = contract.functions.register_results(results).transact()

# Wait for the transaction to be included in the blockchain and receive the receipt
receipt = web3.eth.waitForTransactionReceipt(transaction_hash)
```

Source: own processing

In the example above, “register_results” is a smart contract function that takes the results (e.g., cluster_labels) as input and records them on the blockchain. The transaction is sent from the private key, and once confirmed by the network nodes, the results will be immutably recorded on the blockchain.

This way, the experts can access the results recorded on the blockchain and verify that they have not been altered after the initial classification.

The blockchain ensures that the data is authentic and tamper-proof, providing a reliable basis for evaluation and analysis by a team of experts.

3.3.4. Smart contract and blockchain approach: new ideas into the frame of backcasting method

Blockchain technology overlaps traditional contracts by including the terms of agreements between two or more parties. However, smart contracts surpass them by automating the execution of agreements in a distributed environment when certain conditions are met.

Smart contracts are executable codes that operate on the blockchain to facilitate, implement, and enforce an agreement between untrustworthy parties

without a trusted third party. Smart contracts enabled the automation of the Internet and the transformation of paper contracts into digital ones. Smart contracts enable users to codify their agreements and trust relationships without the oversight of a central authority, as compared to conventional contracts. To prevent contract manipulation, each node in the blockchain network copies smart contracts. To avoid disputes regarding such contracts, human error could be reduced by facilitating the execution of operations by computers and services provided by blockchain platforms. (Khan et al., 2021)

On-blockchain token systems have many applications, including sub-currencies representing assets such as USD or gold, company stocks, individual tokens representing smart property, secure unforgeable coupons, and even token systems with no ties to conventional value used as incentive point systems. A token system is essentially a database with a single operation: subtract X units from A and give X units to B , assuming that (i) X had at least X units before the transaction and (ii) A approves the transaction. Incorporating this logic into a contract to implement a token system is sufficient. (Buterin, 2014)

In our specific case, as anticipated, it is a complex of "utility tokens" represented by scientific papers. Therefore, the object of the transaction scheduled by the smart contract will be the intellectual property of papers together with the evaluation report of each sub-team by three experts.

Finally, they will be non-deterministic smart contracts since they could include information (called oracles or data feeds) from an external party outside the blockchain.

3.3.5. Expert elicitation

The judgment of experts is a way to describe through a number the levels of knowledge of an uncertain quantity. To summarize these distributions and provide information about the degree of uncertainty, the sources of uncertainty, the degree of agreement/disagreement, and the reasons for any disagreement among the group of experts consulted, the method asks each of the various experts to provide a subjective probability distribution for the different aspects of interest.

The approach's central premise is that by using organized protocols, specialists may define the current state of knowledge.

Analysts use different strategies for eliciting expert judgment, but they all involve a number of the same steps: framing the question, reviewing the evidence, identifying and recruiting experts, developing an elicitation protocol, informing experts about well-known biases in human judgment, summarization and presentation of the results.

What "expertise" one seeks and how to identify it is a crucial subject frequently lacking an obvious solution. Any procedure for choosing specialists

must address the issue of “balancing,” including disciplinary, institutional, and political considerations.

Whether or not to pursue balance and, if so, how to do it can be debatable.

Choosing the ideal or necessary number of experts is another problem.

According to the Theory of Expert Competence (Shanteau, 1992), skills that emerge or not in experts depend on five factors: domain knowledge, psychological traits, cognitive skills, decision strategies and task characteristics.

Therefore, a company that wants to identify a team of experts to entrust the analysis procedure presented below should comply with all five parameters mentioned in the assessment of the degree of expertise and the relative selection. In addition, it will be essential that each expert involved is not simultaneously the author of papers submitted to him for analysis.

Once a group of subject matter experts has been chosen, contacted and consented to participate, the team turns its focus to creating the elicitation process. Most protocols start with an informal discussion on the topic. The final protocol is typically developed in conjunction with the experts.

The project starts the elicitation phase after defining the final evaluation procedure. In addition, to ensure the complete reliability of the evaluation expressed by the experts, each scientific paper will be analyzed by sub-teams composed of three experts (both scientific and company researchers); the odd number will ensure the existence of a majority in the evaluation expressed.

The decision of whether and how to integrate the opinions of the participating experts is crucial in reporting results. No matter how the results are aggregated, any summary of the findings must start by providing the report of each expert. Little needs to be done if the experts concur on the general trend. Instead, if the experts offer opinions that are significantly different from one another, it is crucial to talk about why. Here, meticulous documenting of each expert’s reasoning is crucial. The issue of whether and how to integrate the experts’ opinions emerges if there is significant disagreement among them.

3.3.6. Research quality assessment (RQA)

Good narrative and systematic reviews will likely remain crucial. In this study, the following procedures have the potential to be the best grasp of possible developmental paths toward a desirable future.

To assess the quality of this, initially, our considered tool is a very similar version to the SANRA, the Scale for the Assessment of Narrative Review Articles, which is a concise critical appraisal tool for evaluating non-systematic pieces of literature.

Now, for the current study, we apply the SANRA method as argued in Baethge et al. (2019) with findings from a field test examining its practicability, item-total correlation, internal consistency, reliability, and criterion validity.

The current SANRA version results from a 2014 revision by the scale's creators, who aimed to streamline the survey while increasing its reliability. The language of the items was refined, and a question on a manuscript's writing and accessibility was removed since responses varied widely. The redesigned scale's six components are given numeric values between 0 (low standard) and 2 (high standard), with 1 representing a middle ground. The highest possible total is 12.

The SANRA scale's total score is meant to quantify the concept "quality of a narrative review article", which is comprised of the following sub-constructs: (1) an explanation of the review's significance; (2) a statement of the review's aims; (3) a description of the literature search; (4) a citation of relevant sources; (5) a demonstration of sound scientific reasoning; and (6) the presentation of relevant and appropriate endpoint data.

Finally, we have generated a new scale, called SANSER, Scale for the Assessment of Narrative and SystEmatic Review, which includes SANRA score (max score 12), as already described, and the expert elicitation score (SCAST - Scenario CASTing) from 0 to 12, to obtain a unique value able to define the quality assessment of the analyzed review, considering future scenarios related to emerging, frontier or dominant technologies.

Therefore, the final highest possible total SANSER score is 24, as shown below in Fig. 19. This procedure of analysis and evaluation through the application of the tests above, will be carried out by each sub-team of three experts (specifically identified by the company according to its research needs using the available scientific indicators and the Scopus platform) within the blockchain procedure illustrated in the following sections.

Figure 19: SANSER scale

Scale for the Assessment of Narrative and Systematic Review (SANSER)

Please, in this first section, rate the quality of the narrative and systematic review article in question, using categories 0-2 for each of the following six aspects. So the first total score can be max 12.

	QUALITY ITEMS (SANRA)	SCORE (0-2)
1.	<i>Justification of the article's importance for the readership</i>	
2.	<i>Statement of concrete aims or formulation of questions</i>	
3.	<i>Description of the literature search</i>	
4.	<i>Referencing</i>	
5.	<i>Scientific reasoning</i>	
6.	<i>Appropriate presentation of data</i>	
TOTAL SANRA SCORE		... / 12

Please, in this second section, rate the quality assessment of the analyzed review, considering future scenarios related to emerging, fronttering or dominant technologies, using a 0-12 scale.

	SCAST	SCORE (0-12)
7.	<i>Expert Elicitation on future scenarios</i>	

TOTAL SCORE (SANSER = SANRA + SCAST)	 / 24
---	-------------------

Source: own processing

3.3.7. Choquet Integral Method to rank papers inside blockchain

The multidimensional nature of considered scientific papers raises the problem of aggregating results in simple indexes that can be accessed by stakeholders willing to compare different technologies based on their preferences. In particular, for this research work, it is possible to apply the Choquet integral based Multi-Attribute Value Theory to elicit stakeholders' preferences on different attributes chosen by the same panel of experts to construct a robust index allowing to rank them. This tool can support the decision-making process of the panel of experts looking for emerging technologies with the highest probability of

realization according to company context. In fact, this procedure can be straightforwardly adapted to much richer environments, such as the analysis of the reviews mentioned above. (Ferrara et al., 2016)

To rank scientific papers using this methodology, first of all, it is necessary to define attributes and a value function that reflects the decision-maker's preferences.

Let's apply this approach to our specific case, identifying as attributes the criteria considered by the SANSER test and associating to each of them the value previously indicated by the evaluation of the team of experts for each paper.

So, we have the following steps:

1. *Define the Attributes*: identify attributes i that characterize the quality of scientific papers (from the SANSER test: Justification of the article's importance; Statement of concrete aims or formulation of questions; Description of the literature search; Referencing; Scientific reasoning; Appropriate presentation of data; Future technologies scenario - SCAST).
2. *Define Marginal Value Functions*: for each attribute, create a marginal value function $u_i(x_i)$ that measures the decision-maker's satisfaction regarding that attribute. These functions assign a real value to each paper x based on its performance in the respective attribute, as emerged from the previous evaluation of the team of experts.
3. *Define a set function μ (Capacity – fuzzy measure) on N^7* : to account for the importance of individual attributes or combinations of attributes (subset of criteria, A), define a capacity (set function), denoted as μ over the set of attributes N . This function assigns values in the range $[0, 1]$ to subsets of attributes (Hüllermeier and Labreuche, 2022).

$$\mu: 2^N \rightarrow [0, 1]$$

$$\text{Normalization: } \mu(\emptyset) = 0 \text{ and } \mu(N) = 1$$

$$\text{Monotonicity: } A \subseteq B \subseteq N \Rightarrow \mu(A) \leq \mu(B)$$

4. *Calculate the overall value (Choquet Integral) for each paper*: utilize the capacity μ and the marginal value functions u_i to compute the overall value for each paper using the Choquet Integral defined as:

⁷ In the context of Multiple Attribute Value Theory (MAVT) or decision analysis, "N" typically represents the set of decision attributes or criteria used to evaluate and compare alternatives. In this case, "N" is defined as the set of attributes used to assess and rank scientific papers. Each of these attributes contributes to the evaluation of a scientific paper, and the decision-maker's preferences are based on how well each paper performs on these criteria.

$$C_{\mu}(u(x)) = \sum_{i=1}^n [u_{\sigma(i)}(x_{\sigma(i)}) - u_{\sigma(i-1)}(x_{\sigma(i-1)})] \mu(N_{\sigma(i)})$$

Where σ is a permutation on N , such that (Kaldjob et al., 2023):

$$N_{\sigma(i)} = \{\sigma(i), \dots, \sigma(n)\}, u_{\sigma(0)}(x_{\sigma(0)}) = 0 \quad \text{and} \\ u_{\sigma(1)}(x_{\sigma(1)}) \leq u_{\sigma(2)}(x_{\sigma(2)}) \leq \dots \leq u_{\sigma(n)}(x_{\sigma(n)}).$$

5. *Perform Ranking*: arrange papers in descending order based on the calculated overall values using the Choquet Integral. Papers with higher values rank higher, while those with lower values rank lower.

It's essential to note that the ranking process requires interaction with the decision-maker to acquire their preferences for a subset of papers. This interaction helps accurately build the value functions and the capacity (set function). Additionally, the process can be iterative to refine the representation of the decision-maker's preferences and enhance the ranking of scientific papers.

To implement this model that applies the Choquet integral using Python (Fig. 20), we can create a function that takes as input values of the attributes associated with each paper and returns the overall value (Choquet Integral) for each, as illustrated in the following example.

Figure 20: Choquet Integral Python code (example data)

```
import itertools

# Define the attributes and their values for each paper
# Replace the sample data with actual values for your papers
papers = [
    {"title": "Paper 1", "attributes": [1, 2, 2, 1, 2, 2, 8]},
    {"title": "Paper 2", "attributes": [2, 1, 2, 2, 2, 1, 10]},
    {"title": "Paper 3", "attributes": [2, 2, 1, 2, 1, 2, 6]},
    # Add more papers and their attribute values here
]

# Define the weight (importance) of each attribute
# Replace with your preferences or let the decision-maker specify these
weights = [0.2, 0.1, 0.1, 0.1, 0.2, 0.2, 0.1]

# Calculate all permutations of the attributes for ranking
n = len(papers[0]["attributes"])
attribute_permutations = list(itertools.permutations(range(n), n))

# Define a capacity (set function) based on your preferences
# Replace with actual values if known, or use interactive input
# For simplicity, using equal importance for all subsets
capacity = {}
for i in range(n + 1):
    capacity[i] = 1.0 / (n + 1)

# Calculate Choquet integral-based scores and rankings
scores = []
for paper in papers:
    attributes = paper["attributes"]
    total_score = 0.0
    for perm in attribute_permutations:
        subset_score = sum(weights[i] * attributes[perm[i]] for i in range(n))
        capacity_value = capacity[len(perm)]
        total_score += (subset_score - capacity_value)
    scores.append({"title": paper["title"], "score": total_score})

# Rank the papers based on their scores
ranked_papers = sorted(scores, key=lambda x: x["score"], reverse=True)

# Print the ranked papers
for i, paper in enumerate(ranked_papers, start=1):
    print(f"Rank {i}: {paper['title']} - Score: {paper['score']}")

Rank 1: Paper 2 - Score: 13769.99999999947
Rank 2: Paper 1 - Score: 12329.999999999456
Rank 3: Paper 3 - Score: 10890.000000000504
```

Source: own processing

This part of the procedure of analyzing and evaluating scientific papers can also be part of a blockchain to provide transparency, immutability, and security to the whole process of recording and verifying the evaluations of papers.

Here's a detailed explanation of how we could achieve this:

1. *Smart Contracts*: utilize smart contracts, which are self-executing contracts with the terms of the agreement directly written into code. In this case, you can create a smart contract representing the paper evaluation process. The contract can include functions for submitting evaluations, calculating Choquet Integrals, and storing the results on the blockchain.
2. *Data Structure*: define the data structure that represents a paper evaluation. This structure should include the paper's attributes, criteria scores, the capacity function, and the calculated Choquet Integral.
3. *Evaluators*: identify the experts who will assess the papers. Each will interact with the smart contract to submit their scores for the attributes and criteria. These interactions can be recorded as transactions on the blockchain.

4. *Consensus Mechanism*: choose an appropriate consensus mechanism for the blockchain network. Depending on the specific use case, we can opt for a public blockchain (e.g., Ethereum) or a private/permissioned blockchain (e.g., Hyperledger Fabric). The choice depends on factors like the level of decentralization we need and the participants in the network.
5. *Transaction Validation*: configure the smart contract to validate incoming evaluations. For instance, we can set rules to ensure that scores fall within acceptable ranges, and that all required fields are filled out.
6. *Calculating Choquet Integrals*: implement the logic for calculating Choquet Integrals within the smart contract. This code should take the submitted scores, perform the Choquet Integral calculations, and store the results on the blockchain.
7. *Data Storage*: store the paper evaluations and Choquet Integral results directly on the blockchain. This ensures the immutability and transparency of the data. The data can be stored within the smart contract or referenced from an external storage solution like IPFS (InterPlanetary File System), with the IPFS hash recorded on the blockchain.
8. *Access Control*: define access control mechanisms to ensure only authorized participants can submit evaluations or access the results.
9. *User Interface*: develop a user interface (UI) or application that allows evaluators to easily submit their scores and view the results. This UI can interact with the blockchain smart contract.
10. *Testing and Deployment*: thoroughly test the smart contract and the application in a development environment. Once tested and validated, deploy the smart contract to the chosen blockchain network.
11. *User Training*: train evaluators and other stakeholders on using the system, including interacting with the blockchain and submitting evaluations.
12. *Monitoring and Maintenance*: continuously monitor the system for any issues or anomalies. Perform regular maintenance and updates as needed.

By following these steps, we can create a system for evaluating and classifying papers that leverages the transparency and security of blockchain technology.

Blockchain ensures that the evaluation process is tamper-proof and auditable, which can be crucial in scenarios where data integrity and evaluations is paramount.

3.4. Procedures and Results

Based on what was previously explained on the methodology adopted and on the reference classification of the reviews illustrated in the paragraph relating to the background, we proceed with describing the procedures adopted to subject both narrative review and systematic review to analysis to obtain an evaluation and therefore a scientific classification of the same.

3.4.1. Blockchain-Based Procedures

A blockchain is a distributed database that documents every transaction that has ever taken place on the blockchain network. This database is replicated and made available to all network participants. The primary characteristic of blockchain is that it enables untrusted parties to communicate and transmit transactions securely without needing a trusted third party. Each block is designated by its cryptographic hash in a blockchain, which is an ordered catalog of blocks. Each block contains a reference to the block that preceded it, creating a chain of blocks. Each block is made up of a collection of transactions. Once a block has been created and added to the blockchain, its transactions cannot be altered or undone. This is to ensure the integrity of transactions and prevent the occurrence of double-spending.

Verification of network transactions is performed by specialized nodes (called miners). Verifying a transaction involves examining both the sender and the transaction's contents. After solving a mathematical problem (known as Proof of Work), miners generate a new block of transactions, which is then broadcast to the network. Other nodes in the network can validate the generated block's correctness and can only build upon it if it was generated correctly.

The second generation of blockchain enables the development of complex distributed applications beyond cryptocurrencies, such as smart contracts, which are regarded as the generation's defining characteristic.

There are two varieties of blockchain: public and private. In a public blockchain, any anonymous user can join the network, peruse the blockchain's content, transmit a new transaction, or verify the blocks' correctness.

In a private blockchain, only authorized users can join the network, write to the blockchain, or transmit transactions. Typically, a company or group of companies is accountable for granting these permissions to consumers before they join a network.

There are numerous applications for which smart contracts are applicable. One of these applications is associated with the Internet of Things and smart property: billions of devices are exchanging data via the Internet. A potential application of blockchain-based smart contracts is to enable nodes to share or

access diverse digital assets without a trusted third party (Alharby and Moorsel, 2017).

Therefore, by adapting this last type of blockchain application and making it private, we will allow companies and experts involved in a research project to share scientific material more efficiently and generate a transparent and reliable screening of emerging technologies.

Outside the blockchain, as explained in paragraph 3.3.1, scientific papers related to the technological field for which the company is performing research are selected from the different databases. The selected papers are subjected to the word-embedding, clustering and anonymization procedure before being introduced into the blockchain so that the subsequent evaluation of the experts is explicitly based on content and not influenced by subjective aspects.

Each block will consist of a sub-team of three experts. Each sub-team will be subjected to a defined number of papers concerning which it will start the analysis and evaluation procedures described above in the methodologies.

Finally, we have defined the whole analytical procedure NR4CASTING for classifying scientific papers that make up a narrative review or SR4CASTING for the classification of scientific papers that make up a systematic review based on the previously exposed characteristics.

3.4.2. Content Validity and Reliability

The first step of both procedures is replication, which is a way of confirming scientific research and is seen as an essential condition for adopting new hypotheses and information. In the framework of empirical research, replication necessitates the repetition of “experiments” so that we may be relatively assured that the results of two experiments are comparable and, thus, measure the same phenomenon.

The method relies heavily on repetition; however, reiterating an entire action does not always entail doing so in its entirety each time. The end product will be comparable to the source material, but it will never be a replica in all respects. Considering the challenges of planning and carrying out precise replications, it could be good for us to adopt more practical modes of carrying out replication in our field.

If the data of the entire study are available, the results are validated following the procedure indicated in the research article (Drost, 2011).

Regarding quantitative research, the availability of the data used in the study can be allowed both by the authors and using the same datasets used by the authors. Instead, as regards qualitative research, based on data made available by the authors (for example, questionnaires), it is necessary to use the same data used in the research (Golafshani, 2015). If the original data are missing, the evaluation was carried out based on the impact factor of the journal in the reference sector.

However, the validity of the results is considered positively approved when the journal where the research article examined is published is placed in the Q1, Q2 or Q3 of the Thomson Reuter's Journal Citation Report (JCR).

3.4.3. NR4CASTING

In this case, therefore, we consider P-blinded narrative papers ($B_1, B_2, B_3, \dots B_n$), selected using the database and applying the search strategies and clustering set out in paragraphs 3.3. Among these, those that pass the validation step illustrated in the previous paragraph will be renamed, keeping the same numerical reference, for example, $V_1, V_3, \dots V_n$, completely discarding those resulting unsatisfactory.

The sub-team of experts in each block will first proceed with applying the SANRA test, assigning a score between 0 and 2 to each of the six evaluation criteria adopted by this method for a maximum total score of 12 points, as presented in paragraph 3.3.6.

After that, the same sub-team of experts will also perform the SCAST procedure that assigns a score based on the probability that the technology described in the analyzed paper is to be considered emerging, frontier or dominant in future scenarios, so readapting the second of the previously exposed time symmetries, namely Backcasting – Pastcasting, to identify the optimal path that will allow the company to implement the expected technological innovation scenario effectively.

The maximum total score provided by SCAST is also 12.

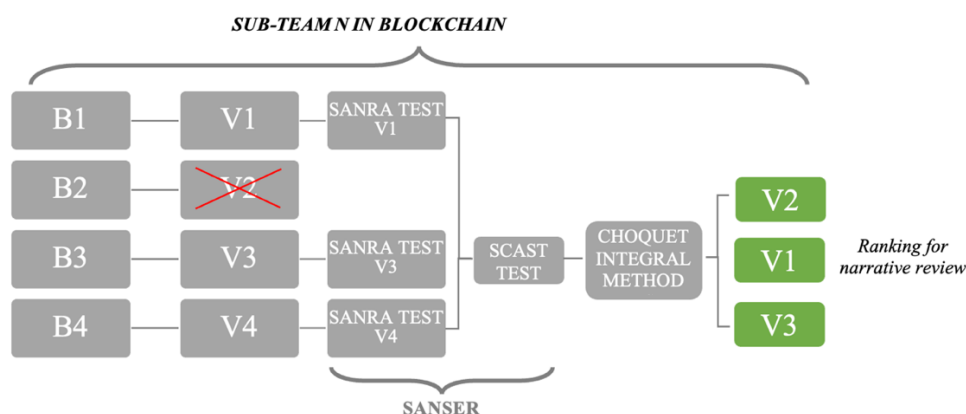
The sum of the scores obtained by SANRA and SCAST generates the total considered by the new SANSER methodology (maximum 24 points) through which it is possible to draw up a provisional ranking of the papers thus analyzed.

After that, in the same block, the Choquet Integral Method will be applied to verify and confirm or modify the previous ranking according to the mathematical results to give a result that is as truthful and objective as possible.

In conclusion, each of these papers will be contained in the narrative review, which is the final result of the NR4CASTING procedure.

The following Fig. 21 shows an application example of this procedure.

Figure 21: Schematic representation of NR4CASTING approach in blockchain



Source: own processing

3.4.4. SR4CASTING

In this case, as in the previous one, we consider P-blinded systematic papers ($B_1, B_2, B_3, \dots B_n$) always identified using the database and applying the search strategies and methods indicated in paragraph 3.3.

The first step of the procedure remains unchanged: papers that pass this verification will be renamed, keeping the same numerical reference, for example $V_1, V_3, \dots V_n$, completely discarding those resulting unsatisfactory.

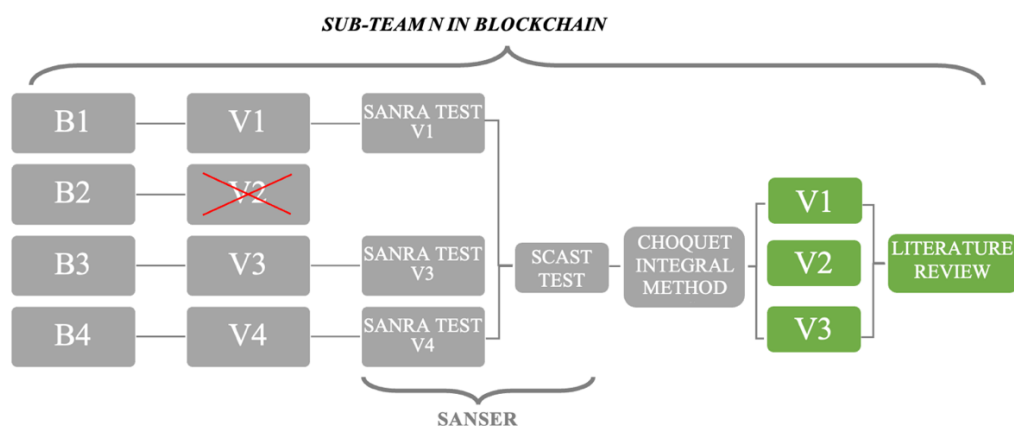
Then, as for the NR4CASTING procedure, a sub-team of experts in each block will first proceed with applying the SANRA test to validated papers and then the SCAST procedure to obtain the final general score required by our SANSER method.

Even this result will be subjected to evaluation through the application of the Choquet Integral Method.

Thus, the final result of the SR4CASTING procedure is not the collection of all the papers selected and appropriately classified by the procedure as in the previous case but the drafting of a single literature review containing references to the papers that have passed all the selection and evaluation steps.

The following Fig. 22 shows an application example of this procedure.

Figure 22: Schematic representation of SR4CASTING approach in blockchain



Source: own processing

3.5. Discussion and future developments

This study is limited to describing a research activity related to detect emerging and/or potentially dominant technology. We know that technological growth is not solely recorded by the state of the art on present research activity. However, one advantage of this strategy is that it may be merged into a larger one that includes other information sources, such as bibliometric data on research activities (Bildosola et al., 2017).

Scientists, corporate executives, and policymakers are increasingly interested in using new technology to address societal concerns and accomplish sustainable objectives. Aside from big data and AI-driven technologies, blockchain-based solutions are claimed to provide many prospective answers, especially in anticipation and foresight. Because decision-making and regulation should be based on current knowledge and projections about upcoming changes, it is clear that future methodologies and foresight may offer enormous value to blockchain systems.

Now, they are still evolving in a dynamic interaction with other global trends, such as socio-environmental change, and new technology applications are being investigated worldwide.

The technology as a whole certainly has a lot of promise, particularly in terms of community efforts to accomplish progress. So, even more, adopting blockchain is not just a method to reflect on and demand changes in different areas.

Furthermore, blockchain will be just one component of a broader multi-system architecture, the components of which must be understood in terms of their complicated relationships. In an era of combining technical architectures based on artificial intelligence, distributed ledger technology, and cyber-physical systems, the future of “thinking” will demand our close attention. (Schulz et al., 2020)

However, each stage must adhere to particular standard characteristics for the above-mentioned approach to be formalized.

These factors include, among others, the anonymity of the research's authors, the journal of publication, bibliometrics information, the panel of experts and the integrity of their judgment linked with non-repudiation. These research ideas will be developed in the sequel of this ongoing study.

3.6. Conclusions

In this study, we present an innovative research approach based on a literature review (both narrative and systematic) and on a future-facing approach that enhances backcasting to support decision-making processes better thinking about an actually feasible future.

Suppose you can anticipate crucial decisions or occurrences in advance. In that case, you can take measures better to inform decision-makers on the best course of action to adopt, especially as regards technological innovation opportunities, to contain costs and optimize the use of all kinds of resources, material, immaterial and human during such a transition.

As the introduction states, this study proposes a blockchain-based procedure with two different output methods - NR4CASTING and SR4CASTING - that consider numerous specific aims.

A private blockchain procedure, based on smart contract and the concept of "research tokenization," which can enable nodes to share or access different digital assets without a trusted third party, could become a valid and organic tool for experts and R&D companies' areas to share scientific works improving efficiency and transparent and reliable decision process as regard the investment choice in emerging technologies projects.

Therefore, selected scientific papers related to the technological field for which the company is performing research will be introduced into the blockchain for the subsequent expert analysis and evaluation in each block, according to the new Research Quality Assessment, which apply the experimental SANSER scale, obtained by SANRA and SCASST test.

Its primary objective was to collect (NR – narrative review) relevant scientific articles about promising technologies, validating the scientific results to identify emerging and/or dominant technologies without bias and to identify and resume (SR – systematic review) emerging and/or dominant technologies. These outputs will be helpful to establish the preferential order of achievability of the technologies considered by the research subjected to each procedure.

Nevertheless, not all futuristic techniques are equally helpful. While each of the four approaches (forecasting, recasting, backcasting, pastcasting) can be utilized in various ways, each is uniquely positioned to assist futurists in pursuing a particular line of research.

Backcasting provides a robust framework for democratizing policymaking by opening up decision-making processes to a wide range of stakeholders, whereas pastcasting, although much more elusive than the other three approaches, appears useful for unfolding past decision-making processes and disclosing the types of biases that undermined and declined past possibilities and hopes.

We encourage researchers to consider these approaches a critical tool for decision-making to detect emerging and/or dominant new technologies since we see them as providing the future strategic planning environment with the vision, adaptability, and transparency essential to seizing opportunities.

***INDUSTRIAL STRATEGY
AND COMPETITIVENESS STUDIES FOR
TALTECH PROJECT***

&

GLOBAL VALUE CHAIN ANALYSIS

in collaboration with:



CHAPTER 4

R&I application in TalTech Project and Global Value Chain analysis in emerging countries for catching-up sectors

4.1. Introduction: Research and Innovation in PNRR era

Since the onset of the initial cases of COVID-19 in Europe, governmental bodies and the European Commission have implemented exceptional measures to provide economic assistance to the Member States. The outcome of this procedure resulted in the development of National Recovery and Resilience Plans (PNRR). The proposal put forth by Italy entails the distribution of a total sum of 222.1 billion euros. The Plan is organized based on three horizontal axes: digitization and innovation, ecological change, and social inclusion. A sum of 82 billion euros will be directed towards the *Mezzogiorno* region, focusing on investing in the younger population and women.

Some observers consider this program of support and stimulus to the markets as a significant and crucial step towards fiscal cohesion within the European Community. Notably, the resources for this program will be obtained through the issuance of Community debt securities, which are expected to be repaid by the year 2058 (Buti and Messori, 2020).

Two highly exceptional events were the Great Recession of 2008 and the pandemic crisis. However, in the first scenario, Europe reacted with apprehension by implementing stringent fiscal measures. In contrast, in the second scenario, it introduced a European assistance program resembling the post-war Marshall Plan. The Marshall Plan successfully facilitated Italy's transition towards industrialization, creating additional employment opportunities, income growth, urban development, and infrastructure improvements (DeLong and Eichengreen, 1991).

The PNRR, indeed, situates research policy into a broader restructuring of the Italian economic framework, aiming to incorporate public research expenditure into a more comprehensive framework encompassing experimental development, technology transfer, private investment in research and innovation, and training.

Within this framework, it is evident that public research assumes a crucial function as a prospective catalyst, capable of stimulating investments in private research and innovation. The objective is to foster the development of innovative ecosystems wherein research is effectively translated into tangible innovation. This, in turn, generates employment opportunities characterized by substantial value addition and facilitates the active involvement of the most dynamic productive sectors in global markets.

Research is widely recognized as the primary sector capable of generating significant returns on investments, owing to its inherent capacity to stimulate private research, facilitate technology transfer, and foster innovation (Salter and Martin, 2001; Archibugi and Filippetti, 2018). This phenomenon occurs when scientific study, conducted at the forefront of knowledge, paves the way for developing novel technology pathways.

Simultaneously, technology transfer can catalyze the most conventional domains of the Made in Italy industry. The cross-disciplinary nature of technological applications in specific fields of fundamental science, such as microprocessors, nanomaterials, the internet of things, chemistry, and digital technology, enables the transfer of technological innovation to sectors such as furniture, precision mechanics, tourism, and cultural heritage. With its long-standing knowledge base and esteemed reputation for high-quality products, Italy holds a favorable position in these sectors.

The situation's complexity arises from Italy's enduring structural delay in research investments, encompassing both public and private sectors, alongside the absence of significant corporations that play a crucial role in Science-Based industries. Furthermore, a limited integration exists between public research institutions and the industrial sector.

The theme of research and innovation is transversal to the entire PNRR, representing the cornerstone on which to build the country's environmental and digital transformation. For this reason, although a component is specifically dedicated to R&D (component 2, Mission 4), the lines of action for this area can also be found in the other Missions.

The primary objective of Mission 4 within the National Recovery and Resilience Plan (PNRR) is to tackle the existing skills gap that hampers the growth prospects of our nation and its capacity to respond to technology advancements and environmental demands effectively. The mission comprises two distinct components: firstly, enhancing educational services across the entire spectrum from early childhood education to higher education, and secondly, fostering the transfer of knowledge and innovation from academic research to practical application in the business sector.

The primary objective of the second component is to achieve comprehensive investments and reforms as follows:

- Enhance research efforts and promote the sharing of novel frameworks for fundamental and practical research carried out collaboratively by academic institutions and enterprises.
- Examine the many mechanisms and procedures that facilitate the advancement of innovation and the transfer of technology.
- Enhancing innovation is bolstering research infrastructures, providing financial resources, and fostering the development of talents.
- Enhance private investment in research and development (R&D) by fostering improved collaboration between the corporate sector and academic institutions.

The component titled "From Research to Business" is structured into three distinct axes:

- Enhancing the advancement of knowledge is to bolster the efforts of public research institutions and promote the sharing of novel methodologies for both fundamental and practical research. This can be achieved through fostering collaborative partnerships between businesses and universities, thereby capitalizing on the synergistic effects of such collaborations.
- Provision of assistance for the facilitation and advancement of innovation and technology transfer processes;
- Enhancing the framework for facilitating research and innovation involves bolstering the criteria and requirements for providing support.

The first axis of notable strategic significance and interest pertains to the national champions in research and development. These champions are centers or networks established through public-private partnerships and operate within a network. They are actively engaged in various cutting-edge technological domains, including but not limited to artificial intelligence, quantum computing, biopharmaceuticals, energy, hydrogen, digital financial markets, and agri-food.

This measure aims to enhance and establish collaboration among universities, research institutes, and companies to generate research focused on innovation.

This collaboration will be centered around thematic-technological areas that align with the priorities outlined in the National Research Plan (PNR) for the period 2021-2027, as well as the critical areas of focus in Horizon Europe and the contents of the National Recovery and Resilience Plan (PNRR).

The second axis aims to enhance the research system across various technological development phases and enhance the economic system's growth potential by promoting private investment in research and development (R&D). This is achieved by bolstering support for innovation and facilitating technology

transfer processes. Furthermore, the strategies and initiatives proposed within this intervention seek to enhance the nation's technology transfer network.

The third axis of this initiative seeks to enhance the enabling conditions that facilitate the development of research and innovation activities. The proposed measures aim to improve infrastructure resources, foster the acquisition of specialized skills tailored to the requirements of companies (such as industrial doctorates), and augment the financial allocation of the National Innovation Fund.

The fund utilizes Venture Capital as an operational mechanism to directly and indirectly invest in minority stakes of innovative start-up companies.

In addition to the investment programs, the Italian Ministry of University and Research and the Ministry of Economic Development have devised reform initiatives to address structural impediments that impede research and innovation in our nation.

The implementation of reforms aimed at enhancing research and development (R&D) support measures should prioritize the simplification and facilitation of processes, as well as the promotion of mobility within the R&D sector.

The proposed reform aimed at promoting research and development emphasizes three key elements.

Firstly, it advocates for enhancing and facilitating the reciprocal mobility of esteemed individuals, such as researchers and managers, between universities, research infrastructures, and companies. This can be achieved through the provision of incentives.

Secondly, the reform seeks to streamline the administration of funds allocated to funded projects, simplifying the management process.

Lastly, it aims to establish a unified career trajectory that amalgamates the existing categories of temporary researchers, namely type A and B, enabling greater dedication to research endeavors and offering a more transparent career progression.

Furthermore, the objective of “Intellectual Property Reform”, as outlined in the EU Commission's Action Plan titled "Making the most of the EU's innovative potential – Intellectual Property Action Plan to support the EU's recovery and resilience" (adopted on 25 November 2020), is to establish a national strategy that addresses the five challenges identified by the Commission.

These challenges aim to enhance the protection and enforcement of industrial property.

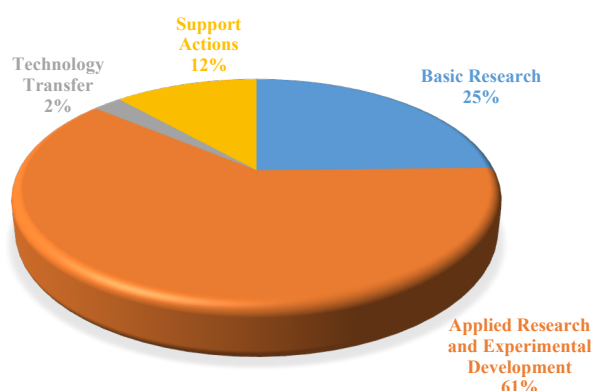
The challenges include enhancing the IP protection system, promoting the utilization and dissemination of IP, particularly among small and medium-sized enterprises (SMEs), facilitating access to and sharing of intangible assets while ensuring equitable returns on investment, ensuring stricter compliance with industrial property regulations, and strengthening Italy's involvement in European and international forums related to industrial property.

Figure 23 depicts the allocation of resources among four key domains that significantly influence planned actions. These domains include fundamental

research, applied research and experimental development, technology transfer, and transversal actions to support the research and development system.

As depicted in Figure 23, most investments are directed towards applied research and experimental development, amounting to around 10 billion. This is followed by the allocation of 4 billion towards the financing of fundamental research, 1.88 billion towards transversal and support operations, and a final allocation of 380 million towards technological transfer.

Figure 23: Division of resources between four research areas (values in % of the total)



Source: Adapted from CNR, 2021

The analysis of these target groups allows us to summarize below the direct impacts related to individual projects, clustered based on the final beneficiaries, namely researchers, universities, research centers, and enterprises.

RESEARCHERS:

- 15.000 additional grants designated explicitly for the pursuit of innovative doctorate degrees.
- 15.000 doctoral degrees awarded in the field of industry.
- 120 research grants available for young researchers.
- 5.350 projects that have received funding through the PRIN-PNR program.
- 1.000 researchers have been recruited on a temporary basis, with 40% of the new hires being women.

UNIVERSITIES AND RESEARCH CENTERS:

- 30 funded research infrastructures.
- 12 ecosystems of territorial innovation.
- 15 research programs carried out by partnerships extended to Universities, research centers and companies.
- At least 5 National R&D and development champions created.

ENTERPRISES:

- 42 new technology transfer centers.
- 650.000 euros of technology transfer services provided.
- 250 projects submitted by companies financed under Horizon.
- 20 companies supported for participation in IPCEI projects.
- 250 start-ups supported.
- 13.304 companies benefiting from the R&D tax credit.
- 1 billion in subsidized investments for R&D projects.

Based on a range of productivity metrics, such as scientific publications, Italian research consistently ranks among the top globally, although facing challenges in funding for research and development (R&D) and the number of researchers.

Upon examining the internal geography, it becomes evident that there are significant variations in knowledge networks among the regions of Italy. The dissemination of knowledge across various areas exhibits an inherent imbalance, accompanied by a discrepancy between the centrality resulting from initiatives and the centrality stemming from scientific publications.

Furthermore, notable impacts of the overall economic situation of the provinces on the performance of organizations in Horizon 2020 are observed.

The benefits of engaging in framework programs in Western European countries are widely acknowledged in terms of financial gains and as a crucial catalyst for the globalization of research endeavors. These programs foster interdisciplinary collaboration on strategic topics and enable participation and potentially leadership, in exceptional research networks (Di Cagno et al., 2014; Ciffolilli et al., 2016).

The well-documented positive impacts of Italy's strategic location as critical nodes within the European research network have been widely acknowledged (Enger, 2018). The aforementioned positive impacts manifest in the capacity of organizations occupying central positions within networks to exert dominance over participation in framework programs. The centrality of these organizations is associated with two key factors: the presence of a substantial number of researchers within the organizations themselves, which serves as an indicator of their robust research capabilities, and the publication of high-quality research in internationally recognized journals, which serves as an indicator of their scientific reputation and excellence. Moreover, in a broader context, the likelihood of securing funding is contingent upon the institution's scale and its capacity to generate a substantial volume of proposals (Piro et al., 2020).

Numerous scholarly works have demonstrated that establishing a robust national scientific and technical system relies on a persistent collaboration among government entities, universities, and the business sector (Etzkowitz and Leydesdorff, 2000; David et al., 2000). A nation characterized by significant

industrial innovation relies on using ideas, innovations, and experiments conducted within the academic and governmental sectors as primary sources.

It is widely acknowledged that prominent enterprises in technical competitiveness derive their expertise from universities and government research institutions. Similarly, it is imperative that a corresponding emphasis accompanies a substantial allocation of public funds towards advanced training on production specialization in high-tech sectors.

Failure to do so may result in a situation where highly skilled individuals, who have incurred significant social costs through their training, cannot secure employment that aligns with their expertise.

The following calculations are presented in the form of figures (Fig. 24 - 34) and table (Table 15) to offer a concise overview of key indicators about science, technology, and innovation in Italy, as well as in several European and non-European nations.

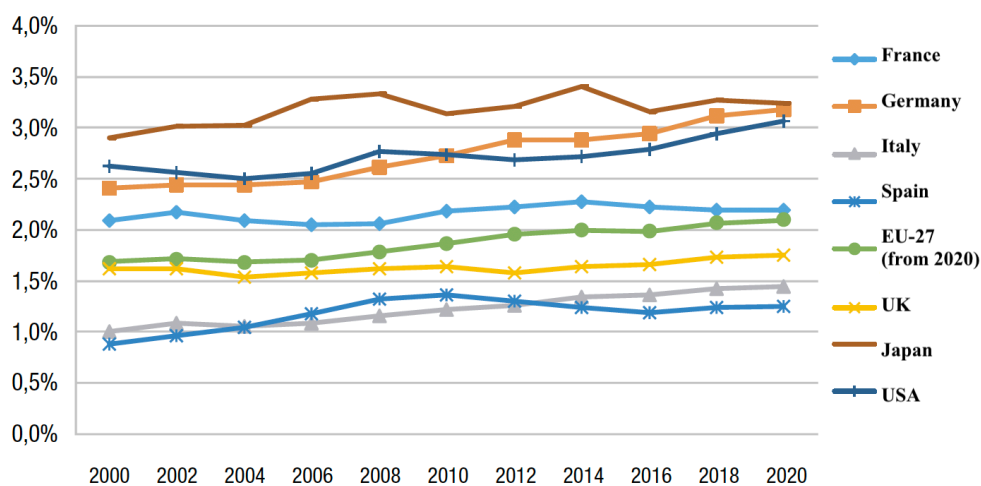
The data primarily examines the input resources incorporated into the national research and innovation system, as well as the outputs generated by the system during the specified period. Additionally, the data includes information obtained from innovation surveys done by EUROSTAT and OECD.

The data is presented in several graphical representations with comparable data from other European and worldwide nations, facilitating comparative analysis.

The sources utilized in this study consist exclusively of official national and international statistical data, including ISTAT, EUROSTAT, OECD, and the Ministry of University and Research.

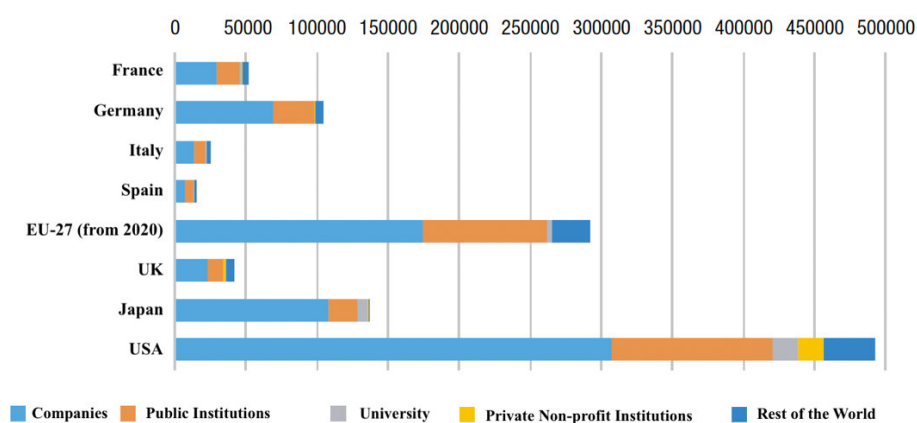
The Web of Science (WoS)-Clarivate Analytics data was utilized for scientific publications. The European Patent Office (EPO) provides the data on patents, while the data on innovation is sourced from the Community Innovation Survey and the European Innovation Scoreboard (EIS).

Figure 24: R&D spending as a percentage of GDP in selected OECD countries from 2000 to 2020.



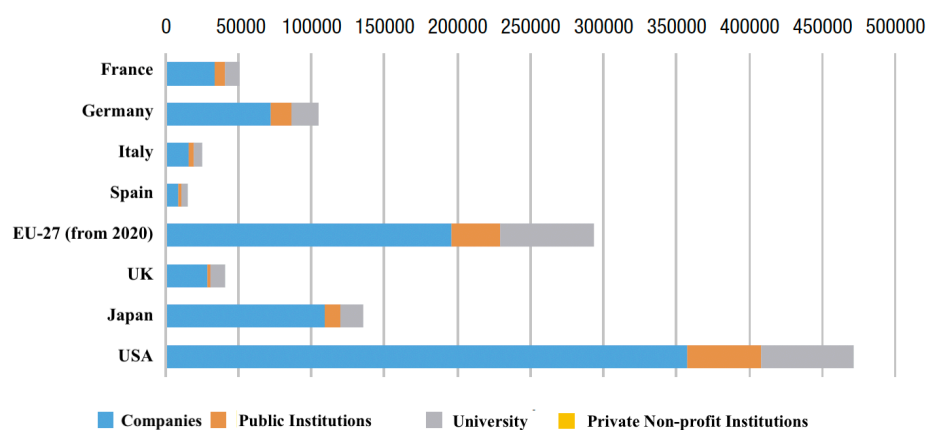
Source: Adapted from CNR, 2021

Figure 25: R&D spending by funding sector in selected OECD countries in 2018



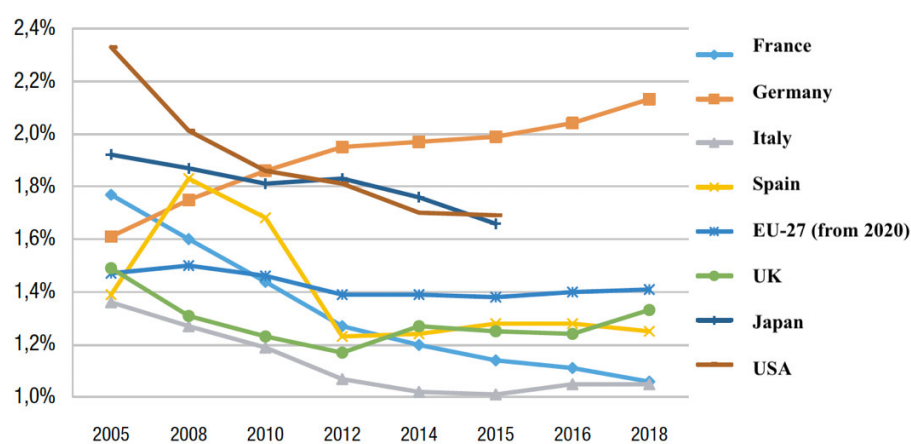
Source: Adapted from CNR, 2021

Figure 26: R&D spending by execution sector in selected OECD countries in 2018



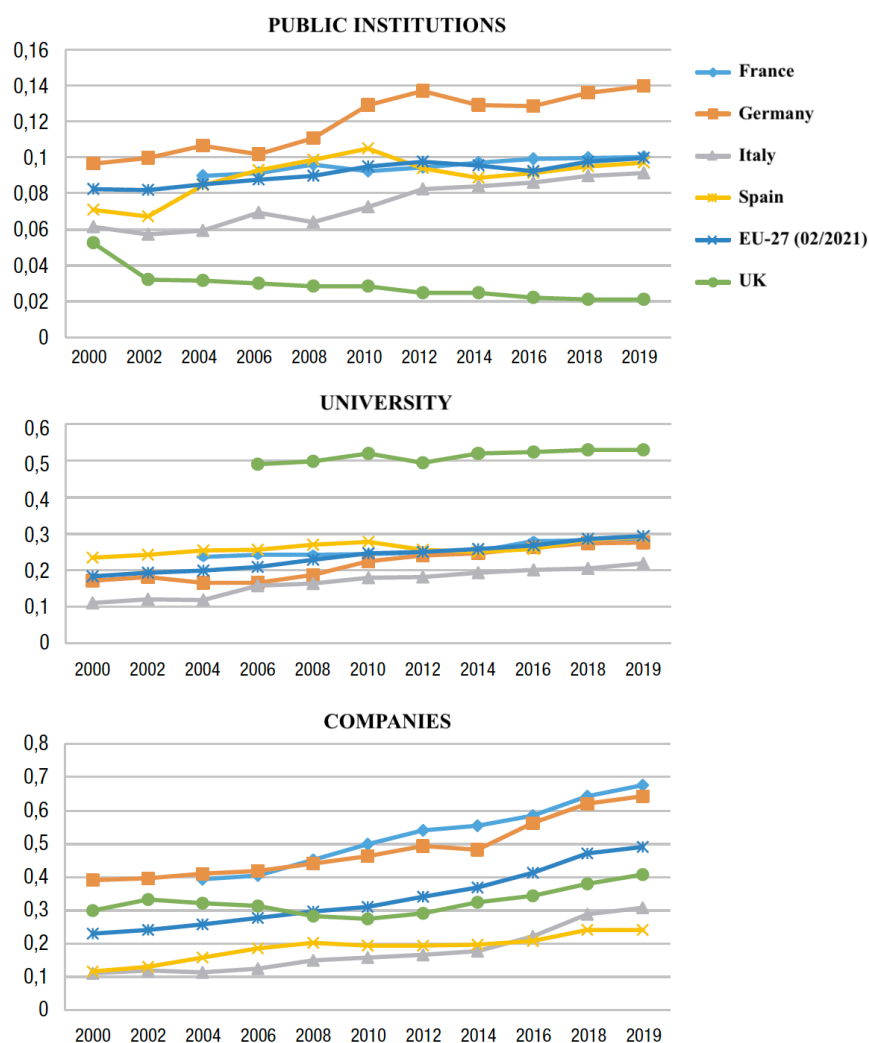
Source: Adapted from CNR, 2021

Figure 27: Public funds as percentage of total public spending on R&D in some OECD countries from 2005 to 2018



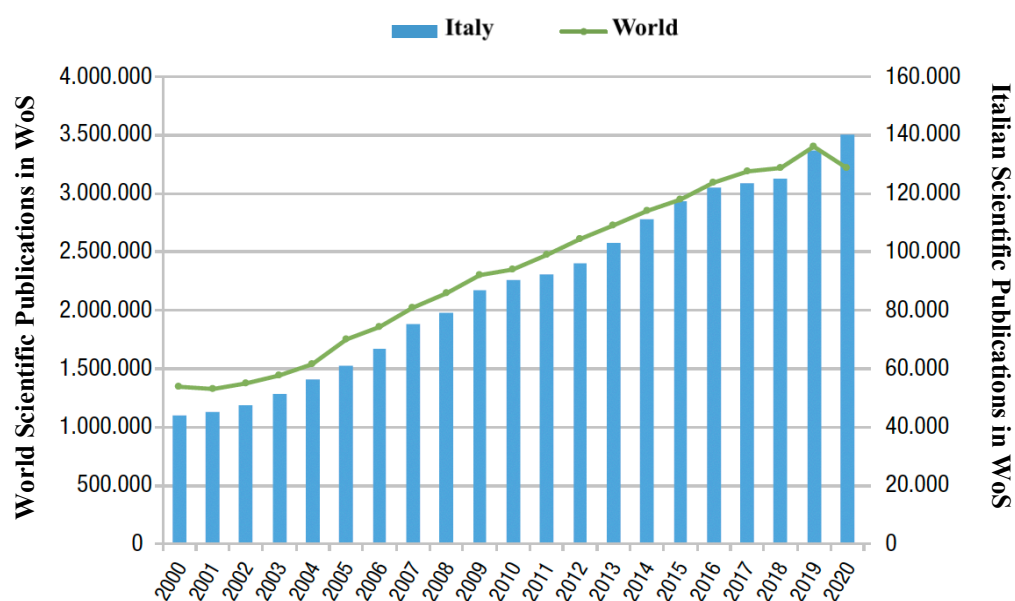
Source: Adapted from CNR, 2021

Figure 28: Percentage of researchers in the total active population (in FTE) by institutional sector in some OECD countries from 2020 to 2019



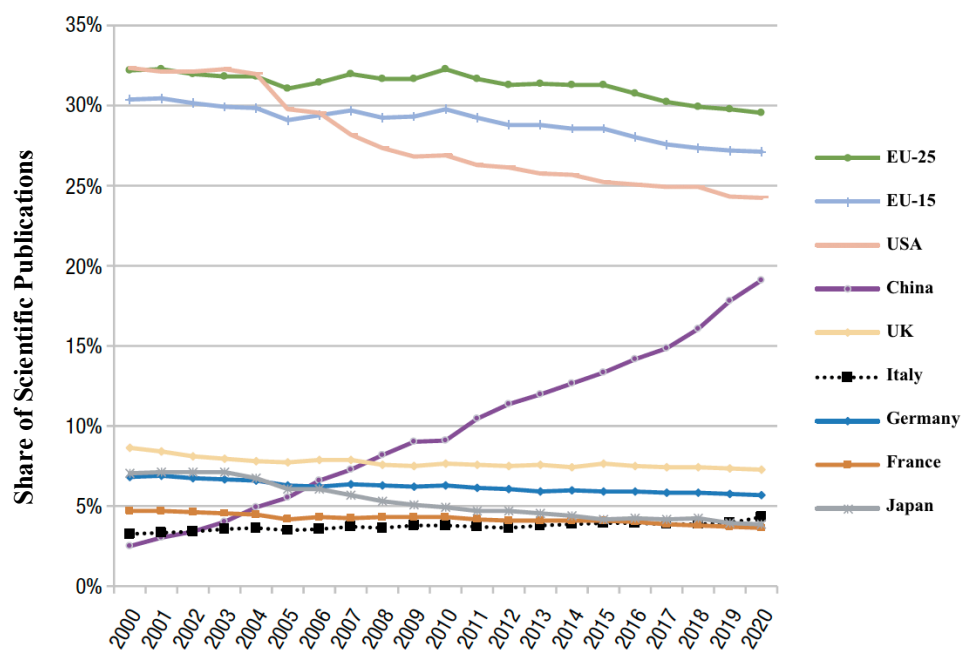
Source: Adapted from CNR, 2021

Figure 29: Scientific publications indexed in WoS



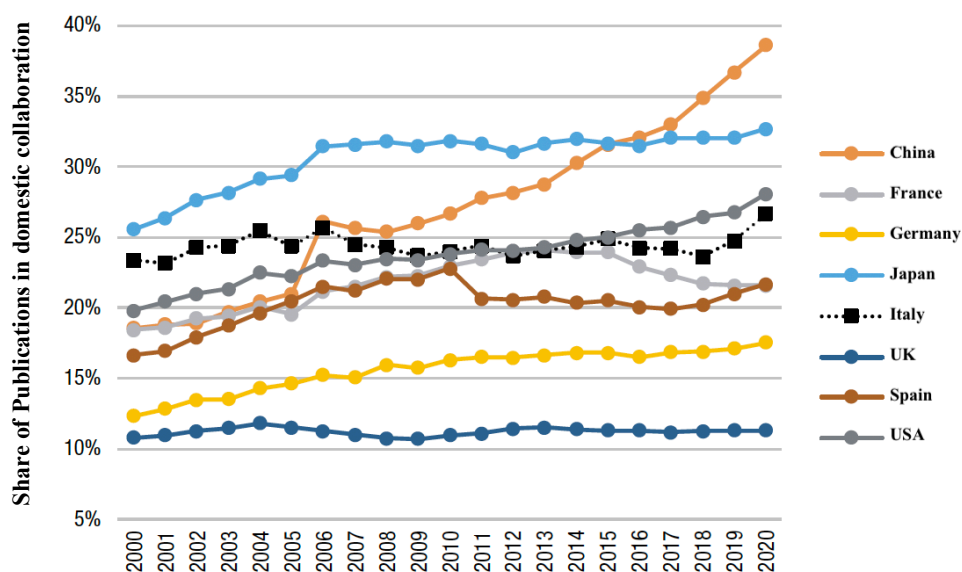
Source: Adapted from CNR, 2021

Figure 30: Shares of global scientific publications by country



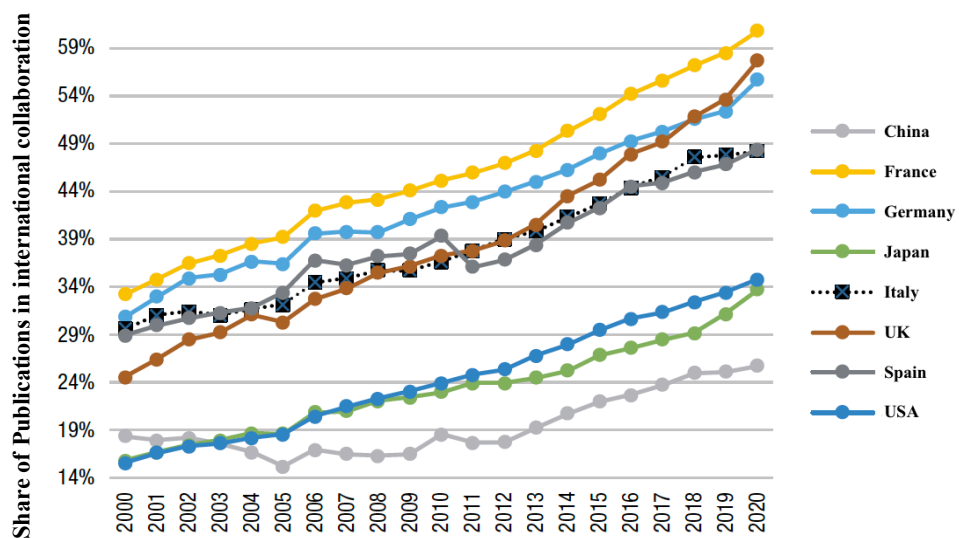
Source: Adapted from CNR, 2021

Figure 31: Shares of national publications resulting from collaboration within the country



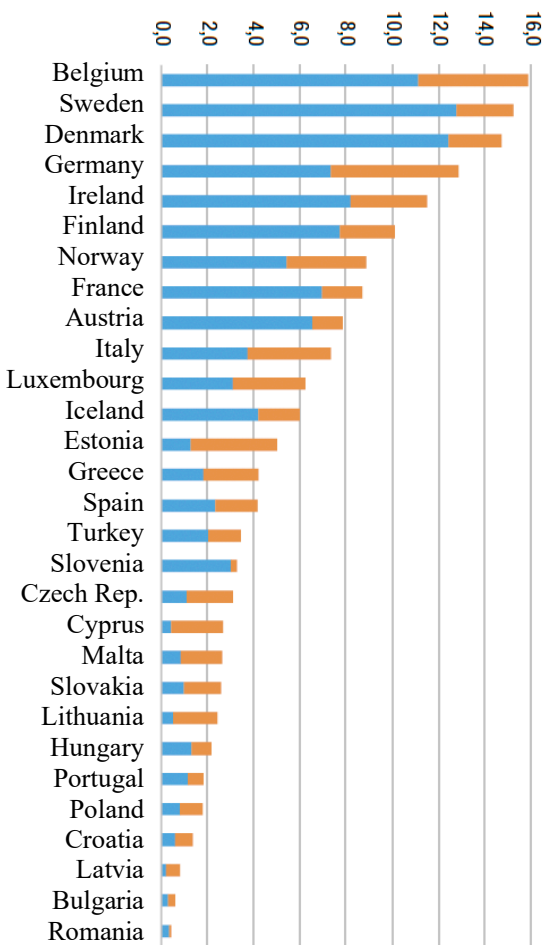
Source: Adapted from CNR, 2021

Figure 32: Share of national publications resulting from international collaborations



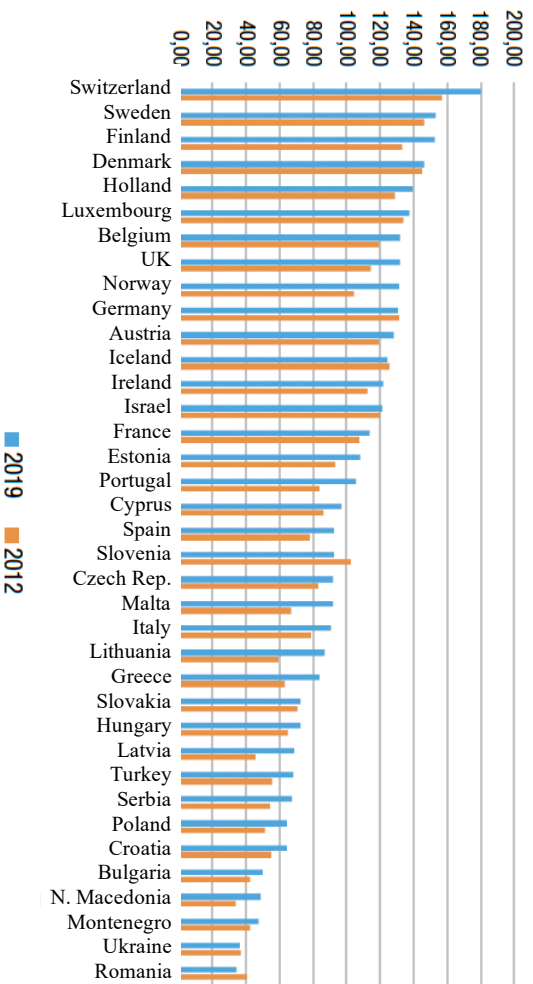
Source: Adapted from CNR, 2021

Figure 33: Business innovation expenditure per employee in the EU
(split between R&D expenditure and other expenditure components)



Source: Adapted from CNR, 2021

Figure 34: Innovation Index, European Innovation Scoreboard, 2012-2019



Source: Adapted from CNR, 2021

Table 15: Patent applications filed at EPO, major industrialized countries, from 2000 to 2020

	2000	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
China	162	2.061	2.542	3.751	4.075	4.680	5.728	7.092	8.641	9.401	12.227	13.432
France	6.789	9.575	9.617	9.897	9.835	10.614	10.760	10.484	10.619	10.317	10.233	10.554
Germany	20.057	27.328	26.202	27.249	26.510	25.633	24.807	24.932	25.539	26.734	26.762	25.954
Italy	3.195	4.078	3.970	3.744	3.706	3.649	3.986	4.154	4.360	4.399	4.469	4.600
Japan	17.117	21.626	20.418	22.490	22.405	22.118	21.421	20.943	21.774	22.615	22.086	21.841
South Korea	977	4.732	4.891	5.721	6.333	6.166	6.407	6.687	6.457	7.296	8.339	9.106
Netherlands	4.477	5.965	5.627	5.067	5.852	6.874	7.147	6.860	7.043	7.140	6.942	6.375
Spain	532	1.430	1.404	1.544	1.504	1.471	1.518	1.574	1.671	1.776	1.885	1.791
Sweden	2.314	3.590	3.638	3.518	3.674	3.873	3.839	3.547	3.783	4.050	4.395	4.423
Switzerland	3.602	6.864	6.553	6.746	6.742	6.910	7.116	7.302	7.354	7.927	8.266	8.112
UK	4.270	5.381	4.746	4.716	4.587	4.764	5.051	5.175	5.321	5.736	6.129	5.715
USA	28.350	39.508	35.050	35.268	34.011	36.668	42.597	40.032	42.463	43.612	46.177	44.293
WORLD	116.649	151.015	142.822	148.562	148.027	152.703	160.004	159.087	166.594	174.481	181.532	180.250
ITALY/WORLD SHARE	2,74%	2,70%	2,78%	2,52%	2,50%	2,39%	2,49%	2,61%	2,62%	2,52%	2,46%	2,55%

Source: Adapted from CNR, 2021

4.2. TalTech Proposal: objectives and expected impacts

This project relates to the twinning topic of the pillar spreading excellence and widening participation in the Horizon 2020 Work Programme 2018-2020.

The primary aim of the TALTECH INDUSTRIAL project is to enhance the research capabilities of Tallinn University of Technology in Estonia.

This will be achieved through two main areas of focus:

1. the study of industrial strategy and competitiveness;
2. the development of advanced data analytics skills.

These enhanced capabilities will enable improved analysis of Global Value Chains and clusters, as well as the identification and analysis of the effects of pertinent public policies. Collaboration with international partner institutions within the European Union will be crucial in achieving these objectives.

The overall objective of the current project is to strengthen the research excellence of TALTECH in:

1. evolution of industrial value chains (clusters) in the era of the 4th Industrial Revolution;
2. catching up dynamics and windows of opportunities for upgrading along the Global Value Chains, and by applying;
3. advanced data science methods in these fields.

To achieve this goals, TalTech Industrial intends to strengthen a strategic relationship with TalTech as the beneficiary and Bocconi University (Italy), Aalto University (Finland), and Nesta (United Kingdom) as the primary sources of knowledge. The network aims to establish a long-term cooperation that will endure beyond the project duration.

The primary objective of this partnership is to enhance the capabilities of TalTech and its regional collaborators to contribute to developing industrial strategies, both domestically and in other European Union cohesion regions. The network will facilitate the co-creation of socially-relevant research that benefits industrialists, policymakers, and entrepreneurs.

Additionally, it will promote policy learning and the development of more effective policies that align with the needs and expectations of society.

Furthermore, the network will establish an executive training system to enhance the accessibility of cutting-edge research for businesses and policymakers.

The TalTech Industrial project aims to foster collaboration between TalTech and leading research and policy analysis entities.

By implementing a demand-driven capacity building strategy, the project seeks to enhance the research capabilities of the participating organizations, advance the professional development of researchers, and position TalTech as a prominent regional research hub. The primary innovative characteristic of TalTech Industrial is its emphasis on developing research domains, novel data, and research methodologies with significant industrial and policy implications.

TalTech and its partners have a solid foundation to assume a leading role in Europe.

Overall, this project responds directly to the challenges outlined in the twinning action of the H2020-WIDESPREAD-2018-2020 call. It also supports the upgrading of the competitive position of Estonian businesses in GVCs and, thereby, the socio-economic development of Estonia, implementation of RIS3 and EU Strategy for the Baltic Sea Region, and achievement of the objectives of the EU regional development and cohesion policies.

More specific objectives of the current project are the following:

- **Objective 1:** Enhance the scientific and research capabilities of TalTech and its Twinning partners in industrial strategy and competitiveness studies by collaborating with international partner institutions within the European Union and other regions. This mission aims to enhance and strengthen collaborations with esteemed institutions, both worldwide and Estonian, like Harvard Business School, to facilitate the exchange of knowledge and expertise. TalTech aims to expand its capacity for analyzing market conditions, corporate strategies, university-industry collaborations, and the impact of these interactions on technical advancement and economic competitiveness. Moreover, this objective aims to strengthen TalTech's capacity to delineate and evaluate the significance of different industrial clusters in the Baltic Sea Region and other areas in the context of Global Value Chains (GVCs).

This initiative is expected to facilitate TalTech's integration into global research networks and establish it as a prominent research center in the Baltic Sea region. By undertaking this initiative, the project will encourage the active participation of TalTech in various European programs, including H2020, Interreg Europe, and the Baltic Sea Region Programme, among others. This will serve to enhance the existing scientific collaboration between Estonian researchers and their European and linked colleagues. The attainment of this target necessitates the promotion of collaborative project proposals that emphasize cooperation among partners, with the lead partner assuming the responsibility and guiding the process. This includes the inclusion of new partners from the Widening countries. TalTech will be able to utilize its enhanced capacities, enhancing its ability to undertake international research initiatives. One further specific purpose is to attain favorable information spillovers, and the consortium members will provide

backing to TalTech, serving as the primary applicant, as a research hub for Estonia and the broader Baltic Sea region.

- **Objective 2:** This objective aims to strengthen the research capabilities of TalTech and its twinning partners by enhancing their skills in research methodologies, specifically in sophisticated data analytics. These improved skills will be utilized to undertake a more comprehensive analysis of Global Value Chains (GVCs) and clusters, as well as to identify and analyze the effects of pertinent public policies. This objective is to improve TalTech's analytical skills by implementing various activities within the project. The primary emphasis will be placed on advanced methodologies in data science and machine learning as their significance continues to grow within academia and business. The utilization of Big/Open Data presents a novel opportunity to leverage the substantial volume of emerging data sources effectively. Consequently, it enables enhanced analysis and evaluation of information about the engagement of national clusters in Global Value Chains (GVCs). Researchers will enhance their analytical abilities and acquire knowledge in various techniques for collecting and managing substantial volumes of data, frequently characterized by a lack of organization or structure. Enhancements in Big/Open Data skills in the context of public services and their impact on policy-making, including advanced data visualization techniques, will be facilitated. Additionally, the collaborative involvement of stakeholders in developing and delivering these services will be strengthened.
- **Objective 3:** Facilitate the advancement of socio-economic development in Estonia and Europe. The project suggests the active participation of local businesses, researchers, and policymakers to find and analyze exemplary methods and enhance opportunities inside the Estonian sector. This will enable them to improve their competitive advantages within Global Value Chains (GVCs). This study analyzes the various characteristics of public support activities pertinent to different stakeholder groups. It examines the interrelationships between these dimensions and their impact on entrepreneurial activities. One of the project's primary goals is to enhance existing collaboration with pertinent stakeholders, such as the Estonian Ministry of Economic Affairs and Communications (EMEA), the Foresight Centre of the Parliament of Estonia, and the Estonian Chamber of Commerce and Industry. This will be achieved by sharing and disseminating the outcomes of the twinning project.
- **Objective 4:** Implementing and promoting inclusive innovation and sustainable development in specific technological domains contribute to the Smart Specialisation Strategy (RIS3) and European regional development and cohesion policies. This also involves the design of effective public policies to facilitate the trans-nationalization of RIS3. Furthermore, it

provides valuable insights into the essential components that should be included in a policy toolbox to assist policymakers. The project aims to enhance TalTech's ability to examine the methods of adjusting public policies to facilitate smart specialization in Estonia. This, in turn, will encourage clusters to participate in Global Value Chains and involves assisting effective national innovation systems centered around the development of Research and Innovation Strategies for Smart Specialisation (RIS3). Particular emphasis will be placed on advancements in sustainable development to equip TalTech with the most suitable tools and techniques to comprehend the conversion of innovation processes' potential into tangible actions. In this particular strategy, research organizations play a crucial role in facilitating the formulation and implementation of RIS3, as well as contributing to the broader European regional development and cohesion strategies.

The primary objective of TalTech Industrial is to augment the capacities of TalTech in conducting comprehensive analyses of competitiveness within particular industries and regional economies. This will facilitate the formulation of more refined strategies based on location, thereby fostering the development of superior quality strategies in the Baltic Sea Region and other parts of Europe. A considerable portion of the customary technical tasks involved in conducting competitiveness studies is anticipated to undergo automation in the coming 5-10 years. Consequently, research entities and industrialists who possess superior resources for leveraging open and big data, as well as advanced data science, will be capable of attaining substantial and nearly real-time insights for informing industrial strategy.

In industry, acquiring extensive expertise and technology-driven competitive advantages is typically time-consuming, and these advantages tend to undergo gradual transformations. Nevertheless, conventional research studies on industrial competitiveness tend to quickly become obsolete due to the continuous influx of new trade and industry data, which is updated monthly, quarterly, or yearly. The need to monitor the success of the implementation of industrial strategy has resulted in a significant amount of manual labor. Moreover, in the present period, trade patterns can potentially undergo significant transformations within the context of Global Value Chains. This is mostly due to large economies displaying an increased inclination to withdraw from multilateral accords and organizations, opting instead to impose tariffs unilaterally. This project aims to leverage emerging data sources, processes, and approaches facilitated by the advancements in big data and applied data science. Furthermore, the dynamic nature of trade patterns necessitates enhancing flexible analytical capacities at the individual firm, industry organization, and governmental levels.

The adoption of big data analytics has been widespread among large corporations and many small and medium-sized enterprises (SMEs) in recent years.

However, the academic community, particularly universities outside of the United States, has been relatively slow in incorporating new data science and machine learning techniques that have emerged due to advancements in computer science. We aim to employ these novel methodologies in examining economic phenomena, such as clusters and Global Value Chains (GVCs). Previous studies have frequently encountered limitations due to the inadequate availability of quantitative data. This assertion holds particular relevance when examining the examination of inventive endeavors in countries that are in the process of catching up. In such contexts, the primary drivers of innovation and productivity increase are often attributed to experiential learning and the procurement of machinery rather than formal research and development practices. Moreover, it is essential to acknowledge the limits of commonly used sources of public statistics, such as Eurostat or OECD, while conducting analysis on industrial specialization and clustering at the NUTS2/3 level in Europe, as well as the involvement of various European regions and nations in Global Value Chains (GVCs). To address these challenges, our approach involves leveraging big data and positioning TalTech as a significant leader in this research domain within the European context.

4.2.1. Literature review

A decade ago, the European economy witnessed a 3% increase in real Gross Domestic Product (GDP), with particular European Union (EU) member nations observing growth rates in the double digits. The prevailing economic sentiment in Estonia and other European countries was predominantly optimistic. Consequently, they have implemented policies that have resulted in growth but have also led to a significant escalation in risks. According to Tiits, Kattel, Kalvet, and Tamm (2007), there has been a substantial and rapid increase in the financial fragility of multiple Central and Eastern European (CEE) countries. This has resulted in the region being on the verge of an economic collapse. The primary cause of this dire situation can be attributed to errors in macroeconomic management, which ultimately led to a severe economic crisis in European cohesion countries a decade ago.

The primary obstacle to enhancing microeconomic competitiveness persists in the cohesiveness countries in economic growth. According to Eurostat's 2019 data, there remains a significant disparity in labor productivity between cohesion economies and more competitive economies within the European Union (EU), with the former seeing productivity levels that are 2-3 times lower. A significant obstacle faced by the EU cohesion economies is enhancing productivity within the exporting industry, specifically in the context of aligning with the Global Value Chains (GVCs).

The economies of Estonia and Central and Eastern Europe (CEE) can be characterized as operating at the lower end of the value chains in cross-border

clusters within Europe. In these clusters, more advanced economies assume the role of leading in research, product development, production coordination, and marketing. On the other hand, CEE economies, including Estonia, primarily contribute through lower-cost production and support facilities.

However, achieving further progress necessitates transitioning from an investment-driven approach to one centered on knowledge and technology-driven growth. Consequently, there is a need for improved alignment between public policy and the industry's requirements.

The implementation of Smart Specialisation Strategies, which the European Commission has advocated, has led to the incorporation of existing technological and economic specialization, as well as the entrepreneurial discovery of methods to enhance current industries or venture into new technology-intensive sectors, into the forefront of policy development. However, the comprehensive theoretical development of the RIS3 concept is still in progress, which explains the poor comprehension of its consequences among policymakers. Similarly, there is a need to enhance research capability, and industries must reconsider their strategic approach.

In summary, to achieve successful catching-up, research, industry, and government entities in Estonia and other Central and Eastern European (CEE) economies must enhance their comprehension of the current specialization and potential opportunities for catching up within the Global Value Chains (GVCs).

According to Abramovitz (1986), catching-up was relatively uncomplicated.

The process of acquiring and implementing pre-existing technologies is generally less complex than developing novel technologies, goods, or services at the forefront of scientific and technological advancements. The author suggested that economies lagging behind can make significant progress in a relatively short time, provided that their societies possess the necessary capacities to embrace and use cutting-edge technologies.

Globalization in recent decades has resulted in a significant rise in the movement of goods, services, and capital across national borders. Furthermore, it is worth noting that transnational technology transfer has emerged as a significant manifestation of globalisation (Lundvall and Borrás, 1997). It may be postulated that the process of catching up has been facilitated by the liberalization and opening up of economies in recent decades. This development has made access to financial resources, new technologies, and marketplaces more convenient. However, it is evident that Europe still has substantial disparities in living standards across various regions, even long after the admission of the countries involved in the European Union. Therefore, there is an apparent necessity to reconsider the fundamental principles of tactics aimed at catching up (Barca, 2008; Foray et al., 2009, 2011, 2012).

In contrast, Gerschenkron (1962) posited that catching-up was far from straightforward. The empirical evidence from most countries' economic performance in recent decades supports this perspective. Certain countries or regions within larger economies, such as China, have seen a notable and

expeditious process of economic convergence in the past few decades. Several medium-income economies have seen significant economic booms characterized by initial economic solid expansion. However, severe financial or economic crises have often followed these booms, resulting in a substantial decrease in the Gross Domestic Product (GDP). Nevertheless, certain economies have persistently failed to keep pace with others (Rodrik, 2007).

Based on the analysis of economic history, it becomes evident that various economies, industries, and science and technology fields exhibit disparate evolution rates (Freeman, 1987; Freeman and Perez, 1988; Perez, 2002). Hence, the facilitation of increased specialization is not just attributed to globalization and the market expansion, but also to the composition of the sector and the overall economy, which play significant roles in fostering growth and development. An economy's growth rate is expected to accelerate as the proportion of its innovative industries, particularly those engaged in exporting, increases.

According to Perez (2002), the process of industrialization in Europe during the 18th and 19th centuries, as well as the rise of the United States as a dominant global power in the 19th and 20th centuries, were driven by the formation of distinct industries with novel qualitative characteristics. The British Industrial Revolution established the foundation for a progressive process of industrialization in Western Europe, wherein the neighboring countries experienced a sequential improvement in their living conditions through their industrialization efforts. During the 20th century, Japan and East Asia underwent a comparable pattern of development known as the "Flying Geese" model, characterized by the diffusion of industrialization and its consequential effects on living standards from one country to another.

A prevalent trend observed among successful catching-up economies is their ability to assimilate the skills, technologies independently, and frequently even capital from more advanced nations. Each country undergoing industrialization established innovative infrastructures and assumed the role of a consumer of industrial goods. In due course, the company began to export its goods to economically disadvantaged neighboring nations (Pollard, 1973; Pollard, 1981). Nevertheless, significant advancements in technology are infrequent occurrences. Recent empirical data indicates that the endeavor to bridge the gap in technological development, whether at a national or regional scale, is influenced and limited by the preexisting capabilities within a country or region, as well as the intricacy of the technology itself (Balland et al., 2015; Petralia et al., 2017).

The literature on industry life cycles and paradigms, which played a significant role in the initial studies on national innovation systems (Freeman, 1987), is not frequently cited in contemporary literature on knowledge-based economies. However, it provides a valuable framework for understanding the historical advancements and the growing geographical shifts in economic activities resulting from globalization.

Additionally, it provides a valuable framework for analyzing the potential opportunities and challenges associated with economic development. Based on

the existing body of research on life cycles, the development of individual technologies and products, as well as the industries that rely on them, originates from the introduction of innovative technologies and products. Over time, there is a noticeable growth in market size, accompanied by heightened competition, resulting in a decline in profit margins due to the proliferation of comparable rival items. The process of industry consolidation commences. Over time, as the products reach a state of maturity and the initial markets become more saturated, the primary advantage in competition shifts towards cost efficiency, specifically economies of scale. Consequently, production is strategically relocated to low-cost locations conveniently situated near the major markets characterized by high levels of mass consumption. This phenomenon has been observed and discussed by scholars such as Vernon (1966), Wells (1972), and Perez (2002).

The analysis highlights the significant finding that technical and industrial advancements do not transpire haphazardly. Significant technological advancements have facilitated the development of interconnected sets of technological improvements, along with the growth of new industries and infrastructures that support and complement these innovations. The mechanization of the textile industries during the 18th century played a pivotal role in the subsequent transformation of British society.

Furthermore, the invention of the steam engine in the 19th century facilitated the advancement of a diverse range of industrial machinery, ultimately leading to the establishment of extensive railway networks. As a result of these advancements, there was an increase in productivity development and a significant transformation in the perception of time and space for individuals living at that time. The advent of microprocessors, computers, and the Internet precipitated the rise of a contemporary information society during the 20th century (Freeman and Perez, 1988; Perez, 2002).

The aforementioned structural transformation within the industry is the primary factor that leads to a general enhancement in the knowledge and technology intensity of the economy. This transformation involves the substitution of traditional resource or labor-intensive sectors with contemporary scientific and technology-intensive companies. Furthermore, learning, capacity building, and innovation dynamics undergo transformation. During the initial stages of catching up, there is a prevalent tendency to adopt and replicate existing "best practice" solutions, accompanied by the corresponding learning and organizational transformation processes. This innovation method, sometimes called the "DUI" approach, holds significant influence.

The significance of industrial research and development (R&D) activities, namely in the science, technology, and innovation (STI) paradigm, becomes increasingly prominent with modern enterprises rooted in scientific knowledge. According to Moncada-Paternò-Castello et al. (2010), Europe's gross domestic expenditure on research and development (GERD) is comparatively lower than that of the United States. This discrepancy is mostly attributed to the relatively limited presence of modern science-based firms in Europe. The statement holds

for Central and Eastern European economies, as well as other economies that are in the process of catching up, compared to Western Europe. Therefore, the primary concern regarding catching up is not simply raising the overall expenditure on research and development (R&D) but effectively establishing a presence in the quickly expanding modern sectors by enhancing actual production or service capabilities.

Throughout history, significant businesses reliant on advanced technology have arisen either within or as a result of competition between major economies. These economies possess the requisite resources and function as substantial markets that drive the growth of these developing sectors. In the not-so-distant past, it was common for the critical components of an industry's value chain to be situated near one another. Globalization, along with the rapid development of information and communication technologies (ICTs), has significantly facilitated international communication, logistics, remote business unit management, and the offshoring of many components of value chains.

The catching-up in economic development has become more reliant on imported technologies, emerging production capabilities, and the dynamics of the global industry and market. This trend has been facilitated by increased specialization and significant growth in the trade of manufactured intermediate goods (Cattaneo et al., 2010). Hence, it is imperative to broaden the scope of analysis beyond regional or national boundaries when examining specific industries or clusters. Alternatively, it is recommended to conduct a study of industry value chains (also known as clusters) within a broader cross-border context or, in some instances, as Global Value Chains, as suggested by Humphrey and Schmitz (2002), Tiits and Kalvet (2012), and Lee-Malerba et al. (2016).

The variation in geographic locations leads to significant differences in the knowledge intensity and other sector aspects. This variation is of utmost importance. Frequently, even the most prosperous economies striving to catch up with more advanced nations begin their foray into modern sectors by initially engaging in simpler manufacturing or support roles. Over time, they gradually progress within these specific businesses, taking on more complex jobs that require more excellent knowledge and technological expertise. This illustrates how East Asia has developed its dominant position in the electronics industry in recent decades (Cattaneo et al., 2010). The augmentation of the medium and high-tech industries, together with the internal enhancements inside specific businesses, are both crucial components for achieving a successful catch-up in the economy (McMillan and Rodrik, 2011).

The notion of leapfrogging possibilities for latecomers, wherein they capitalize on new techno-economic paradigms and make preemptive investments in new technology to exceed the incumbent, was initially introduced by Perez and Soete (1988). In their study, Lee, Lim, and Song (2005) employed this notion to elucidate the phenomenon of Korean producers surpassing their Japanese counterparts in the consumer electronics industry throughout the digital era. The concept of windows of opportunity, as discussed by Lee and Lim (2001),

provides a more comprehensive interpretative framework. This framework identifies three patterns of catching-up: path-following, stage-skipping, and path-creating catch-up. Additionally, the theoretical framework associated with the "catch-up cycle" proposed by Lee and Malerba (2016) further enhances our understanding in this area. The latter paradigm offers a broader perspective on the combination of technology-based windows with other discontinuities, leading to the creation of possibilities for catching up.

The second opportunity window is associated with the economic cycle, wherein latecomers may see reduced entry costs during downturns (Mathews, 2005; Lee and Mathews, 2011). Government participation in the industry presents an additional avenue for capitalizing on a potential opportunity. In their study, Guennif and Ramani (2010) analyzed the impact of regulatory system changes on the growth opportunities of Indian enterprises within the pharmaceutical industry.

The government plays a significant role in various catch-up scenarios, as evidenced by the examples of the telecom equipment business in China (Mu and Lee, 2005) and the high-tech industries in Korea and Taiwan (Lee and Lim, 2001; Mathews, 2002) and according to the study conducted by Lee, Mani, and Mu (2012), government interventions in China and Korea yielded distinct results when compared to Brazil and India. Specifically, the effective development of indigenous telephone switches was observed solely in the former nations, underscoring the significance of regulatory measures. The contributions in this study explore the dynamics of leadership transitions by employing the theoretical framework of Sectorial Innovation Systems (SSI) as proposed by Malerba (2004). Diodato et al. (2017) and Morrison et al. (2008) demonstrate through theoretical and empirical analysis that in addition to technological leadership, demand conditions are a crucial factor in creating new avenues for opportunity. Leadership change transpires when customers attain awareness of the exceptional quality inherent in a novel product. Nevertheless, establishing a reputation poses significant challenges and risks for countries later entering the scene. Public policies have a crucial role in this particular sphere as well.

According to Lee and Malerba (2016), it may be argued that the occurrence of leadership shifts and catch-up by latecomers can be projected to occur periodically. The authors also note that although latecomer countries have access to windows of opportunity, not all effectively utilize these opportunities. The strategic decisions made by latecomer enterprises play a crucial role in this regard.

According to Porter (1990), the initial basis for identifying and analyzing industrial specialization was trade statistics, particularly the identification of interconnected products and product groupings in which an area or country possesses a significant global market share. In contemporary cluster mapping methods, industries are initially categorized as "traded" or "local." Traded industries exhibit concentration within specific geographic areas and engage in commerce with other regions and countries. Local industries refer to industries found in most, if not all, geographical regions and primarily sell their products or services within the local area. The two major groups are further subdivided into

traded clusters consisting of trade-related industries. These clusters are organized based on a comprehensive assessment of the interconnections between individual industries.

This assessment considers factors such as input-output measures, utilization of labor occupations, and co-location patterns in terms of employment and establishments. Local industries are primarily classified based on commonalities in activities that are represented in aggregated industry groups.

According to Delgado, Porter, and Stern (2016), it is essential to note that just concentrating on local employment and output data is inadequate, as it fails to consider the broader significance of specific regions and countries in cross-border and Global Value Chains. It is imperative to recognize that significant efforts have been undertaken to delineate the competitive standing of nations on a worldwide scale through the utilization of the product space framework, which is predicated on trade data and network techniques (Hidalgo et al., 2007).

Numerous academic investigations on Global Value Chains (GVCs) utilize input-output data sources such as the World Input-Output Database (WIOD) or the OECD inter-country I-O model to assess the value added and identify significant clusters at a sectoral level (Dietzenbacher et al., 2013; Yamano and Ahmad, 2006). Frequently, these statistics are combined with international trade data. One benefit of employing this methodology is the ability to ascertain the length of supply chains and identify the countries that contribute value throughout these chains.

Furthermore, many metrics have been devised to assess the extent of global integration, specialization, and fragmentation within Global Value Chains (GVCs). Various indicators of country or industry participation within Global Value Chains (GVCs) can be discerned and tracked over some time (Amador and Cabral, 2014). The field of quantitative analysis at the business level is relatively nascent, however, there exists a substantial body of qualitative case studies on Global Value Chains (GVCs). These studies have the potential to pinpoint specific domains where information systems (IS) academics can amalgamate concepts from various theoretical frameworks and make valuable contributions to innovation policy. The methodologies of Industrial Sociology (IS), clusters, and Global Value Chains (GVC) highlight distinct phenomena and variables, yet all three are pertinent to innovation, social, and economic policy. The integration of diverse methodologies will provide the evaluation of the primary factors that contribute to the development of innovative capacity in different regions of the European Union. Additionally, it will allow for examining the impact of Global Value Chains on numerous outcomes, including but not limited to human capital development, productivity, economic growth, sustainability, and poverty reduction.

The utilization of open and large-scale data, along with innovative data science methodologies, is widely recognized as a catalyst for significant changes in socioeconomic policy and research (Einav and Levin, 2014). Moreover, these

advancements have also demonstrated their potential to revolutionize business management and decision-making processes.

Scholars have initiated discussions regarding "non-traditional sources of social and economic data" (Blazquez, 2018), acknowledging the considerable detail, unpredictability, and multidimensional nature of emerging data, which has numerous potential benefits. However, there are several well-recognized obstacles associated with this issue. These challenges encompass the accessibility of the data, the technological skills necessary to manage and analyze it effectively, and the incorporation of the data into existing theoretical frameworks without succumbing to the pitfalls of excessive reliance on data.

The conventional data analytics methodologies commonly employed in computer science departments encompasses regression, classification, clustering, dimensionality reduction, ensemble methods, neural networks and deep learning, transfer learning, reinforcement learning, natural language processing, word embeddings, and other techniques. These methodologies are frequently integrated into larger analytical systems. To date, there has been limited utilization of novel data analytics methodologies in economics and business management research. The existing body of research primarily consists of exploratory studies that examine the possible impact of modern data analytics on the field of economics.

The operationalization of research and policy frameworks aimed at resolving the disparity between technical advancement, economic progress, and societal requirements necessitates using accurate and appropriate data. Conventional data sources, such as company surveys and descriptive studies of overall research and development and innovation trends, have limited applicability in this context. The rationale behind this is that the available data sources and methodologies lack the necessary level of detail and timeliness to accurately capture the intricate network of scientific and technological domains, as well as the interconnections between them. These factors are crucial for identifying the current areas of specialization within an economy, predicting potential paths of evolutionary development, and determining the possibility of achieving more radical combinations through policy interventions. Due to their aggregated and anonymized nature, the current data sources provide insights on the characteristics of collective innovators rather than individual ones. Consequently, this limits the effectiveness of policy targeting in terms of accuracy (Bakhshi and Mateos-Garcia, 2016; Hain and Jurowetzki, 2018). The assessment frameworks used to assess innovation often overlook the societal perceptions and attitudes towards new technologies despite their significant influence on the practical implementation of these technologies.

The field of economic complexity and related variety has significantly improved our comprehension of economic development and evolutionary economic geography. These advancements can facilitate the integration of complex research, development, and innovation policies with straightforward indicators derived from official sources (Balland et al., 2018; Balland and Rigby, 2017).

The frameworks above utilize trade and regional economic data, as well as technological specialization data, to construct maps that effectively depict the similarities and disparities across various products, industries, sectors, research areas, and technologies (Hausmann et al., 2014; Guevara et al., 2016). Policy actions are necessary to increase the likelihood of connections between distant domains. The conceptualization of economic development as a progression through a knowledge space, wherein specific paths exhibit varying gradients, aligns with fundamental concepts in third-wave models. These models emphasize the importance of targeted interventions in facilitating the emergence of intricate combinations of knowledge that hold significant value (Frenken, 2017).

Nevertheless, the complexity analyses commonly depend on static classifications of products, industries, and technologies, which are not well-equipped to account for the emergence of novel productive and technological activities. This is a crucial aspect of economic development and represents a gap in the evidence for third-wave innovation policies (Bishop et al., 2018).

Over the past ten years, there has been a rise in the development of a novel discipline known as science and innovation mapping. This field aims to produce more accurate depictions of intricate research and development and innovation domains (Börner, 2015; Börner et al., 2018; Rotolo et al., 2014, 2017).

The categorizations of disciplines, technologies, and sectors in these maps are determined using Natural Language Processing and Scientometric analyses of extensive textual data found in patents, publications, and other sources of information about activities, capabilities, and resources within innovation systems. The measurement of proximity between fields is conducted through research and industrial collaborations, as well as by assessing semantic similarity based on term co-occurrence in research and development and innovation (R&D&I) corpora. Additionally, the predictive transfer of scientific, technological, and industrial categories across domains is achieved by applying supervised machine learning methods, as outlined by Klinger et al. (2018).

These maps have the potential to visually represent the organization of science and technology, the connections between different fields and communities, and the potential for collaboration. They offer unparalleled depth and timeliness, making them a significant resource for informing research, development, and innovation strategies. Nevertheless, there are two significant constraints associated with their utilization. Firstly, these methods have conventionally focused on mapping a solitary "layer" of research and development and innovation (R&D&I) activity, such as science or technology, without considering the interconnections between them that are commonly observed in innovation processes. Secondly, these methods have traditionally been employed for descriptive analyses rather than for explanation and prediction.

However, efforts are being made to solve these constraints as the number of maps incorporating many domains increases. These maps take into account the interconnections between activities and capacities across diverse domains, which collectively influence the advancement of new technologies.

Several recent studies have examined the field of data science, including Börner et al.'s analysis of research, patenting activity, and skills supply (2018). Another example is the Tweetoscope project by Chavalarias et al., which integrates scientific research on climate change with public discussions on Twitter (2015).

These maps are additionally utilized for the purpose of forecasting prospective trajectories of technological and industrial advancement, with the intention of providing insights to guide policy-making. In their study, Alshamsi et al. (2018) employ the network structure of scientific publication networks to make predictions about the future specialization of individuals, institutions, and countries in various disciplines. Similarly, Hain and Jurowetzki (2018) utilize longitudinal semantic analyses to identify groundbreaking patents in the electric vehicles industry, as well as interface technologies in the realm of human-machine interaction (Jurowetzki and Hain, 2014).

Additionally, there is an increasing amount of economic research that integrates mapping data into econometric analyses to examine the factors and dynamics influencing research and development (R&D) and innovation (I) activities. This integration serves as a crucial source of "causal knowledge" that informs R&D and innovation policy. An illustration may be seen in the study conducted by Bloom et al. (2013), wherein they examine the analysis of research and development (R&D) spillovers. The study evaluates the impact of neighboring entities' investments in knowledge space (resulting in knowledge spillovers) and market space (leading to intensified rivalry) on a company's outcomes. In a more recent study, Kelly et al. (2018) conducted a semantic analysis of patent text data to identify patents that might be considered "breakthrough patents" in the long term. Subsequently, they utilized these patents to examine the relationship between radical innovation and the financial performance of sectors and firms at the sectoral and firm level.

Competitiveness studies still face challenges due to the absence of comparable quantitative data, which hinders the ability to make meaningful comparisons of creative activity across various industries and nations.

The OECD Frascati and Oslo Manuals provide a structured approach for gathering statistical information on research and development (R&D) and innovation. The European Commission has also devised the Community Innovation Survey to facilitate this data collection process further.

However, the current data collection efforts generally focus on research and development (R&D) activities and patenting, which are considered inputs to innovation. These efforts provide limited insights into less formalized forms of innovation, such as learning by doing, which are more prevalent in areas and nations that are catching up. The subject of discussion pertains to the regions of cohesion within Europe. Similarly, there is a lack of knowledge regarding the extent of significance that a product or process innovation, as identified in the European Innovation Survey, has had for the respective firm.

Quantitative data would also benefit cluster and Global Value Chain (GVC) research. Statistical agencies commonly release input-output data that depict inter-industry trade with notable temporal lags. The examination of Global Value Chains (GVCs) is hindered by the absence of comprehensive data regarding arms-length and intra-firm imports and exports conducted by multinational corporations, which often exert significant influence over GVCs. This is the point at which the exploration and adoption of alternative sources of big data, as well as novel methods for organizing and analyzing vast quantities of data frequently lacking in structure, can be of significant assistance.

In addition, the adoption of privacy-preserving computing techniques on encrypted data, such as Sharemind, can enable the utilization of previously inaccessible sensitive datasets. Furthermore, innovative methodologies and technologies for examining open and large datasets, as well as machine learning, offer novel avenues for analyzing diverse data. Illustrative instances of this phenomenon encompass the creation of analytical dashboards that are capable of automatic updates, as well as the utilization of machine learning algorithms to uncover previously unimagined connections between disparate situations.

4.2.2. Data sources

To achieve the objectives of research training and capacity building, multiple data sources will be utilized.

When examining traditional statistical data, the primary sources to be considered are as follows: The user mentions several databases commonly used for statistical analysis in academic research. These databases include the Statistics Estonia statistical database; the Eurostat database, which encompasses trade, regional development, and structural business data; the OECD statistical database, which includes Inter-Country Input-Output Tables; the World Input-Output Database; the OECD-WTO Statistics on Trade in Value Added; the UN Comtrade International Trade Statistics database; the UNIDO Industrial Statistics Database; the World Bank Open Data; IMF Data, among others.

Estonia possesses a notable abundance of administrative significant data sources that are not readily accessible in other regions. These sources can provide significant benefits when utilized for analyzing the performance of individual enterprises, regions, or economies within a globalized economic context. The administrative data sources that are of considerable importance encompass, but are not restricted to, the following:

The data sources used in this study include experimental statistics and data science applications from Statistics Estonia's newly established big data lake. Additionally, data from the Estonian Research Information System, which contains information on Estonian researchers, their research projects, and publications, was utilized. Annual firm-level business data, including machine-

readable balance sheets and profit and loss statements, were collected from the Estonian Business Registry. Quarterly firm-level revenue and tax data were obtained from the Estonian Tax and Customs Board. Furthermore, monthly firm-level inter-industry input-output data from the Estonian Tax and Customs Board were included. Lastly, proprietary firm-level interview and survey data from previous studies on industrial competitiveness, such as the study on the competitiveness of the Estonian forest and wood processing industry, were incorporated.

In addition, the project's partners possess their own data sources that offer valuable contributions to ongoing research training.

TalTech is affiliated with the Estonian Mobility Data Infrastructure, which gathers and merges diverse socio-economic data. This includes the anonymous tracking of mobile phone locations for subscribers of Estonian network operators. ICRIOS maintains its own PATSTAT-ICRIOS patent database, which offers users access to disambiguated inventors and applicants' names, along with other standardized information. These details are often challenging to locate in alternative patent databases, specifically for applications originating from the European Patent Office (EPO). TalTech will receive complimentary training and a software license for this database.

Moreover, the utilization of diverse data sources that offer open APIs, such as Financial Times Market Data or Yahoo Finance, for assessing the performance of publicly listed companies will be valuable on a global scale. In addition to the aforementioned points, this paper will address the practice of web scraping large volumes of data from publicly accessible websites, like ResearchGate, job portals, and websites of specific organizations. Furthermore, the technologies utilized for the purpose of collecting such data will also be examined.

4.2.3. Existing Methodologies and evolving research methods

The assessment of TalTech's existing strengths has led to the identification of several themes that hold promise for cutting-edge research and subsequent capability-building efforts.

- *Methodologies for evaluating research and technology capacities, and corresponding tactics:* this domain of capacity development centers on examining strategies and business models, as well as identifying advanced knowledge and technology advantages possessed by research institutions, businesses, and/or entire economies. This type of analysis will utilize interviews and surveys conducted with management, data about the pool of competent labor, academic publishing and citation data, as well as information on patenting operations, among other relevant inputs.

- *Methodologies for examining the current status and prospective developments of distinct regional industrial clusters within the framework of the global division of labor:* this section centers on the methods used to conduct an in-depth study of the operations of specific regional, national, and cross-border economic clusters, to maintain and enhance their competitive standing in global marketplaces. This section will address the utilization of fundamental sales, export, productivity, and employment data, alongside forward-looking indicators such as purchasing managers' indexes, costs associated with international container and fly cargo services across different regions, and other relevant factors.
- *Analytical Approaches for Examining Global Value Chains and Prospects for Advancement within GVCs:* this capability-building field primarily focuses on quantitative approaches used to analyze the growth of Global Value Chains. These methodologies encompass several aspects, such as the intensity of trade links, the value-added component of exports, the processing of imported inputs for exports, and intra-industry trade. This section will also examine windows of opportunity and strategies for catching up within Global Value Chains in the context of the fourth industrial revolution.
- *Methodologies for examining the business models of knowledge-intensive start-ups and the formation of new industries focused on research and technology:* previous scholarly research has examined the sequential process by which corporations initially establish their presence in a domestic market and subsequently expand their operations internationally. The emergence of a new category of knowledge-intensive enterprises, referred to as ostensibly root-loose born-global businesses, has been facilitated by the thriving start-up culture and the growing accessibility of international venture capital. Notable examples of such organizations include Skype and Transferwise, both of which originated in Estonia and have achieved multi-billion euro valuations. This section will focus on the development of knowledge-intensive start-ups, specifically examining their business strategies, the availability of financing options such as venture capital, and the changing public policy landscape.
- *Methodologies for examining the utilization of qualitative and quantitative methods in evaluating public policies and policy initiatives:* the primary obstacle in public policy evaluation lies in demonstrating the appropriate techniques for analyzing and assessing policy interventions that impact various facets of society. This section overviews the primary approaches and methodologies employed in evaluating public policies. This paper will emphasize utilizing contemporary empirical methods alongside the interplay between statistics, policy analysis, and decision-making. This paper will also

explore the potential for near real-time monitoring of the success of policy programs and the use of predictive modeling to assess their effects.

The assessment of TalTech's existing strengths has highlighted several themes that have the potential to become emergent pathways of cutting-edge research. These topics will serve as the basis for ongoing skill-building initiatives.

- *Methodologies and techniques utilized in the storage, analysis, and visualization of massive data sets:* the primary objective of open and big data is to effectively use extensive quantities of data and leverage novel data processing methods to facilitate research and inform decision-making based on knowledge. Many interconnected advancements have rendered open and big data an exceptionally appealing domain. Recent advances in applied statistics and computer science have significantly enhanced the accessibility of innovative data science tools for economists. The progress in computer hardware and the emergence of various cloud computing platforms, such as Amazon AWS or Google Cloud, have facilitated the availability of virtually unlimited computing power and storage for data science and machine learning purposes.
- *Methodologies to explore the quantitative and qualitative approaches employed in mapping industry specialization at both the national and regional levels:* in the context of examining quantitative cluster mapping methodologies, the utilization of statistical data sources, such as international trade data from UN and Eurostat, as well as structural business statistics from Eurostat, will be explored. Additionally, alternative sources of 'big data,' such as web scraping of job-seeking and job opportunity data from public websites and national business registries, will be considered. This discussion is informed by Delgado, Porter, and Stern (2016) work and other relevant literature.
- *The utilization of open and big data, along with the involvement of e-government, plays a crucial role in enhancing the caliber and efficacy of economic development strategies:* this section explores the potential applications of open and big data, as well as the role of e-government in analyzing clusters and Global Value Chains (GVCs). This encompasses innovative methodologies in big data and applied data science for web scraping and analyzing diverse data about education and research funding, academic publishing and patenting activities, geographical location, as well as the product and service offerings of specific businesses (Foster et al., 2016).
- *Ethics, data protection, and privacy-preserving computing are of significant academic interest:* collecting and analyzing data necessitates responsible

research that adheres to established ethical guidelines, safeguards privacy and data protection, and upholds intellectual property rights. Open and massive data are susceptible in this regard. The aforementioned technology can alter the methodologies employed in research, the formulation and assessment of public policies, and their subsequent implementation and evaluation. However, the utilization of open and large data, if mishandled, might potentially compromise privacy. Hence, this particular domain focuses on enhancing capabilities in ethics, privacy, data protection, and privacy-preserving computing, which enables the extraction of generalized information from sensitive data.

4.3. Global Value Chain, Innovation, Value Added and its Mapping

The phenomena of globalization and the involvement of multinational corporations in pursuit of increased advantages and cost savings have directed their attention toward enhancing value at each stage of the manufacturing process. This emphasis on value addition aims to enhance competitiveness and gain a higher share of consumer choice. According to Sandoval (2015), multinational corporations strategically distribute their productive operations over various geographic regions in order to maximize their value-added benefits. Hence, an essential component in the analysis of international production and commerce is the concept of Global Value Chains (GVCs).

Baldwin and Venables (2013) suggest that a Global Value Chain (GVC) refers to the sequential progression of phases involved in producing a product or service, with each stage contributing to the overall value of the final offering. The process includes both physical alteration and the introduction of diverse services (Kaplinsky, 2013).

The current organization of production processes has a multi-stage structure that frequently spans multiple countries. In product manufacturing, companies acquire intermediate inputs from various vendors, sometimes situated in other countries. Consequently, each phase contributes value to the manufacturing process, and commodities may traverse international boundaries multiple times before ultimate consumption.

The Global Value Chain (GVC) is a well-recognized multinational production-sharing arrangement (Gunnella et al., 2019). A Global Value Chain (GVC) entails the fragmentation of the industrial process among multiple nations. Consequently, enterprises adopt a strategy of specialization wherein they focus on a particular activity and refrain from manufacturing the complete product (World Bank, 2020).

Over the last two decades, trade associated with Global Value Chains (GVCs) has exhibited substantial economic expansion in numerous countries around the globe. The driving forces behind this openness can be attributed to the decrease in

transportation and communication expenses, as well as the reduction of trade restrictions.

Nevertheless, it is essential to acknowledge that trade advantages have not consistently been distributed evenly. Numerous nations lack the necessary human resources, institutional framework, and infrastructure ability to engage in trade effectively. This deficiency in trade capacity is further exacerbated by the growing prevalence of protectionist measures and the emergence of challenges to global and regional trade agreements. Furthermore, recent advancements in technology, like robotics, big data, and the Internet of Things (IoT), have initiated a process of further reshaping and transforming Global Value Chains (GVCs) (World Trade Organization, 2019).

As per the World Trade Organization (2019), most worldwide trade is facilitated via Global Value Chains (GVCs), wherein production traverses one or more borders, often multiple borders, before final assembly.

De Marchi et al. (2018) identified three distinct categories of innovators inside Global Value Chains (GVCs). The initial cohort consists of the foremost pioneers, distinguished by their elevated levels of innovation and comprehensive utilization of all available avenues of knowledge acquisition within the Global Value Chain (GVC). Specifically, these organizations directly collaborate with prominent corporations to train the local workforce. In certain instances, the impetus for innovation arises from the necessity to adhere to stringent manufacturing standards set forth by prominent corporations. This is frequently accomplished through acquiring supplementary knowledge inside the Global Value Chain (GVC). Furthermore, the effective utilization of learning channels inside supply chains is complemented by the advantageous connections established with local stakeholders such as suppliers, colleges, and business associations. These affiliations enable innovation activities to draw inspiration from and replicate the best practices observed within these entities.

The second category comprises autonomous innovators. The limited access to knowledge for generating innovation through Global Value Chain (GVC) channels is mainly attributed to the reliance on the leading firm for knowledge acquisition, which restricts the scope of tasks performed and necessitates in-person meetings with the leading company's managers. These companies refrain from exploiting alternative GVC learning channels and rely predominantly on internal research and development (R&D). To maintain their innovation endeavors, these organizations acquire knowledge by recruiting proficient personnel, generally individuals who have previously worked for the company or expatriates, and by engaging in capital arrangements such as acquisitions, joint ventures, and licensing. These arrangements are frequently regarded as highly pertinent, facilitating swift and pragmatic innovation.

The third type comprises marginal innovators, characterized by local firms that have brought solely new organizational or product innovations for their respective companies. The company does not engage in internal research and development (R&D), and a notable drawback of its local innovation strategy is its

lack of emphasis on utilizing local learning resources. Furthermore, it is worth noting that their reliance on Global Value Chain (GVC) knowledge is limited, as highlighted by De Marchi et al. (2018).

The World Bank (2020) identifies four distinct categories of country participation in Global Value Chains, characterized by their integration patterns. These categories include backward and forward participation, encompassing commodities, limited manufacturing, advanced manufacturing and services, as well as innovative activities.

Technological innovations are crucial in driving innovation within Global Value Chains (GVCs), primarily due to their ability to lower transportation and communication expenses. Furthermore, these innovations enable the fragmentation of manufacturing processes into increasingly granular stages, as Baldwin (2006) highlighted. Moreover, the advent of novel digital technologies, such as robotics and big data, fundamentally transforms these industries, generating fresh avenues for engagement and involvement.

According to Salazar-Xirinachs (2016), to attain long-term economic growth, a nation must possess not only the necessary factors of production, such as investment, capital, and human resources but also must consistently integrate technology and knowledge into its production processes. This is because acquiring knowledge and adopting technology foster innovation in its diverse forms while also attracting investments to enhance productivity and competitiveness.

Ramírez (2014) asserts that there has been a notable progression in the services realm, specifically in information and communication technology. This development has led to the emergence of intricate networks to interchange data and information beyond all geographical boundaries. Information and Communication Technologies (ICTs) have played a significant role in facilitating the standardization of many service activities. This has enhanced commercialization opportunities between service providers and clients in geographically diverse places. Therefore, policymakers must ensure equitable distribution of benefits and promote the appropriate utilization and uptake of information and communication technologies (ICTs).

Wang et al. (2017) classified production activities within Global Value Chains (GVCs) into four distinct types based on the extent of shared production across many nations. These types are as follows:

1. The initial category pertains to the value-added generated domestically and consumed inside the country's final domestic demand without involvement in international trade. The phenomenon of factor content crossing national borders is observed in the production and consumption process, wherein the value added by other countries is utilized to manufacture goods for domestic consumption.
2. The second category pertains to domestic value added that is incorporated in the exports of finished products, commonly referred to as traditional trade. In

this scenario, items are manufactured only using domestic resources, and the factor content only crosses a national border once, solely to consume.

3. The third category pertains to a domestic value incorporated into the intermediate trade of a nation's sector, which is then utilized by the partner country to produce its domestically consumed goods. Alternatively, it can refer to a foreign value directly imported from partner countries and employed in domestically consumed products. The factor content is used in production outside the territorial boundaries of its origin and traverses a neighboring country once throughout the production process.
4. The fourth category pertains to the value-added that is incorporated in intermediate exports/imports, which are utilized by a partner nation to manufacture exports (either intermediate or final) for other countries. In the present scenario, the factor content undergoes several crossings of national borders, earning the designation of Global Value Chain (GVC) complex operations. In other words, countries utilize the value-added contributions of other nations to generate their total exports.

Production activities in the two categories above are exclusively conducted within the confines of a nation's boundaries, with no inter-country exchange of production taking place. Nevertheless, the two categories transcend geographical boundaries (World Trade Organization, 2019).

According to the research conducted by Todeva and Rakhmatullin (2016), mapping Global Value Chains (GVCs) can provide various benefits to regions. These benefits include conducting a capability audit, identifying potential areas for growth, implementing strategies for industrial revival and innovation, and developing a smart specialization strategy. By engaging in these activities, regions can effectively capture inter-regional collaborative advantage and achieve sustainable growth.

The process of identifying value-added activities within an organization is then translated into an external representation of industry sectors and structure, which is captured through hierarchical codes within industrial classification systems. Throughout history, companies have consistently relied on suppliers to acquire essential resources such as raw materials, technology, and services, as well as distributors to facilitate market access. Therefore, managing supply and distribution chains is a crucial aspect of company operations, as it allows for understanding the interconnectedness between enterprises and input and output markets. Supply networks can be understood as the interconnected series of activities that encompass the upstream value chains.

The midstream value chains are established within organizations, while downstream value chains are acknowledged as networks of intermediaries involved in wholesale and trade activities, facilitating the delivery of final products and services to end customers. Industry classifications are utilized to

delineate the hierarchical arrangement of value-added activities, wherein the effects of one industry serve as inputs for another.

Consequently, all firms operating within these two industries are engaged in these interdependent input-output interactions. Four fundamental principles exist pertaining to mapping Global Value Chains (GVCs).

The components of the industry value chain can be categorized into four main aspects:

1. the input-output structure, which outlines the transformation of raw materials into finished products;
2. a geographical dimension that needs to be taken into account;
3. the governance structure plays a crucial role in determining how the value chain is managed and controlled;
4. the institutional context in which the industry value chain operates provides a framework for its functioning.

Moreover, Todeva and Rakhmatullin (2016) have identified four fundamental Global Value Chains (GVCs) mappings. These mappings encompass:

1. an input-output structure, which delineates the conversion of raw materials into finished goods;
2. a geographical dimension;
3. a governance structure which elucidates the mechanisms of control within the value chain;
4. an institutional context that encompasses the industry's value chain.

4.3.1. Methodologies and data sources for Global Value Chains analysis

To obtain a more accurate assessment of the significance of Global Value Chains (GVCs), it is imperative to comprehend three key elements: the proportion of exports attributed to GVCs, the many phases of production involved, and the specific position occupied by a participating nation.

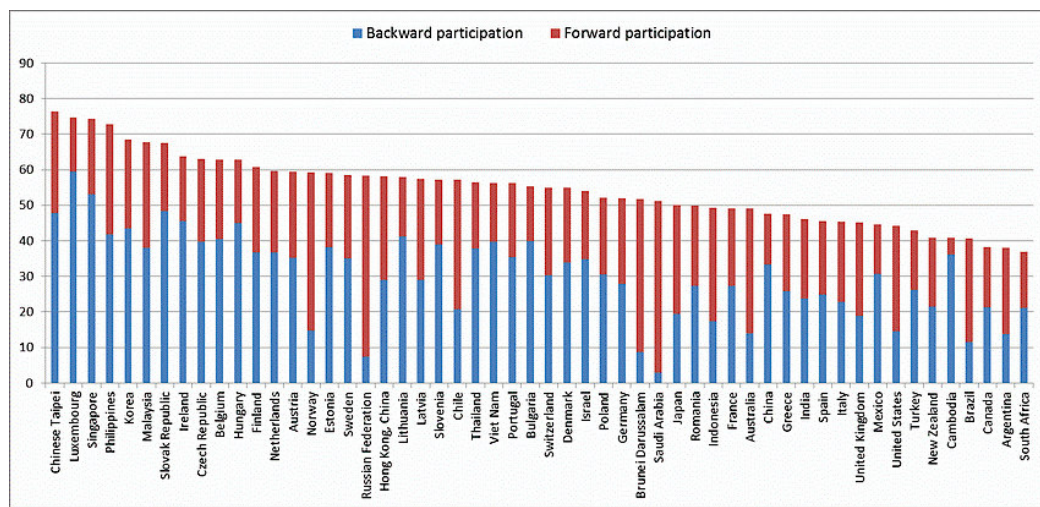
The proportion of exports refers to the degree of involvement of countries in a fragmented production process of final goods. In the past, researchers have employed the vertical specialization share (VS) metric to analyze the proportion of imported inputs within the total exports of a specific country. The measure under consideration considers the significance of foreign suppliers, while the

corresponding action for exported goods and services utilized as imported input is denoted as VS1 (Hummels et al., 2001).

In summary, a nation that participates in Global Value Chains (GVCs) acts as an importer of foreign inputs (referred to as upstream link or backward participation of value chains) and as an exporter of intermediary goods that are subsequently utilized in other nations (referred to as downstream link or forward participation of value chains) (Koopman et al., 2010).

Figure 35 displays the participation index at the national level for countries belonging to the Organisation for Economic Co-operation and Development (OECD).

Figure 35: The GVC participation index-Backward and forward linkages



Source: OECD-WTO TiVA Database, adapted from Degain et al., 2016

Additionally, it is important to consider the length of Global Value Chains (GVCs), which indicates the number of production processes involved. Including horizontal integration is crucial in conjunction with vertical specialization, as both vertical specialization (VS) and vertical specialization 1 (VS1) fail to offer any insights into the specific extent of value chains.

In the scholarly literature, it is common to utilize an average propagation length indicator or a weighted average of the production length (Dietzenbacher and Romero, 2007; Fally, 2012). The measure for the length of the Global Value Chain (GVC) can vary depending on factors such as the economic cycle, level of fragmentation, and unit of analysis.

Furthermore, measuring the distance to final demand offers significant insights into a country's position within the value chain. For instance, nations engaged in upstream production primarily focus on extracting and processing raw materials or intangible commodities. Conversely, countries involved in downstream activities tend to emphasize assembly operations or specialize in service-based industries.

Fally (2012) introduced the concept of "upstreamness" as a metric for quantifying the number of manufacturing stages that need to be completed before the finalization of products. An augmentation in the degree of "upstreamness" thus signifies the heightened focus on the production specialization of primary inputs that possess applicability across several industries.

4.3.2. Benchmarking Production Efficiency

Benchmarking is a systematic process utilized to achieve continual improvement. The practice involves evaluating an organization's plans and performance compared to leading organizations, both within and outside the industry.

Production benchmarking is a widely recognized method used to uncover performance deficiencies by comparing the performance of all participating units to that of the highest-performing units.

This is often done by calculating the following ratio:

$$PB\ ratio = \frac{Actual\ Output}{Standard\ Output} \times 100$$

Production benchmarking employs quantitative and qualitative methodologies to assess and measure the efficiency of diverse operations. The process of quantitative benchmarking involves the collection of performance data from several touchpoints.

The predominant nature of key performance indicators (KPIs) is in their numerical representation, with the metrics primarily focused on enhancing the financial viability of the nation. Qualitative benchmarking is predicated upon the adoption of best practices and the evaluation of their collective execution. Best practices in the realm of process focus, pull production, equipment productivity, innovation, and environmental compatibility seem to be evident.

Implementing a benchmarking procedure can enhance the operational efficiency of an organization, enabling it to match or surpass its competitors. Additionally, there is potential for collaboration with top-performing enterprises globally.

Organizations can enhance their operations by analyzing their competitors' shortcomings and operational strategies, enabling them to adapt and incorporate the most effective techniques.

Through the utilization of benchmarking, an enterprise can enhance its efficacy and implement the requisite modifications to attain a prominent position within its industry or establish itself as a globally renowned corporation. Implementing strategic benchmarking techniques is expected to yield significant

beneficial outcomes for organizations, enabling firms to effectively initiate such initiatives.

Integrating benchmarking into a comprehensive and inclusive Continuous Quality Improvement (CQI) program is a fundamental characteristic. The prerequisites for achieving successful benchmarking entail meticulous planning of the benchmarking process, diligent monitoring of relevant performance indicators, active engagement of personnel, and conducting inter-organizational visits.

The benchmarking method has demonstrated its utility in aiding specific organizations in evaluating their competitive standing relative to their competitors.

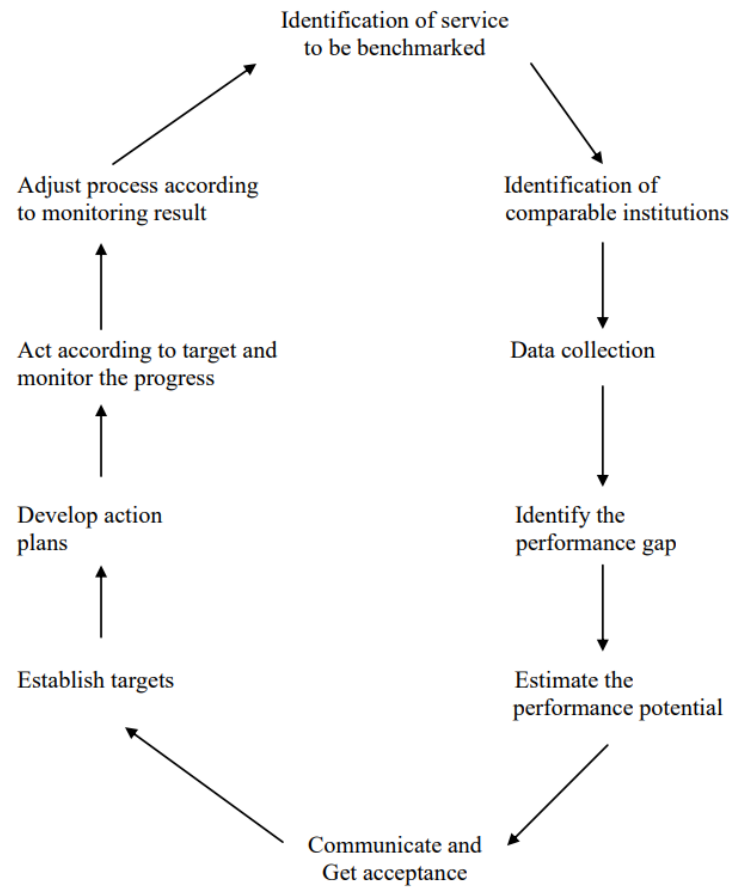
Organizations endeavor to achieve optimal performance to attain a prominent position within their respective industries and effectively contend with existing competitors, emerging rivals, and new entrants (Cooper et al., 2004). The utilization of benchmarking can be advantageous in the development and execution of comprehensive action plans aimed at enhancing competitive edge and organizational benefits. This approach facilitates the planning and implementation of change processes that contribute to organizational improvement.

Continuous expansion in industrial businesses leads to the acquisition of competitive advantages and offers numerous international opportunities.

Hence, to sustain their competitive advantage, organizations must demonstrate inventiveness and adaptability in response to the challenges presented by competitors and the increasingly high expectations of customers.

The graph below presents the benchmarking process:

Figure 36: The Benchmarking Process



Source: Adapted from Camp, 1989

The diagram presented in Figure 36 illustrates Camp's proposed benchmarking methodology, comprising ten sequential steps.

The benchmarking process begins by identifying the specific service to be evaluated. Subsequently, comparable institutions are recognized for comparison. Data is then collected to facilitate the assessment of performance gaps. The identified gaps are estimated and communicated to relevant stakeholders to gain acceptance.

Following this, targets are established and action plans are developed to address the identified gaps. These action plans are implemented in alignment with the established targets. Progress is continuously monitored, and adjustments are made as necessary based on the monitoring process results.

4.3.3. Industrial Benchmarking

Companies are incentivized to effectively and reliably manage their operations efficiently to maximize their financial gains.

The primary objective of performance analysis is to assess the cost-effectiveness, reliability, and timeliness of corporate management and design.

As a result, performance analysis can be utilized to discover areas where these activities can be improved. Objective quantitative assessments are essential in ensuring that planning and decision-making processes remain aligned to operate efficiently.

The current procedures may exhibit deficiencies such as inconsistency with corporate objectives and bias.

Firstly, metrics can be incongruent with the aims of an organization. For example, including defective products in the output calculation may occur, even though they do not contribute to overall profitability.

Furthermore, it is essential to consider that bias can potentially influence measures. Often, assessments are employed to gauge the comprehensive effectiveness of an organization think resources and services to a limited extent.

Industrial benchmarking is a strategic procedure employed by organizations to assess and compare their performance with industry standards and best practices.

The primary objective is to identify areas that require enhancement, establish performance objectives, and facilitate ongoing improvement efforts.

The process involves carefully measuring and analyzing many key performance indicators (KPIs) across multiple operational areas, including productivity, quality, cost, efficiency, safety, and customer satisfaction. By comparing themselves to other firms, both within their industry and across different industries, organizations can gain significant insights into their strengths and weaknesses. This enables them to find possibilities that can be leveraged to strengthen their competitiveness.

The process of benchmarking industries often encompasses several sequential stages. The first phase involves establishing the parameters and goals of the benchmarking endeavor, as well as determining the particular domains or procedures to be subjected to benchmarking. This may encompass several aspects, such as industrial procedures, supply chain management, marketing strategies, or customer service.

The data collection process can begin once the focal areas have been identified. This process may involve collecting data from several sources, including internal resources like corporate records and performance measurements, as well as external sources like industry publications, market research, and competition analysis.

The third phase involves identifying appropriate benchmarking partners or firms that exemplify best practices or exhibit superior performance in the designated domains. These partners can encompass competitors, prominent

players in the industry, or even companies from adjacent sectors that have successfully implemented novel methods or achieved notable outcomes.

The data that has been gathered is afterward compared to the performance indicators of the benchmarking partners and subjected to analysis to find any disparities in performance, prospective areas for improvement, and potential best practices that may be implemented.

Once the study has been concluded, companies can formulate action plans to address the identified gaps and improve their overall performance. This may involve implementing procedural modifications, embracing novel technologies, reevaluating tactics, or improving personnel competencies through training and development programs. Prioritizing chances for development is a crucial undertaking that necessitates careful consideration of their potential impact and feasibility while also accounting for the resources and capabilities of the business.

Benchmarking is a continuous and iterative process that necessitates perpetual monitoring and adjustment rather than being a singular event. It is imperative for organizations to regularly assess and modify their benchmarking data to maintain its relevance and alignment with the prevailing conditions of the industry.

Furthermore, it is advisable for individuals to consistently track their progress over some time, by evaluating their performance about the initial benchmarking outcomes and evaluating the effectiveness of their efforts to enhance their performance.

The concept of a production function is used to demonstrate the highest level of output that can be achieved with a specific combination of inputs while ensuring optimal efficiency in their utilization.

According to the Data Envelopment Analysis (DEA), one approach to assessing the efficiency of a company involves comparing its actual output level with the output level determined by the production function.

Let $X = (x_1, x_2, \dots, x_n)$ be a vector consisting of n inputs, such as labor, equipment, and space, that a firm consumes. The observable output is denoted as y , and the production function is represented by $f(X)$. The firm's output efficiency can be expressed mathematically as the ratio $y / f(X)$.

In an alternative approach, input inefficiency can be assessed through the utilization of a production function, which enables the evaluation of the extent to which inputs can be lowered while sustaining an identical level of output.

Comprehending a production function is undeniably advantageous in calculating efficiency within contexts involving various inputs. In parametric analysis, a production function is postulated with an explicit functional form a priori.

The Cobb-Douglas production function, as exemplified by Ghobadian and Husband (1990), is widely recognized in academic circles.

In contrast, nonparametric analysis involves examining data to infer the production function in an implicit manner without specifying a functional form or

estimating parameters. One disadvantage of non-parametric techniques is the substantial computational effort they demand.

The non-parametric method known as Data Envelopment Analysis (DEA) was developed by Charnes, Cooper, and Rhodes (1978).

Let $X_j = (x_{1j}, \dots, x_{ij}, \dots, x_{nj})$ signify the vector of observed inputs for firm j and $Y_j = (y_{1j}, \dots, y_{rj}, \dots, x_{nj})$ denote the vector of observed outputs.

In DEA, technology is defined by the production possibility set as

$$T = \{(X, Y), Y \geq 0 \text{ produced from } X \geq 0\}.$$

The first DEA assumption is that the set T is convex, which means that if $(X_j, Y_j) \in T, j = 1, \dots, J$ and $\lambda_j \geq 0$ are non-negative scalars such that

$$\sum \lambda_j = 1, \quad \text{then } \sum \lambda_j X_j, \sum \lambda_j Y_j \in T.$$

The second assumption is allocative efficiency, which states that if $(X, Y) \in T$ and $X' \geq X$, then $(X', Y) \in T$; similarly, if $(X, Y) \in T$ and $Y' \leq Y$, then $(X, Y') \in T$.

Allocative efficiency has two components, one for inputs and the other for outputs.

The input aspect of allocative efficiency conveys the notion that increasing inputs does not diminish outputs in a multiple-input, one-output instance.

A third assumption is that T has constant returns to scale, which means that if $(X, Y) \in T$ and $k > 0$, then $(kX, kY) \in T$ as well.

If this assumption is not made, the DEA technology definition is known as variable returns to scale technology.

In multiple-input and multiple-output DEA, it is considered that each company is made up of different “Decision Making Unit” (DMU); every DMU seeks to optimize its efficiency by selecting the most advantageous allocation of weights for all inputs and outputs. In this context, there is a fundamental constant returns to scale DEA model with multiple inputs and multiple-outputs, to provide a comprehensive analysis:

$$\max h_0 = \frac{\sum_{r=1}^s u_r y_{ro}}{\sum_{i=1}^m v_i x_{io}}$$

subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1; j = 1, \dots, n; \quad u_r, v_i \geq 0; \quad i = 1, \dots, m; r = 1, \dots, s$$

with n DMUs, m inputs and s outputs; $x_{ij}, y_{rj} > 0$ represents input and output data for DMU j ; $u_r, v_i \geq 0$ are the variable input and output weights to be determined relative to the DMUs contained in the reference set.

In terms of technology Y , the input, output and scale efficiencies for a firm with X_0 as the input vector and Y_0 as the output vector are (Schefczyk, 1993):

$$\min \{x: (xX_0, Y_0) \in T\}, \text{input efficiency}$$

$$[\max\{y: (X_0, yY_0) \in T\}]^{-1}, \text{output efficiency}$$

$$\max \{y/x: (xX_0, yY_0) \in T\}^{-1}, \text{scale efficiency}$$

In the context of multiple input data envelopment analysis (DEA), it is noteworthy that equipment is considered as an independent dimension that holds similar significance to labor. As a partial elucidation for the limited tangible impact of equipment productivity on DEA efficiency, it is hypothesized that when a warehouse exhibits low productivity, its deficiency is likely attributable to multiple factors (Schefczyk, 1993).

4.4. How to perform Catch-Up analysis along the Global Value Chain

Global Value Chains (GVCs) are significant in economic development for less developed nations. According to Fagerberg et al. (2018), engagement in Global Value Chains (GVCs) presents many prospects for these nations to expedite their economic expansion, raise productivity, and bolster their overall competitive edge. To begin with, the process of integrating into Global Value Chains (GVCs) enables entities to access sophisticated technologies and information that are intricately woven throughout the many stages of value creation. Through engaging in partnerships with developed economies and multinational corporations, less advanced economies can gain insights from established methodologies, acquire valuable technological proficiencies, and effectively narrow the existing technological disparity. The exchange of knowledge and technology facilitates the development of new ideas, enhances efficiency gains, and facilitates the process of narrowing the gap between entities.

Additionally, GVCs provide a means for underdeveloped nations to enter international markets and enhance their prospects for exporting. According to Rodrik (2018), these countries can access larger consumer markets, leverage the advantages of global commerce in terms of scale and scope, and overcome obstacles to entering new markets by integrating themselves into value chains. Integrating into GVCs enables market integration, diversification of exports, and the establishment of worldwide commercial ties.

Moreover, the engagement of less developed nations in GVCs catalyzes the improvement of their productivity and efficiency levels, as highlighted by Rodrik (2018). Due to their expertise in particular segments of the value chain, wherein they possess a relative advantage, these entities can concentrate on tasks that align with their areas of proficiency. The specialization and division of labor allows organizations to attain economies of scale, enhance operational efficiency, and improve overall production. Through a persistent effort to enhance their capabilities, embrace cutting-edge technologies and processes, and enhance the quality of their offerings, these nations can effectively reduce the disparity in productivity compared to more developed economies, thereby establishing a competitive stance within the global marketplace.

However, the recognition of the potential advantages associated with engaging in Global Value Chains (GVCs) to narrow developmental gaps necessitates the implementation of conducive policies and the establishment of supportive institutional frameworks. Governments of underdeveloped nations must place emphasis on allocating resources towards education and the enhancement of skills to foster a proficient labor force capable of actively participating in value chain operations (Kohler-Koch, 1996). The importance of infrastructure development in meeting the demands of logistics, transportation, and connectivity has been emphasized by Harmatuck (1996). In addition, it is crucial to cultivate technical innovation, build institutional frameworks, and enact policies that facilitate entrepreneurship and empower local enterprises to ascend the value chain. The enhancement of the catching-up process can be further facilitated by establishing a conducive environment that encourages participation in Global Value Chains (GVCs) and by aggressively fostering the growth of local enterprises and value-added activities.

Within the realm of development economics, the notion of "Catching up" pertains to the endeavor undertaken by comparatively less developed nations or regions to narrow the economic disparity with more advanced economies (Abramovitz, 1986).

The concept is sometimes linked to the notion of "convergence," which posits that less developed economies experience higher growth rates than developed economies, resulting in a gradual reduction of the disparity between them. Convergence can be evident across various sectors and indices, including per capita income, industrial productivity, education, healthcare, and technological innovation.

Catching up encompasses a range of intricate and multidimensional tasks, which in turn give rise to various obstacles.

One of the foremost challenges lies in surmounting the substantial disparities in technology and knowledge between developed and developing nations. The acquisition of modern technology and knowledge necessitates significant investments in research and development, education, and infrastructure, which can impose strain on finite resources and impede growth (Radosevic, 1999).

Furthermore, catching up frequently entails the intricate task of maneuvering through the intricacies of global markets, wherein established rivals already maintain substantial market dominance and possess well-established networks (Shin, 2013). One of the critical challenges that emerging economies encounter in their pursuit of development is the need to address institutional and governance inadequacies, such as corruption and bureaucratic inefficiency (Keefer and Knack, 1997).

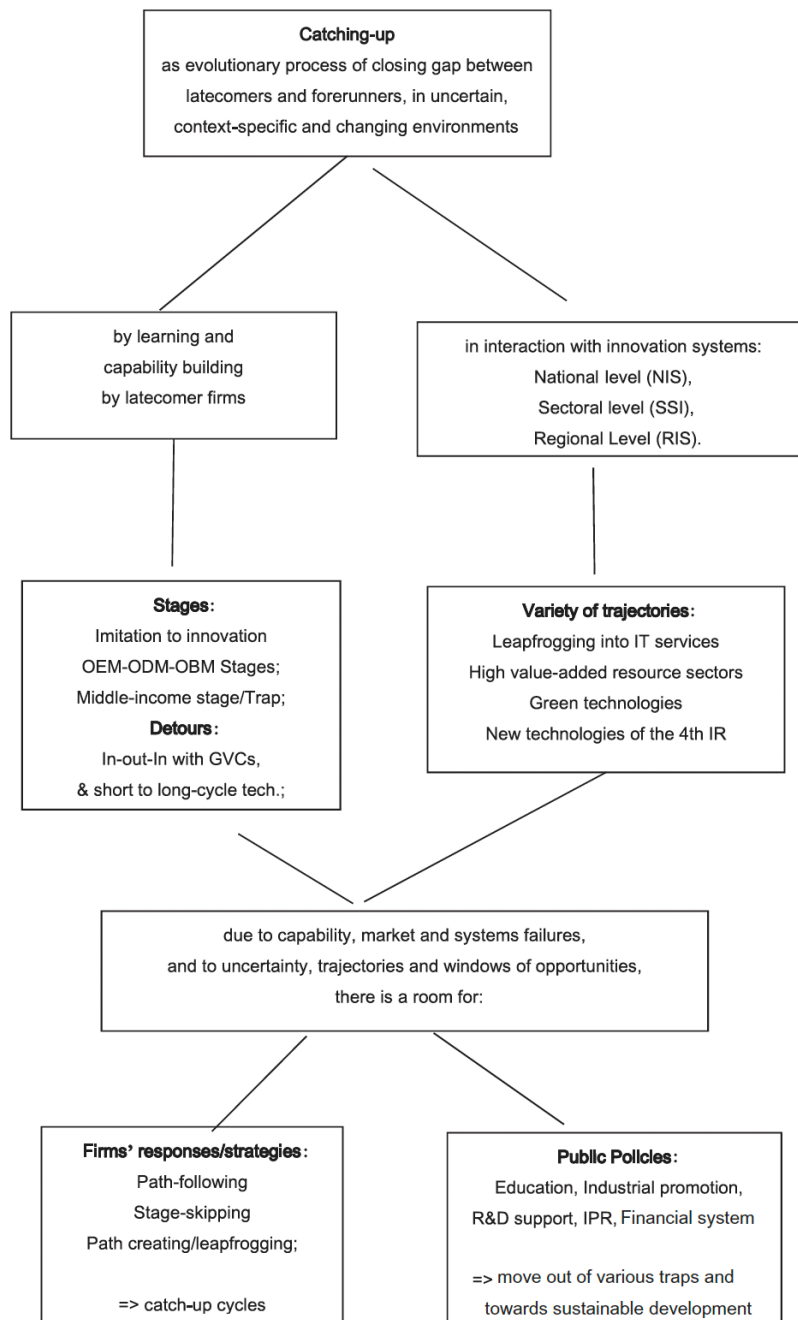
In addition to geopolitical risks, concerns over environmental sustainability and socioeconomic inequality contribute to the complexities involved in catching up.

Governments can implement a range of policies aimed at facilitating the process of catching up and fostering economic progress. One strategy involves allocating resources towards human capital development through education and improving the availability of high-quality healthcare and social services (Kohler-Koch, 1996).

Additionally, researchers acknowledge the significance of technological advancements and the allocation of capital towards research and development endeavors to foster innovation and the generation of knowledge (Radosevic, 1999).

Moreover, establishing infrastructure, including transportation systems and digital connections, plays a crucial role in providing the necessary groundwork for economic operations and fostering the influx of private investments (Lall and Narula, 2004).

Figure 37: *Evolutionary perspectives on economic catch-up.*



Source: *Malerba and Lee (2021)*

Figure 37 summarizes the main points and highlights the main dimensions and variables of the framework discussed in Malerba and Lee's (2021) article about an evolutionary perspective on the phenomenon of economic catch-up by latecomers. It conceptualizes this process as a gradual endeavor to narrow the disparity in capabilities through the facilitation of learning and innovation. This endeavor occurs through the dynamic interplay between the latecomers and various innovation systems at the national, sectoral, or regional level.

From this particular standpoint, catch-up is perceived as a dynamic evolutionary phenomenon that lacks determinism and cannot be meticulously orchestrated due to its exposure to uncertainty and ongoing fluctuations. It is intertwined with a range of external occurrences (referred to as windows of opportunity) and arises from the distinctive actions of diverse actors who possess varying perspectives, interpretations, and backgrounds. Latecomer enterprises and countries exhibit various responses and strategies in the face of comparable external technology or market conditions. A significant observation that arises from this viewpoint is a robust correlation between the acquisition of knowledge and skills by domestic companies and the broader national, sectoral, and regional frameworks within which these companies function.

4.4.1. Catch-Up Performance Index: from traditional measurement to the indices of average Catch-up and average Catch-up speed

The Catch-Up Performance Index (CUPI) is a quantitative metric employed to evaluate the advancement of a nation in narrowing the income or economic development gap with more advanced economies.

The utilization of an index is prevalent within the realm of economics to assess the extent to which a nation is reducing income disparities or achieving parity with a benchmark country or a set of countries, frequently including the United States.

The main CUPI index is defined as follows:

$$CUPI_{0,T}^i = \ln \left[\frac{rel_y_T^i}{rel_y_0^i} \right] / T \times 100$$

In this formula, $rel_y_T^i$ is the relative difference between the per capita level of income between the emerging country i selected for analysis and the US at year T (y_T^i/y_T^{US}), while $rel_y_0^i$ is the same difference but at the base year (y_0^i/y_0^{US}), measured in purchasing power parity (PPP) dollars at constant prices.

By definition, $CUPI_{0,T}^i > 0$ if country is catching up ($rel_y_T^i > rel_y_0^i$), $CUPI_{0,T}^i < 0$ if it is falling behind ($rel_y_T^i < rel_y_0^i$), and $CUPI_{0,T}^i = 0$ if it is neither catching up nor falling behind ($rel_y_T^i = rel_y_0^i$).

So, the CUPI index, in terms of both its sign and magnitude, offers a significant measure for evaluating a country's catch-up performance in per capita income throughout the specified period of analysis. It is essential to acknowledge that the index can be broadly understood as the per capita growth differential between the country under consideration and the United States (Vu and Nguyen, 2022).

In order to conduct a more in-depth analysis, we propose to calculate the considered Index as an average of level and size to obtain an Index of Average Catch-Up and an Index of Average Catch-Up Speed.

The Index of Average Catch-up is formulated to assess the extent of catch-up. At the same time, the Index of Average Catch-up Speed is designed to evaluate the rate at which catch-up occurs because the rapidity of catch-up's process holds significance within the context of catch-up itself.

Furthermore, it is imperative to integrate a country's global income share and the rate at which it grows into the catch-up index's speed calculation.

Two fundamental indicators can be utilized to assess economic conditions concerning the measurement of these cited new indicators: income level and economic size.

The first one (Income Level) considers the measurement of a country's living standard, which is often represented by the Gross Domestic Product (GDP) per capita in real terms, adjusted using Purchasing Power Parity (PPP) to account for differences in the cost of living.

The second one (Economic Size) represents a country's economic strength and market size, which are determined by its present Gross Domestic Product (GDP).

Through this approach, it becomes possible to manage the impact of currency devaluation on the present Gross Domestic Product (GDP) regarding price competitiveness.

For instance, if there is a 10% devaluation in the national currency and a subsequent 10% growth, the resulting impact on the current GDP in USD would be 0%.

The *Average Catch-up Index* quantifies a country's performance in terms of its ability to achieve both income level and economic size catch-up. The metric is derived from combining a level catch-up index and a size catch-up index, resulting in an averaged score.

The income level catch-up index is a metric used to assess a country's per capita GDP about that of a country with the highest per capita GDP in purchasing power parity (PPP), such as the United States. Similarly, the size catch-up index measures a country's share in global GDP compared to that of a country with the biggest share in global GDP, also referring to the United States.

$$\begin{aligned} \text{Average Catch - Up Index} &= \\ &= \frac{\text{Level Catch - Up } (z_i) + \text{Size Catch - Up } (s_i)}{2} \end{aligned}$$

$$z_i = \frac{(y_i - y_{\min})}{(y_{\max \text{ USA}} - y_{\min})} \times 100 ,$$

$$y_i = \text{Country } i\text{'s per cap GDP in PPP level}$$

$$s_i = \frac{(x_i - x_{min})}{(x_{max\ USA} - x_{min})} \times 100, \quad x_i = \frac{Y_i \text{ (current country } i \text{'s GDP)}}{\sum_{j=1}^n Y_j \text{ (sum of world'GDP)}}$$

The *Average Catch-up Index Speed* is a metric that evaluates the relative performance of a country in terms of both level catch-up speed and size catch-up speed. The metric is derived by taking the average of a level catch-up speed index and a size catch-up speed index.

The level catch-up speed index quantifies a country's annual growth rate of per capita GDP in purchasing power parity (PPP) relative to the average of a hundred countries.

The size catch-up speed index is a metric used to assess a country's annual growth rate of its GDP share in relation to the global GDP, as compared to the average of 100 nations.

$$\begin{aligned} \text{Average Catch - Up Speed Index} &= \\ &= \frac{\text{Level Catch - Up Speed } (z_i) + \text{Size Catch - Up Speed } (s_i)}{2} \end{aligned}$$

$$z_i = \frac{(y_i - y_{min})}{(y_{max\ USA} - y_{min})} \times 100, \quad y_i = y_i^* - \bar{y}$$

Where: y_i^* is the country i 's GDP growth rate (PPP) and $\bar{y}$ is the average of GDP growth rate (PPP) for sample countries.

$$s_i = \frac{(x_i - x_{min})}{(x_{max\ USA} - x_{min})} \times 100, \quad x_i = x_i^* - \bar{x}$$

Where: x_i^* is the country i 's growth rate of GDP share and $\bar{x}$ is the average of sample countries' growth rate of GDP share.

The two indexes exhibit distinct dimensions of catch-up:

1. Average Catch-up Index measures a country's performance in attempting to narrow the gap between itself and a rival or leading country (e.g. US) in an absolute sense.
2. Average Catch-Up Speed Index, on the contrary, is indicative of a country's rate of change relative to the other countries in the sample. It is a relative

index because it is compared with the demeaned growth rate of per capita GDP and GDP share over the world.

Both indices are transformed into a scale that ranged from 0 to 100.

Furthermore, it is possible to adapt these last two average indicators, calculated for each country, to the analysis of the catch-up of a specific sector by modifying the parameters considered above as follows:

$$\begin{aligned} \text{Average Catch - Up Index}_{SEC} &= \\ &= \frac{\text{Level Catch - Up } (z_{i-SEC}) + \text{Size Catch - Up } (s_{i-SEC})}{2} \end{aligned}$$

$$z_{i-SEC} = \frac{(L_i - L_{min})}{(L_{max} - L_{min})} \times 100, \quad L_i = \text{sector's country } i \text{ labor productivity}$$

$$s_{i-SEC} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \times 100,$$

$$x_i = \frac{S_i (\text{country } i \text{'s sales volume of sector} - \text{market share})}{\sum_{j=1}^n S_j (\text{sum of world sales volume of sector})}$$

$$\begin{aligned} \text{Average Catch - Up Speed Index}_{SEC} &= \\ &= \frac{\text{Level Catch - Up Speed } (z_{i-SEC}) + \text{Size Catch - Up Speed } (s_{i-SEC})}{2} \end{aligned}$$

$$z_{i-SEC} = \frac{(L_i - L_{min})}{(L_{max} - L_{min})} \times 100, \quad L_i = L_i^* - \bar{L}$$

Where: L_i^* is the sector's country i growth rate of labor productivity and $\bar{L}$ is the average of growth rate of labor productivity for sample countries.

$$s_{i-SEC} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \times 100, \quad x_i = x_i^* - \bar{x}$$

Where: x_i^* is the country i 's growth rate of market shares and $\bar{x}$ is the average of sample countries' growth rate of market shares.

4.4.2. A regression model to measure “convergence” with experimental Python simulation

As anticipated, the notion of catching-up is sometimes linked to the notion of "convergence".

According to Im and Lee (2021), to determine whether firms of a certain country are moving towards convergence with US firms in terms of key financial variables such as profitability, investment rates, and sales growth, it is possible to estimate a regression equation for each financial variable using model specifications similar to those employed by Lee (2013) and Cheong et al. (2010).

The possible variables to consider are:

- Investment ratio: $(\text{physical capital}_t - \text{physical capital}_{t-1}) / \text{physical capital}_{t-1}$
- Dividend payout ratio: $(\text{dividend}_t / \text{net income}_t)$
- Debt ratio: $(\text{total liabilities}_t / \text{total assets}_t)$
- Growth:
 - Sales growth rate: $[\log(\text{sales})_t - \log(\text{sales})_{t-1}]$
 - Total assets growth rate: $[\log(\text{total assets})_t - \log(\text{total assets})_{t-1}]$
- Profitability:
 - Net income to sales (ROS): $(\text{net income}_t / \text{sales}_t)$
 - Net income to total assets (ROA): $(\text{net income}_t / \text{total assets}_t)$
- Firm Value:
 - Tobin's Q: $(\text{market capitalization}_t + \text{book value of total debt}_t) / \text{total assets}_t$

To ensure comparison across various time periods, it is important to choose firms that were present in all three sub-periods and that had at least three years of complete asset or sales data within each sub-period.

The subsequent criteria are employed to exclude the outlier that fulfills one of the subsequent conditions:

- The ratio of research and development (R&D) expenses to sales exceeds 100%.
- The gross income is in a negative state.
- The ratio of operating income to sales is less than negative 100%.
- The growth rates for gross income, operating income, sales, and equity surpass 10.000% in absolute value.
- Tobin's Q, which represents the market-to-book ratio, exceeds 100.

Despite the utilization of regression analysis to mitigate the influence of firm-specific attributes, there is a substantial disparity observed across firms in two distinct countries regarding their magnitude, longevity, and sectoral mix, among other factors.

Therefore, it is necessary to create a sample of US firms that is equivalent to the other country's sample to conduct a thorough analysis.

Hence, the US sample is created using the propensity score matching technique (Abadie et al., 2004), as Chari (2012) outlined. When implementing this approach, the initial step involves calculating the propensity score for each firm within each sub-period. This ensures that the sample consists of firms that are similar in size and public age, as indicated by their propensity score values. The U.S. sample comprises enterprises from various industries with a propensity score closely resembling their counterparts in the other considered country.

So, in the following regression model, the objective is to determine whether the country's firms are converging with US firms regarding key financial variables such as profitability, investment rates, and sales growth. The model specifies a regression equation for each financial variable for different time periods using a sample of both Countries firms. The equation is as follows:

$$y_{it} = a + \beta_1 D_i + bControl_{it-1} + cIndustry_{it} + T_t + F_i + \varepsilon_{it}$$

- y_{it} represents the financial variable of interest (e.g., profitability, investment rates, sales growth) for firm i in year t .
- D_i is a dummy variable indicating whether the firm is from the considered country.
- $Control_{it-1}$ is a set of control variables for the specific financial variable under consideration.
- $Industry_{it}$ consists of dummy variables based on the 4-digit ISIC4 industrial classification code⁸.
- T_t captures the year effect.
- F_i represents firm-specific factors.
- ε_{it} represents the random error term.
- The parameter β_1 measures the overall difference in the dependent (financial performance) variable y between considered country and US firms while controlling for basic firm-specific factors and other controls.

⁸ ISIC stands for "International Standard Industrial Classification" and is a classification used globally for statistical and economic purposes to classify economic activities according to the industrial sector to which they belong. The ISIC4 classification is a more detailed version of ISIC to identify specific subsectors.

- a is the intercept or starting point for the dependent variable, while b and c represent the effect of the control variables and industrial dummy variables on the dependent variable.

In the second regression model, the focus is on explaining firm performance as a function of innovation-related variables and other traditional control variables. The goal is to examine how the role of innovation-related variables in explaining various measures of firm performance, such as sales growth, profitability, and firm value, has changed over time. The regression equation for this model is as follows:

$$y_{it} = a + \beta INNOV_{it} + bControl_{it-1} + cIndustry_{it} + T_t + F_i + \varepsilon_{it}$$

- y_{it} represents the firm's performance measure (e.g. sales growth, profitability) for firm i in year t .
- $\beta INNOV_{it}$ includes innovation system variables.
- $Control_{it-1}$ is a set of control variables for the specific financial variable under consideration.
- $Industry_{it}$ consists of dummy variables based on the 4-digit ISIC4 industrial classification code.
- T_t captures the year effect.
- F_i represents firm-specific factors.
- ε_{it} represents the random error term.
- a is the intercept or starting point for the dependent variable, while b and c represent the effect of the control variables and industrial dummy variables on the dependent variable.

In this case, the analysis focuses on how innovation-related variables influence firm performance over time for the considered country's firms, with a benchmark provided by results obtained from US firms in the same period, as reported in Lee (2013). The goal is to examine the evolution of the innovation system in these firms over time.

Below is the implementation of both regression models in Python (Fig. 38, 39) with purely illustrative data to represent the usable libraries:

Figure 38: "Convergence" regression model in terms of key financial variables

```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import numpy as np

# Generate synthetic data
np.random.seed(0)
years = np.repeat([1990, 2000, 2010], 50)
emerging_country = np.random.choice([0, 1], size=150)
financial_variable = 100 + 5 * emerging_country + np.random.normal(0, 10, 150)
control_variables = np.random.normal(0, 5, 150)
industry_dummies = np.random.choice([0, 1], size=150)
firm_specific_factors = np.random.normal(0, 2, 150)

# Create synthetic 'Year_Dummies' variable
year_dummies = [year for year in range(1990, 2020) for _ in range(5)]

data = pd.DataFrame({'Year': years,
                    'Is_Emerging_Country': emerging_country,
                    'Financial_Variable': financial_variable,
                    'Control_Variables': control_variables,
                    'Industry_Dummies': industry_dummies,
                    'Firm_Specific_Factors': firm_specific_factors,
                    'Year_Dummies': year_dummies})

# Create empty lists to store coefficient values and years
coefficients = []
years = []

# Create a loop to analyze differences over time
for year in range(1990, 2020, 10): # Synthetic data spans from 1990 to 2010
    # Filter data for the specific time period
    subset = data[(data['Year'] >= year) & (data['Year'] < year + 10)]

    # Define the dependent variable and independent variables
    y = subset['Financial_Variable']
    X = subset[['Is_Emerging_Country', 'Control_Variables', 'Industry_Dummies', 'Firm_Specific_Factors', 'Year_Dummies']]

    # Add a constant to the independent variables
    X = sm.add_constant(X)

    # Fit the regression model
    model = sm.OLS(y, X).fit()

    # Store the coefficient value and year
    coefficients.append(model.params['Is_Emerging_Country'])
    years.append(year)

# Visualize the results: Coefficient of Is_Emerging_Country
plt.figure(figsize=(8, 6))
plt.plot(years, coefficients, marker='o', label='Coefficient')
plt.xlabel('Year')
plt.ylabel('Coefficient Value')
plt.title('Coefficient of Is_Emerging_Country Over Time')
plt.legend()
plt.grid(True)
plt.show()
```

Source: own processing

- Import necessary libraries, including pandas for data manipulation, statsmodels for regression analysis, Matplotlib for visualization, and NumPy for generating synthetic data.
- Generate synthetic data to simulate the dataset. This includes variables like 'Year,' 'Is_Emerging_Country,' 'Financial_Variable,' 'Control_Variables,' 'Industry_Dummies,' 'Firm_Specific_Factors,' and 'Year_Dummies.'
- Create a loop to analyze differences over time for three decades (e.g., 1990s, 2000s, and 2010s). Filter the dataset for each decade using the 'Year' variable.
- For each time period, define the dependent variable ('y') as 'Financial_Variable' and independent variables ('X') as a combination of 'Is_Emerging_Country,' 'Control_Variables,' 'Industry_Dummies,' 'Firm_Specific_Factors,' and 'Year_Dummies.'
- Add a constant to the independent variables for regression analysis.

- Fit a linear regression model using statsmodels, capturing the relationship between financial variables and independent variables.
- Store the coefficient value of 'Is_Emerging_Country' and the corresponding year in lists.
- After the loop, visualize the coefficient evolution over time for the 'Is_Emerging_Country' variable using Matplotlib.

This example demonstrates how to analyze and visualize the temporal evolution of the relationship between emerging country firms status and financial variables using synthetic data.

Figure 39: "Convergence" regression model in terms of innovation-related variables

```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import numpy as np

# Generate synthetic data
np.random.seed(0)
years = np.repeat([1990, 2000, 2010], 50)
innovation_variables = np.random.normal(0, 2, 150)
control_variables = np.random.normal(0, 5, 150)
industry_dummies = np.random.choice([0, 1], size=150)
firm_specific_factors = np.random.normal(0, 2, 150)

# Create synthetic 'Year_Dummies' variable
year_dummies = [year for year in range(1990, 2020) for _ in range(5)]

data = pd.DataFrame({'Year': years,
                    'Innovation_Variables': innovation_variables,
                    'Control_Variables': control_variables,
                    'Industry_Dummies': industry_dummies,
                    'Firm_Specific_Factors': firm_specific_factors,
                    'Year_Dummies': year_dummies})

# Create empty lists to store coefficient values and years
coefficients = []
years = []

# Create a loop to analyze performance over time
for year in range(1990, 2020, 10): # Synthetic data spans from 1990 to 2010
    # Filter data for the specific time period
    subset = data[(data['Year'] >= year) & (data['Year'] < year + 10)]

    # Define the dependent variable and independent variables
    y = subset['Innovation_Variables']
    X = subset[['Control_Variables', 'Industry_Dummies', 'Firm_Specific_Factors', 'Year_Dummies']]

    # Add a constant to the independent variables
    X = sm.add_constant(X)

    # Fit the regression model
    model = sm.OLS(y, X).fit()

    # Store the coefficient value and year
    coefficients.append(model.params['Control_Variables'])
    years.append(year)

# Visualize the results: Coefficient of Control_Variables
plt.figure(figsize=(8, 6))
plt.plot(years, coefficients, marker='o', label='Coefficient')
plt.xlabel('Year')
plt.ylabel('Coefficient Value')
plt.title('Coefficient of Control_Variables Over Time')
plt.legend()
plt.grid(True)
plt.show()
```

Source: own processing

- Import the necessary libraries, similar to the example above.
- Generate synthetic data to simulate the dataset, including variables like 'Year,' 'Innovation_Variables,' 'Control_Variables,' 'Industry_Dummies,' 'Firm_Specific_Factors,' and 'Year_Dummies.'
- Create a loop to analyze performance over time for three decades (1990s, 2000s, and 2010s), filtering the dataset for each decade using the 'Year' variable.
- For each period, define the dependent variable ('y') as 'Innovation_Variables' and independent variables ('X') as a combination of 'Control_Variables,' 'Industry_Dummies,' 'Firm_Specific_Factors,' and 'Year_Dummies.'
- Add a constant to the independent variables for regression analysis.
- Fit a linear regression model using statsmodels, capturing the relationship between innovation variables and independent variables.
- Store the coefficient value of 'Control_Variables' and the corresponding year in lists.
- After the loop, visualize the coefficient evolution over time for the 'Control_Variables' variable using Matplotlib.

Using synthetic data, this example demonstrates how to analyze and visualize the temporal evolution of the relationship between innovation variables and firm performance.

4.5. Future developments of GVC and Catch-up analysis

Despite the abundance of research on the analysis of Global Value Chains (GVC) and their value addition, the intricate and dynamic nature of GVCs makes it challenging to assess the generated value comprehensively. Consequently, this significantly impacts the interpretation of global production.

The manifestation of foreign value added in production exhibits significant diversity, encompassing a spectrum of structures that vary from rudimentary to intricate. These structures sequentially involve value creation through various phases, often involving numerous components and across international boundaries on multiple occasions.

The study undertaken in this chapter has yielded significant tools to analyze the strategic positioning of businesses and countries within the global economic

context. Using benchmarking techniques to evaluate production efficiency, meticulous examination of industrial processes, and the quantification of catch-up performance, a holistic comprehension of the areas that present potential for enhancement and expansion is attained.

Hence, the objective of future developments of the studies already described is to examine the influence of conglomerate participation on Global Value Chains at the national level by employing the clustering technique to assess the added value.

Moreover, the objective will be to examine the value chain via a methodological lens that enables the analysis of nations in groups based on their similarities and differences compared to countries in other clusters.

So, in anticipation of future progress, future advancements in Global Value Chain (GVC) analysis must concentrate on enhancing methodological approaches. This entails using the potential of big data and artificial intelligence to acquire a more profound understanding of the intricacies within value chain dynamics.

Furthermore, incorporating environmental and social aspects into GVC analysis will gain significance in light of the growing prominence of sustainability and ethical issues in global company operations.

One notable focal point in forthcoming research on this topic will be the supply chain management domain. The complex and interconnected relationship between supply chain networks and value generation significantly influences the competitiveness of both nations and organizations. Through conducting more comprehensive investigations into the intricacies of supply chain dynamics, it will be possible to unveil novel aspects of value generation and examine how advancements in supply chain management can be utilized to attain strategic benefits, thanks to the increasing integration of the most modern technologies such as the blockchain which promises to be increasingly characteristic of cutting-edge production processes and, for this reason, it is essential to understand its impact and prospects for the industrial future of countries.

Moreover, the field of catch-up analysis exhibits significant potential for further investigation. The advancement of intricate models, such as regression models that gauge convergence, offers a sturdy framework for evaluating the progress of nations and areas in their pursuit of economic equality with more developed counterparts. Subsequent investigations in this domain should extend the existing models by integrating supplementary factors and enhancing the precision of catch-up speed measurement.

In conclusion, examining Global Value Chains (GVCs) and catch-up analysis extends beyond a purely scholarly pursuit and holds substantial policy and commercial ramifications. As the investigation into the intricacies of these economic phenomena persists, we enhance our understanding and acquire the necessary resources to navigate the ever-changing global economic environment effectively. The future developments presented in this document serve as a guiding light, providing direction for researchers, policymakers, and industry

leaders as they strive to make well-informed decisions and implement sustainable growth strategies.

Conclusions

Each section of this doctoral thesis has a distinct focus but together contribute to a comprehensive understanding of knowledge, innovation, and their significant implications in present-day organizations and economies.

The opening section highlights the crucial significance of knowledge as a unifying element that connects these distinct yet interrelated domains. The recognition of knowledge as a dynamic force that drives innovation, sustainability, and competitiveness has been a guiding principle throughout the discussion.

In the first part of the study, the field of knowledge management has been deeply analyzed. The problems and opportunities associated with the digital era were examined, with a detection of the crucial role that effective knowledge management plays in achieving success within a knowledge-based economy delving into the intricacies of its conceptualization and understanding its transformative potential within knowledge-intensive organizations, the adaptability required for the best impact on organizational dynamics, and its role in shaping strategic decision-making procedures.

The study evaluates knowledge maturity and its capacity to adapt within the context of Industry 4.0. Additionally, an in-depth analysis was conducted to explore the interplay between knowledge maturity and sustainability frameworks as well as business analytics.

Understanding how organizations harness knowledge for strategic advantage will serve as a guiding light as the research delves deeper into contemporary organizations' intricate dynamics, where knowledge and innovation reign supreme.

Furthermore, obtaining the B Corp certification offers several advantages in terms of reputation, legitimacy, networking, and perhaps financial gains; the efficacy of incorporating social values into business practices, as identified by the certification, is contingent upon the actions and strategies employed in utilizing and further developing the certification.

The attainment of certification marks an initial milestone, prompting the need for further exploration into the subsequent actions undertaken by firms, with a particular focus on stakeholder engagement and corporate governance.

In addition, concerning ESG impact-investing, the Python method that has been built not only automates the analyzing process but also can generate forecasts.

A proficient predictive model that examines the correlation between ESG sustainability parameters and financial performance has the potential to yield significant insights regarding the financial implications of sustainable practices. By quantifying the impact of environmental, social, and governance (ESG) aspects, this approach allows corporate decision-makers to make well-informed choices, directing their investments towards sustainability programs that contribute to the betterment of society and the environment and generate favorable financial results. The use of a forecasting model serves as a strategic instrument, facilitating a positive cycle of sustainable decision-making, corporate accountability, and enduring financial expansion.

In the subsequent section, the discussion shifted toward the practical domain, specifically examining pioneering enterprises situated within Science Parks. In this context, we observed knowledge management's tangible impact on innovative companies' financial performance within these vibrant ecosystems.

The analyses explores how business intelligence, organizational learning, and innovation act as critical drivers of success in this knowledge-intensive milieu thanks to their interconnection. In particular, a positive impact relation emerged by business intelligence on organizational learning, by business intelligence and organizational learning on innovation, by business intelligence and innovation on financial performance.

On the other hand, based on the findings of this study, it was determined that there is no significant correlation between organizational learning and the financial performance of innovative enterprises within the considered statistical population. Consequently, the hypothesis proposing a relationship between these two variables is rejected. One of the factors contributing to the observed disparity is the contrasting levels of organizational maturity exhibited by start-up organizations as compared to their larger counterparts.

Incorporating the Agent-Based Model (ABM) introduced a novel aspect to the already published work, offering a dynamic tool for further research which highlights the evolving landscape of research methodologies in knowledge management and innovation. A valuable method to connect theoretical frameworks with real-world applications for examining the interactions between Science Parks and start-ups, both from the point of view of territorial and sectoral analysis, thus being able to provide even more valuable results for the implementation of industrial and governmental policies.

The third chapter brings to the forefront of cutting-edge research approaches and the significant ramifications of emerging technology. It provides an introduction to the notion of backcasting, a proactive methodology that utilizes information and technology to influence the trajectory of future events. The revolutionary potential of blockchain technology has been observed in its application as a tool for performing comprehensive literature reviews, leading to a paradigm shift in the analysis and comprehension of emerging technologies.

The utilization of backcasting has facilitated the emergence of a novel research paradigm, wherein the evaluation of current information is supplemented

with proactive endeavors to exert influence and mold the development of nascent technologies. The proactive strategy described is in accordance with the ever-changing nature of knowledge management and innovation since both firms and researchers consistently adjust and develop their strategy.

The integration of blockchain technology in the research process has demonstrated the capacity to enhance transparency, security, and rigor in the conduct of literature reviews. This statement underscores the potential of developing technology to augment our capacities in knowledge synthesis and analysis processes. This is in line with the central theme of the present thesis, which explores the intersection of information and technology as catalysts for innovation and sustainability.

In summary, this chapter serves to strengthen the concept that knowledge possesses a dynamic nature that transcends the confines of both academia and industry; it emphasizes the significance of proactive methodologies such as backcasting and the incorporation of emerging technologies in order to define the future trajectory of knowledge management and innovation.

Finally, in the fourth section of this thesis, it is possible to appreciate the intersection of research, innovation, and global economic dynamics. This last chapter has provided a practical lens through which to view the application of Research and Innovation (R&I) strategies in bolstering competitiveness and fostering growth, while also connecting these tactics with the knowledge-driven approaches that were previously mentioned.

The exploration of the TalTech Project has showcased how research and innovation can be harnessed to drive economic growth, regional competitiveness, and sustainability. It reinforces the central role of knowledge and innovation in shaping not only individual organizations but entire regions and industries. The methodologies and evolving research methods discussed highlight the dynamic nature of R&I activities.

The deep description of Global Value Chains (GVCs) has revealed the intricate net of knowledge, innovation, and economic value creation, especially as regard emerging economies. The analysis of GVCs, benchmarking production efficiency, and the introduction of novel indices like the Catch-Up Performance Index have underscored the dynamic nature of economic convergence. This empirical dimension deepens our understanding of how knowledge-driven strategies and innovation play a pivotal role in shaping the actual global economic landscape.

This chapter reaffirms that knowledge and innovation are not isolated concepts but integral to the fabric of organizations, industries, and global economic systems.

In summary, this Ph.D. thesis has explored the complex and diverse domains of knowledge, innovation and their significant impact on businesses and economies. The analysis conducted in this study highlights the pervasive presence of knowledge management, which plays a crucial and ever-changing role in influencing sustainable strategies, financial performance, developing

technologies, and the competitiveness of businesses operating within Global Value Chains. Thus, it provides an enhanced comprehension of the fundamental role that information, innovation, and strategic thinking play in the evolution and prosperity of modern companies and economies.

This thesis highlights the significant impact of knowledge and innovation and their ongoing significance in the constantly changing realm of contemporary academics and industry.

Within these conclusions, it is vital to acknowledge the contribution of a final innovative approach that could best unify the implementation of what is set out in the previous chapters within a business organization, namely the Design Thinking as a cross-cutting tool that further enriches the aforementioned approach to knowledge management and innovation, in a historical period in which it is important to make it clear that the value of human resources is not negatively affected by technological progress. Through its application, Design Thinking emphasizes the importance of empathy for users, interdisciplinary teamwork, and rapid iteration, aspects that resonate deeply with the themes discussed in this research. Adopting this approach allows tackling managerial challenges with a renewed perspective, fostering innovative solutions that are both sustainable and economically beneficial, both key objectives of the research presented.

The managerial implications of Design Thinking manifest in its ability to facilitate organizational transformation and to stimulate user-driven innovation, translating into tangible competitive advantages. The Design Thinking methodology offers a framework for integrating knowledge management and innovation with a user-focused business strategy, laying the groundwork for an organizational culture that embraces change, experimentation, and continuous learning.

In conclusion, the linkage between the themes addressed in this thesis and Design Thinking illuminates future paths for research and managerial practice, underscoring how an innovation-oriented approach can significantly enhance the impact of knowledge management and innovation strategies within contemporary organizations. Thus, Design Thinking not only enriches our understanding of the intersection between knowledge and innovation but also highlights its ongoing significance in the ever-evolving realm of academia and industry, offering valuable insights into designing successful business trajectories and economic growth.

Appendix A

Code for Training Regression Models:

This code aims to train regression models to analyze the impact of ESG sustainability factors on corporate financial performance (Return on Assets, ROA) and credit risk (credit rating).

1. *Data:* Let

- n be the number of observations (historical data points).
- Y_i be the corporate financial performance variable (ROA) for observation i .
- X_i be a vector of independent variables for observation i , including:
 - $X_{i,1}$ to $X_{i,4}$: ESG scores (Environmental, Social, Governance and Total ESG score) for observation i .
 - $X_{i,5}$: Debt/Equity ratio for observation i .
 - $X_{i,6}$: Liquidity for observation i .
 - $X_{i,7}$: Natural log of Total Assets for observation i .
 - $X_{i,8}$: Return on Invested Capital (ROIC) for observation i .

2. *Model for ROA (Return on Assets):* The regression model for ROA is represented as

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \beta_3 X_{i,3} + \beta_4 X_{i,4} + \beta_5 X_{i,5} + \beta_6 X_{i,6} + \beta_7 X_{i,7} + \beta_8 X_{i,8} + \varepsilon_i$$

Where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$ are the regression coefficients and ε_i is the error term representing the unexplained variability in Y_i .

3. *Model for Credit Rating:* the regression model for credit rating is represented as a Multinomial Logit model.

Let C_i be the credit rating category (categorical variable) for observation i .

$$\log(P(C_{i=c1})/P(C_{i=ck})) = \alpha_{ck} + \beta_{1,ck} X_{i,1} + \beta_{2,ck} X_{i,2} + \dots + \beta_{8,ck} X_{i,8}$$

$$\text{for } k = 1, 2, \dots, k-1$$

Where $P(C_{i=ck})$ is the probability that observation i belongs to credit rating category ck ; α_{ck} is the intercept term for category ck and $\beta_{1,ck}, \beta_{2,ck}, \dots, \beta_{8,ck}$.

Code for Making Predictions:

This code aims to use the trained regression models to make predictions for future corporate financial performance (ROA) and credit ratings based on forecasted ESG scores and financial indicators.

1. *Data:* Let

- X_{future} be a vector of independent variables for the future period including
 - $X_{future,1}$ to $X_{future,4}$: forecasted ESG scores (Environmental, Social, Governance and Total ESG score).
 - $X_{future,5}$: forecasted debt/equity ratio.
 - $X_{future,6}$: forecasted liquidity.
 - $X_{future,7}$: forecasted Natural log of Total Assets.
 - $X_{future,8}$: forecasted Return on Invested Capital (ROIC).

2. *Predictions:* use the trained regression models to predict the future corporate financial performance (ROA) and credit rating

- For ROA prediction: let $\hat{Y}_{ROA}$ be the predicted future ROA for the future period. Add an additional variable $X_{future,9}$ representing the future year (2022) to the independent variables for prediction

$$\hat{Y}_{ROA} = \hat{\beta}_0 + \hat{\beta}_1 X_{future,1} + \hat{\beta}_2 X_{future,2} + \hat{\beta}_3 X_{future,3} + \hat{\beta}_4 X_{future,4} + \hat{\beta}_5 X_{future,5} + \hat{\beta}_6 X_{future,6} + \hat{\beta}_7 X_{future,7} + \hat{\beta}_8 X_{future,8} + \hat{\beta}_9 X_{future,9}$$

- For Credit Rating prediction: let $\hat{C}$ be the predicted future credit rating. Add $X_{future,9}$ to the independent variables for the credit rating model

$$\log \left(P(\hat{C}=c_1) / P(\hat{C}=ck) \right) = \hat{\alpha}_{ck} + \hat{\beta}_{1,ck} X_{future,1} + \hat{\beta}_{2,ck} X_{future,2} + \dots + \hat{\beta}_{9,ck} X_{future,9}$$

for $k = 1, 2, \dots, k-1$

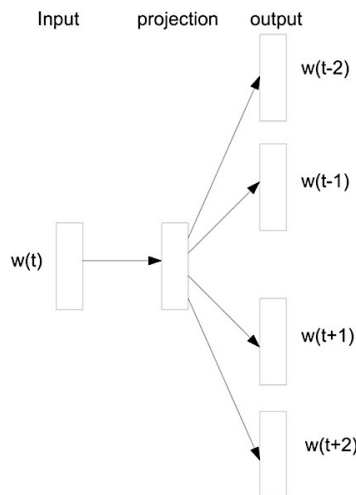
The final predictions for the future corporate financial performance (ROA) and credit rating will be $\hat{Y}_{ROA}$ and $\hat{C}$, respectively.

Appendix B

Derivation of Cost Function for Word2Vec Skip-Gram

The following diagram is featured in the original publication of the Word2Vec study.

Figure 40: Original Skip-Gram model architecture.



Source: Adapted from Mikolov et al., 2013

The model utilizes a neural network architecture consisting of a single hidden layer, referred to as the projection layer. This architecture effectively predicts the context words, namely $w(t-2)$, $w(t-1)$, $w(t+1)$, and $w(t+2)$, given an input word, $w(t)$.

In other terms, the model endeavors to optimize the likelihood of witnessing the collective occurrence of all four contextual words, given a central word.

Mathematically, equation (1) can be represented.

The primary aim of the training is to acquire word vector representations that exhibit a high level of proficiency in predicting the words in close proximity.

As to Mikolov's findings, there exist two distinct models for Word2Vec:

1. Skip-Gram model demonstrates efficacy when applied to a limited quantity of training data, effectively capturing the representation of infrequent words or phrases; it is designed to make predictions about context words based on a given center word.
2. Continuous Bag-of-Words (CBOW) model exhibits a training speed that is significantly higher than that of the skip-gram model; it demonstrates a marginally superior level of accuracy when it comes to predicting frequent words based on the context words.

The Skip-Gram model is often considered a superior choice because it can accurately forecast less common terms. However, this advantage is accompanied by a higher computational burden. If the worry of training time is significant and there exists a sufficiently large dataset to address the challenge of predicting rare words, the Continuous Bag-of-Words (CBOW) model may be a more feasible option.

It is imperative to comprehend that the primary objective of the Skip-Gram model is not the prediction of context words but rather the acquisition of sophisticated vector representations of words. The occurrence of accurate word vector representations is an inherent outcome of predicting context words due to the neural network architecture employed in Skip-Gram. At its core, a neural network involves the optimization of weight matrices θ to accurately anticipate output. In the Word2Vec Skip-Gram model, the weight matrices correspond to the vector representations of words. Hence, the optimization of the weight matrix leads to the generation of high-quality vector representations for words.

The Skip-Gram model endeavors to forecast the context words surrounding a center word. The primary objective is to ascertain the likelihood of specific words occurring close to a designated term. This is achieved through the process of optimizing a weight matrix θ .

$$\operatorname{argmax}_{\theta} p(w_1, w_2, \dots, w_C | w_{center}; \theta) \quad (1)$$

Where:

C is the context size; w is a word vector (context or center word).

It's useful to consider the logarithm of this function to simplify the calculations since it does not change the point at which the original function reaches its maximum value, which is suitable for optimization (in particular, the natural log is a monotonically increasing function).

$$\operatorname{argmax}_{\theta} \log p(w_1, w_2, \dots, w_C | w_{center}; \theta) \quad (2)$$

Then, the Skip-Gram model uses a function called “Softmax” to classify context words. It's essentially a way to convert raw scores into probabilities.

$$p(w_{context} | w_{center}; \theta) = \frac{\exp(W_{output_{(context)}} \cdot h)}{\sum_{i=1}^V \exp(W_{output_{(i)}} \cdot h)} \quad (3)$$

Where:

$W_{output_{(context)}}$ represents a row vector that corresponds to a context word from the output embedding matrix; h is the hidden layer word vector for a center word.

The Softmax function is subsequently used to equation (2) in order to derive a revised objective function that aims to maximize the likelihood of witnessing all context words C , given a center word:

$$\operatorname{argmax}_{\theta} \log \prod_{c=1}^C \frac{\exp(W_{output_{(c)}} \cdot h)}{\sum_{i=1}^V \exp(W_{output_{(i)}} \cdot h)} \quad (4)$$

Machine learning convention is to minimize a cost function, not to maximize it, so a negative sign is added and exploiting the properties of logarithms equation 4 becomes:

$$J(\theta; w^{(t)}) = - \sum_{c=1}^C (W_{output_{(c)}} \cdot h) + C \cdot \log \sum_{i=1}^V \exp(W_{output_{(i)}} \cdot h) \quad (5)$$

The Softmax regression (also called the multinomial logistic regression) is a way to generalize logistic regression for multiple classes.

In the case of Word2Vec, these "classes" are actually individual words in the vocabulary. Therefore, if we have a vocabulary size V , then we are essentially classifying into V different classes.

The general form of the Softmax regression equation is given by:

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{k=1}^K \log \frac{\exp(\theta^{(k)T} x^{(t)})}{\sum_{i=1}^K \exp(\theta^{(i)T} x^{(t)})} \quad (6)$$

Where:

T is the number of training samples; K is the number of classes (or in our case, vocabulary words); θ^k represents the parameters for the k -th class.

In Skip-Gram, rather than trying to predict every possible word in the vocabulary as the context, we consider a "window" of words around the center word. This window size, represented as C , is a hyperparameter that decides how many words before and after the center word we should consider as context.

The adapted softmax regression for Skip-Gram is given by:

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{-c \leq j \leq c, j \neq 0} \log \frac{\exp(\theta^{(t+j)T} x^{(t)})}{\sum_{i=1}^K \exp(\theta^{(i)T} x^{(t)})} \quad (7)$$

This formulation essentially limits the context to words within the window size. While the Softmax function gives a probability distribution across all words in the vocabulary, it's computationally expensive to compute this for a large vocabulary for every training step. To address this, Word2Vec employs a technique called "negative sampling". Instead of updating all word vectors during training, negative sampling updates only a small percentage of them. This results in a much faster training process and even better representations for frequent words.

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SECOND CHAPTER

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