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# Off to the future of creativity and innovation: what AI can – and cannot – do

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# Abstract

The latest developments in artificial intelligence (AI) are pushing it to the edge of computational creativity, reshaping competitive scenarios as a potential game changer. Still, deepened research on novelty elements is required to maximize AI contribution. The aim of this paper is to analyze in a structured way the impact of AI on innovation and creativity and investigate the new paradigm of human-AI interactions. These topics are addressed through semi-structured interviews with 8 Italian startups in finance, healthcare, content-making industries, and AI-solution provider fields. The design of the interviews provided the integration between a technical perspective and a business one to obtain a holistic picture of AI adoption as an enabler of innovation and creativity.

The work sheds a light on the role of AI in supporting innovation in two main phases: *(i)* enabling business opportunities through offer enrichment, generation of synthetic data (images, texts, audio), new patterns identification among variables, and scalability towards new domains thanks to high flexibility; *(ii)* assessment of ideas with AI-powered simulation, increasing the robustness of the process with synthetic data. AI impacts knowledge management, enriching datasets through synthetic data and supporting knowledge sharing among experts. Nevertheless, humans still assume a key role in problem modelling, solution design and output interpretation as AI extends and empowers human creativity and competencies.

This work contributes to framing new AI applications and their impacts with a deep focus on ideas identification and assessment. It enforces the anthropocentric vision of the future of labor and highlights the role of synthetic data as innovation enablers. From a managerial viewpoint, AI contributes to the renewal of competitive advantage, overcomes data scarcity and allows for the democratization of data accessibility. Future research could deepen the phenomenon in a context of higher diffusion, increasing the heterogeneity of the sample and investigating the most innovative aspects also from a more technical viewpoint.

**Keywords:** Artificial Intelligence; Entrepreneurship; Creativity; Innovation; Synthetic Data; Human-machine collaboration

# Estratto in italiano

I recenti sviluppi tecnologici hanno portato l'intelligenza artificiale (IA) alla frontiera della creatività computazionale, rivoluzionando lo scenario competitivo. Tuttavia, è necessario un approfondimento degli aspetti più innovativi per massimizzarne il contributo. Lo scopo della presente ricerca è analizzare l'impatto dell'IA sui processi di innovazione e creatività e approfondire i nuovi paradigmi collaborativi tra uomo e macchina. Tali temi sono stati affrontati tramite delle interviste semi-strutturate ad un gruppo di 8 startup del settore finanziario, medico, content-making e sviluppatori di soluzioni di IA. Le interviste integrano una prospettiva tecnica con una di business per ottenere una visione olistica sull'utilizzo dell'IA a supporto di innovazione e creatività.

I risultati evidenziano il ruolo dell'IA in due fasi del processo di innovazione: *(i) l'identificazione* di opportunità tramite l'ampiamento dell'offerta, la generazione di dati sintetici (immagini, audio, testi), l'identificazione di nuovi legami tra variabili e l'elevata scalabilità della soluzione verso nuovi domini; *(ii) la valutazione* delle idee tramite simulazioni, aumentandone la robustezza grazie ai dati sintetici. L'IA impatta la gestione della conoscenza, arricchendo i database grazie ai dati sintetici e supportando la condivisione di conoscenza all'interno della compagnia. Tuttavia, la tecnologia rimane uno strumento che incrementa – e non sostituisce – la creatività e le competenze dell'uomo, che rimangono centrali e insostituibili nel modellizzare il problema, progettare la soluzione e interpretare il risultato dell'algoritmo.

Questa ricerca analizza l'impatto delle nuove applicazioni dell'IA concentrandosi sull'identificazione delle idee e la loro valutazione. In particolare, evidenzia il ruolo dei dati sintetici nel processo di innovazione e rafforza la centralità del ruolo dell'uomo. Da un punto di vista manageriale, l'IA può contribuire a rinnovare il vantaggio competitivo, rappresenta una soluzione alla scarsità di dati e consente una maggiore democraticità dell'accesso ai dati grazie ai dati sintetici. In futuro, a seguito di una applicazione su larga scala, la ricerca potrà approfondire il fenomeno, aumentando l'eterogeneità delle aziende considerate e/o approfondendo gli aspetti più innovativi da un punto di vista tecnico.

**Parole chiave:** Intelligenza Artificiale; Imprenditorialità; Creatività; Innovazione; Dati Sintetici; Collaborazione uomo-macchina

# Contents

# 1 Introduction

After the introduction of computers in manufacturing during the third industrial revolution, we are now experiencing a new industrial revolution that gives birth to a new paradigm: Industry 4.0 (Muhuri et al., 2019). The new cyber-physical systems, adopted by nearly every industry, are made up of a set of groundbreaking technologies including artificial intelligence (AI), blockchain, internet of things (IoT), and cloud computing (Maynard, 2015). Industry 4.0 differs from the other industrial revolutions from several perspectives. First of all, the rate of change is faster than all the previous technological outbreaks. Coming to AI, it is forecasted that it will spread at an unprecedented pace, driven by advances in machine learning (ML) and the development of a new generation of intelligent processors and quantum computers (Dunjko & Briegel, 2018). The second main difference compared to the previous industrial revolutions is the decoupling of the labor costs from the economic outputs, which leads to significant improvements in the scalability of business models. Indeed, through the new digital technologies, a unit of output can be produced with a lower level of workforce, thus decreasing the marginal costs (near to zero) associated with digital goods (Goldfarb & Tucker, 2019; Schwab, 2017).

In the Manufacturing field, the new paradigm can be defined as the shifting from the traditional configuration, where machines simply run routing tasks, to a digital manufacturing one, with smart and intelligent systems. In smart factories, machines are no more limited and stacked in these activities but can communicate with each other, collaborate autonomously and self-monitoring. This game-changing innovation has enabled higher level of flexibility, faster production pace, and increased efficiency. On the products side, higher level of quality and customization, increasing productivity and resulting, overall, in an industrial growth (Oztemel & Gursev, 2020).

From the manufacturing industry, the groundbreaking revolution can be extended to almost every field since they all have a common factor: big data. The fourth industrial revolution can be called also the “big data revolution” since data constitute a new source of wealth (as many say, “the new oil”), and the future of the market is moving towards this direction with the proliferation of data-driven business models. The data proliferation phenomenon has led to the development of representational approaches to knowledge, in which it is specified, measured, and codified as words, signs and numbers. Such structured databases are used in current learning algorithms to analyze and process information that has been codified and stored (Faraj et al., 2018; Szulanski, 2000). However, this "IT vision" of the firm (Falconer, 2016; Selamat & Choudrie, 2004) presents an important weakness: it neglects the codification of the tacit components of knowledge (Holford, 2018; Sanzogni et al., 2017), missing an important piece of information since practice is infused with knowledge, too (Gherardi, 2009). According to Glasersfeld's constructionist theories (2013), human mental processes lead to subjective or mental constructs of reality. Such processes entail the development of actions and symbolic schemes that contribute to fueling explicit knowledge. However, this leads to a partial view of phenomena since each outcome is "based on particular, individual experiences, which may be similar, but never identical to, other people's creations" (Carter et al., 2008). AI, with its objectivist approach, helps in dissect and store all these experiences in a structured way, traducing the complex and partially ineffable aspects of the experienced phenomena into unambiguous codes. This approach allows for enriching the wealth of knowledge and overcoming the weaknesses which usually lead to a suboptimal formalization of knowledge.

This explains the importance of AI in terms of data codification and places it as one of the key pillars of this revolution. The availability of big data (from businesses, markets, and social networks), the disruptive capabilities of machines to learn on their own (ML), and the ever-increasing power of computers have combined to bring AI to a tipping point (Ferràs-Hernández, 2018). If data is the new oil, AI expert Andrew Ng describes AI as "new electricity", transforming industry and business in the same way that electricity did 100 years ago (Burgess, 2018).

## 1.1. Artificial Intelligence

The aim of this thesis is not to deeply analyze artificial intelligence with its internal mechanism and technicalities, but rather to consider it as an instrument in the hands of humans (in our case, entrepreneurs) to solve business problems and spur entrepreneurship. Nonetheless, we must consider that we are dealing with a very complex instrument with many facets, whose popularity is leading even to the misuse of the term artificial intelligence for mere marketing purposes. Therefore, before going ahead with our reasonings about its applications and impacts, it is crucial for us to provide *(i)* a definition which clarifies what we mean by AI, and *(ii)* an overview of its main branches.

As previously mentioned, AI is one of the hottest words when talking about the future, technology and digitalization. However, the very first introduction to the concept of AI dates back to Alan Turing's milestone in the literature, when in 1950 he started reasoning about the intelligence of machines (Turing, 1950). Since then, the studies on AI have been countless, as well as the definitions that scholars attributed to AI, which have been revised and updated many times, consistently to the evolution of the technology with new branches and applications. However, the starting point always remains the same: AI comprises any technique that enables computers to mimic human behavior to replicate (and/or overperform) human decision-making to solve complex tasks independently (Russel & Norvig, 2012), which normally would require human capabilities (knowledge representation, reasoning, learning, planning, perception, communication etc.). The first research adopted the so-called knowledge-based approach (Goodfellow et al., 2016), i.e. they tried to convert the information into formal language, which the machine can elaborate on through logical inference rules. The main barrier was represented by the limited human capability to explicate all the tacit knowledge that is required to perform complex tasks (Brynjolfsson & McAfee, 2017). This barrier has been overcome with the rise of ML, which learn from experience and adapt over time. The underlying logic can be understood with the following example: it is considered easier to explain to a child the nature of what constitutes a sports car as opposed to a normal car by showing him or her examples, rather than trying to formulate explicit rules that define a sports car. That’s what ML does, autonomously improving by learning meaningful relationships and patterns from examples and observations. ML algorithms iteratively learn from problem-specific training data, finding patterns, insights and correlations among variables which are then applied to new contexts without explicitly being programmed. For this reason, ML algorithms show good applicability in data-rich environments, particularly when dealing with clustering, regression and classification.

Based on the given problem and the available data, we can distinguish three types of ML: supervised learning, unsupervised learning, and reinforcement learning (Bishop & Nasrabadi, 2006; Janiesch et al., 2021).

- *Supervised learning*: supervised learning requires a training dataset that covers examples for the input as well as labeled answers or target values for the output. The pairs of input and output data in the training set are then used to calibrate the open parameters of the ML model. Once the model has been successfully trained, it can be used to predict the target variable $y$ given new or unseen data points of the input features $x$. Regarding the type of supervised learning, we can further distinguish between regression problems, where a numeric value is predicted (e.g., number of users), and classification problems, where the prediction result is a categorical class affiliation. Supervised algorithms (around 70% of ML) are usually adopted in contexts in which we can rely on past data to forecast future events. An example of an application is the financial field, to predict the credit receivable and the non-performing loans of a bank.

- *Unsupervised learning*: unsupervised algorithms identify patterns without any pre-existing labels: we only have the variable $x$ and the algorithm finds structural information of interest, performing clustering or data representation. These algorithms fit well with transactional data, such as data from customer purchases, and thus a typical example of an application is related to the clustering of customers to develop a target-specific marketing strategy.
- *Reinforcement learning*: these algorithms describe the current state of the system, specify a goal, provide a list of allowable actions and their environmental constraints for their outcomes, and let the ML model experience the process of achieving the goal by itself using the principle of trial and error to maximize a reward. The main areas of applications are robotics, gaming and navigation, in which the reinforcement learning algorithm learns the best way to maximize the goal in the minimum amount of time (e.g., succeed in the game, arrive at the destination).

Kaplan and Haenlein (2018) detail a further classification of AI, according to the different capabilities and potential usefulness for business applications:

- *Analytical AI* refers to the capability of supporting future decisions based on past data
- *Human-inspired AI* integrate the previous one with emotional intelligence, thus being useful in analyzing customers interactions
- *Humanized AI*, which concerning the previous adds elements of social intelligence.

Table 1 synthetizes their work and shows how, according to the authors, artistic creativity is what is currently differentiating AI from human beings.

| | Expert Systems | Analytical AI | Human-Inspired AI | Humanized AI | Human Beings |
|---|---|---|---|---|---|
| Cognitive Intelligence | ✗ | ✓ | ✓ | ✓ | ✓ |
| Emotional Intelligence | ✗ | ✗ | ✓ | ✓ | ✓ |
| Social Intelligence | ✗ | ✗ | ✗ | ✓ | ✓ |
| Artistic Creativity | ✗ | ✗ | ✗ | ✗ | ✓ |
| | | Supervised Learning, Unsupervised Learning, Reinforcement Learning | | | |

Table 1 - Types of AI systems (Kaplan and Haenlein, 2018)

## 1.2. The Italian market

Having introduced the concept of AI, we want to provide an overview of the AI market in Italy since it has been chosen as the target nation for the second phase of the present research. According to research by Osservatori Digital Innovation, the AI market[1] in Italy accounted for €380m in 2021, with a growing +27% compared with the previous year and with a doubled value compared to 2019. The wave of market digitization is affecting all branches of AI, with some application fields particularly exposed to the growing trend, with a remarkable +41% in computer vision projects – i.e., analysis of image contents –, + 34% in chatbot and virtual assistant projects, and +32% in intelligent data processing projects – i.e., forecast models, classification, clustering, identification and optimization in different fields. In recent years, the profile of the enterprise approaching technology is changing. While the number of large enterprises that have started at least one project on AI is growing (59% of enterprises vs. 53% in 2020), only 6% of SMEs have done the same (2% have started an actual project, while 4% are already in the testing phase). However, a survey conducted by Osservatorio Intelligenza Artificiale of Politecnico di Milano revealed encouraging results about AI awareness among 205 big and medium Italian enterprises. 90% of companies associate the terms "artificial intelligence" with "system able to replicate some skills and characteristics typically human-based" or a "group of techniques such as machine learning", while only 10% provided a wrong definition of strong AI – i.e. a system able

[1] The AI market was estimated through a model based on quantitative data collected through interviews (55) and secondary sources data related to the financial statements of medium and large-sized Italian companies among different industries (around 350 companies mapped). The assessment is based on the market value generated by AI projects in Italy year after year.

to entirely replicate the human intelligence or associated to the term AI a single application such as chatbot – highlighting low expertise. The companies' level of maturity can be measured through four main dimensions: *(i)* enterprise culture, data, and information assets, *(ii)* algorithms and methodologies, *(iii)* organization, and *(iv)* competences, and relationship with the customer. Italian companies have increased their level of "readiness" for AI compared to the previous year. The "stationary" enterprises – i.e. companies that are still at an initial level in all the main dimensions – have decreased from 45% to 17%, while the so-called "enthusiastic" and "in the journey" – i.e., companies that are in an upper-intermediate stage in all the main dimensions – have been increased from 33% to 57%. Despite the encouraging trend, Italy cannot be defined as a mature country in terms of AI. Rather, it can be defined as a "two-speed" country: on one hand, companies that started the projects first and are currently developing their projects from the testing to implementation phase, while on the other hand companies that are now starting to organize themselves to be able to start projects to embrace the opportunity of this new technology.

Concerning the startup world, the Italian scenario is definitely not as developed as the rest of Europe. The average financing from institutional investors, venture capital funds, investment companies, regional finance companies, angel networks, family offices, and venture incubators in Italy amounts to €890.000, with a European average of €5.4m (CB Insights, 2019). The solution offered on the market can be divided into *(i)* physical solutions (7%) – i.e. all the solutions that have a physical component such as autonomous vehicles and autonomous robots –, *(ii)* software solutions (85%) – i.e., all the startups that offer AI software such as computer vision and natural language processing – and enabling technologies (8%) – i.e. startups which offer structural components for the realization of an AI solution such as database management systems, computing architecture and hardware technology (8%).

## 1.3. AI application

The field of AI experienced periods of expansion and retrenchment, resulting in sporadic development (Haenlein & Kaplan, 2019). Rapid developments in statistical ML techniques have expanded the scope of AI applications including marketing (Davenport et al., 2020), molecule discovery (Gawehn et al., 2016), and automotive manufacturing (Luckow et al., 2018). Deep learning, a subcategory of advanced ML, is gaining momentum. It leverages deep neural networks to create hierarchical layers of neurons and identify different patterns from a given input. Deep learning optimizes the learning process using backpropagation methods, which has accelerated progress in the field (LeCun et al., 2015). These new techniques can be used to develop accurate forecasts of technical and behavioral phenomena (Cockburn et al., 2018). Possible examples of our everyday life could be Facebook computer vision which is used to recognize or tag people or the voice assistants of Amazon and Apple based on natural language processing of the voice. These ground-breaking advances are combined with increased computational power (Taddy, 2018), low-cost sensors, and increasingly cost-effective methods of collecting and preparing training data to fuel a new wave of AI start-up activity. However, the history of early applications of AI dates back many years and leverages some complementarities between distinctive characteristics of humans and machines.

### 1.3.1. Bounded Rationality

The first step we have to make to understand why and how artificial intelligence is disrupting the competitive scenario in nearly every business field is to start from the concept of bounded rationality. After briefly presenting the theory of Herbert Simon, the father of bounded rationality, we start reasoning about how ai helps humans in overcoming such limitations, thus finding a wide application.

Simon's view starts from the critique of classical and neoclassical approaches, according to which the decision maker analyzes all the possible alternatives and chose the optimal one, maximizing its utility function. In his theory, Simon argues that this approach appears far from real decision-making, in which managers and politicians don't have perfect control over the exogenous factor and limitations on their rationality exist "by the disparity between the complexity of the world and the fitness of human computational capabilities, with or without computers" (Simon, 1997). Traditional approaches to strategic decision-making involve identifying a management problem, looking for and analyzing pertinent data, modeling, and assessing potential solutions before coming to a decision (Bharadwaj, 2018). Starting from this process, we can detail the key points of bounded rationality by analyzing the *(i)* gathering of information, *(ii)* utility function definition, *(iii)* evaluation of alternatives, and *(iv)* actual decision.

Even before the evaluation of alternatives, the classical and neoclassical theory ignores both limitations when dealing with collecting the necessary information to decide including, both time and cost in arriving at a decision, which ends up with an incomplete information set.

Another reason why a complete information set is utopistic in real decision-making is that every decision is impacted by exogenous and unpredictable variables which can dramatically change the outcome of the alternative undertaken. This makes an exhaustive evaluation of alternatives almost unfeasible, since "rationality is bounded when it falls short of omniscience. And the failures of omniscience are largely failures of knowing all the alternatives, uncertainty about relevant exogenous events, and inability to calculate consequences" (Simon, 1979).

Concerning the maximization of utility, it represents another pain point of Simon's critique, since real decision-making always concerns a multi-objective function, which further complicates choosing the optimal alternative, given the "severe deficiencies in human knowledge about the consequences of choice, and the limits of human ability to adjudicate among multiple goals (Simon, 1979)."

All these points result in a very limited human capability in formulating and solving complex problems "when compared with the size of the problems whose solutions are required for objectively rational behavior in the real – world or even for a reasonable approximation to such objective rationality" (Simon, 1957).

Finally, when humans take decisions, other factors impact and further limit their rationality, such as skills, habits, culture, values, and perceptions. These variables might not necessarily be compatible with organizational goals, thus making the decision-maker biased and incapable of reaching the optimal solution. Decision-makers, theoretically, aim at behaving according to the concept of substantive rationality (Simon, 1976) – i.e. aim at finding the absolute best action to take to solve a problem. However, given the above-mentioned problems, their behavior is more aligned with procedural rationality, as they find an acceptable solution to a given problem, taking into account not only the objective and constraints but also the knowledge and limits of the computational abilities of the decision maker. As the complexity of the problem faced by the decision maker highlights the computational limits of the latter (be it a machine or a human mind), it emerges the need to use a procedural approach that seeks rationality in the way in which the problem is faced, rather than in its solution: the classical and neoclassical utopia of optimization is abandoned towards the search for a satisfactory solution.

According to the distinction between substantial rationality and procedural rationality, Dosi and Egidi (1991) introduced the concept of substantial and procedural uncertainty:

- Substantial uncertainty is linked to the lack of information, but not to the limitation in the decision-maker's cognitive capability. In other words, those situations characterized by "unknown events or the impossibility, even in principle, of defining the probability distributions of the events themselves".

- Procedural uncertainty is linked to cases in which "the solution of choice problems is constrained by the computational and cognitive capabilities of the agents".

The agents would undoubtedly search for "rational" processes when there is procedural and substantive uncertainty, but the best they can do might be to find a solid and computationally efficient solution. In presence of any competence gap, Heiner demonstrated that decision-makers should try to find solid and structured rules and routinized behavior and follow them rather than seeking the optimization of procedures (Heiner, 1983. 1988). If we can extend this reasoning to every decision-making context, it is also true that over the decades, companies have been facing a highly dynamic and unpredictable environment, globalization of competition, technology proliferation and changing political landscape (Jones et al., 2016; O'Cass & Wetzels, 2018; Spieth et al., 2014). Firms and managers have a massive amount of data available, which potentially represents an invaluable source of competitive advantage, but at the same time, it has increased the effort, time and costs of innovation. The quick creation of new data today provides possible input for developing strategies but on the other side, this easy access to a lot of data comes with its own set of complications. Large amounts of data must be transformed into workable options during the strategy-building process so that decisions may be made (Bharadwaj, 2018). Strategic decision-making, however, continues to be a cognitively taxing process that necessitates the identification and wise selection of relevant possibilities (Hambrick & Mason, 1984). Human decision-makers frequently choose from few possibilities based on their current knowledge base in the interest of time rather than optimizing (Cyert & March, 1963). In this scenario, the adoption of AI as a tool to support decision-making and innovation process can be a win-win solution. Given its capability to process huge amounts of data in a time frame, it allows an increase in the effectiveness of the output and reduces both the riskiness and the costliness of innovation processes (Haefner et al., 2021). Considering the main constraints of bounded rationality, AI helps human decision-makers in overcoming information processing constraints (Nelson and Winter, 1982; Williams and Mitchell, 2004) and ineffective or local search routines (Gavetti et al., 2012; Katila & Ahuja, 2002). The first refers to the limited number of information that a human brain can collect and elaborate on, thus reducing the evaluated solutions in quantity and lowering their quality. The second barrier is referred to the bias of decision-makers who tend to search for a solution in knowledge domains that are related to the firm's and their existing knowledge base (Posen et al., 2018), limiting lateral thinking and thus the possibility of finding creative and innovative solutions.

### 1.3.2. AI application in business fields

With the above-mentioned potential, it appears clear that artificial intelligence has captured the attention of both firms and scholars, as the number of business applications is increasing and becoming more and more valuable. The literature regarding AI's impact on business is largely widespread across several perspectives. The very first evidence, in accordance with the first kind of applications, is about the improvements brought by machines performing operating tasks. AI is a powerful tool to automate structured and operative tasks, leading to both improvements in efficiency and effectiveness given its computational capability (Holford, 2019; Popkova & Sergi, 2020). The advancement in AI functionalities, with ML and predictive capabilities, combined with big data proliferation opened the possibility of applying it as an instrument to support decision-making. Even in this field, the literature agrees about the actual contribution provided by artificial intelligence, which proved its valuable support. Particularly, when dealing with data-rich environments and analytical decision-making, prediction and cluster analysis are among the most useful skills recognized in artificial intelligence (Dellermann et al., 2019; Vincent, 2021).

Coming to the very recent developments in AI, the most interesting applications see it as a tool that might impact even creativity and innovation, thus making AI, even more than in the past, a groundbreaking technology which will arguably reshape entrepreneurship and competitivity. However, before assessing its actual capability, is important to provide a definition, as clear and well-defined as possible, of the concept of creativity and innovation, in order to avoid the risk of misleading and not-generalizable results. Indeed, one of the reasons that explain a literature that is still not aligned with common results can be identified in different starting points concerning what can be defined as creative and/or innovative.

### 1.3.3. Creativity and innovation

Innovation has always represented one of the most crucial processes and capabilities to achieve and sustain a long-term competitive advantage. Innovation is dependent on the ability to recognize patterns and combine and integrate existing properties and knowledge to represent something that is perceived as new by the user, seizing the gap in the market and intuition (Purdy & Daugherty, 2016). But how does exactly this pattern recognition happen in a firm? The idea posited by the behavioral theory of the firm stated that organizational problem-solving can be considered as an information processing system constructed by simple *if-then* algorithms (Cyert & March, 1963). Nowadays, information processing represents a key element in organizations' innovation process. A central activity in innovation management is the process of decision-making, which requires information processing by the manager involved in the information process (McNally & Schmidt, 2011; van Riel et al., 2004). The process is commonly understood as a set of different stages including the recognition, discovery, creation, and generation of innovative ideas, opportunities, and solutions. This stage leverages upon a set of input data, knowledge, and other information analyzed and processed to obtain new knowledge as output. This is followed by the development, evaluation, and selection by the management team of one or several of the most promising ones based on the information available and their capability and experience. The advent of AI and ML allows machines to learn from data and experience without limiting themselves to following predetermined patterns, and, accordingly, the decision-making process inside firms has rapidly changed. The traditional ways companies organize their innovation process need to be challenged to capture in full the advantages of the new technology (Kijkuit & van den Ende, 2007; Samuel, 2000).

This opens an interesting new research field, given the potential of the new technology to take on traditional "human" tasks in an organization. How far this technology can go? Can it represent a game-changer of the most important processes affecting a firm's competitive advantage and long-term survival as the innovation one, traditionally being under the complete control of humans? Is it able to challenge humans even in tasks that have always been under their complete dominance? (Amabile, 2019). The zenith of human intelligence is very often portrayed as the ability to create and to create radically new and/or surprising things. (Wiggins, 2006). This enters into the concept of creativity, and it relates to the innovation process since it can be argued that the first two stages of the innovation process, described before, required significant levels of creativity and *out-of-the-box* thinking (Martin & Wilson, 2016; Shane, 2003).

Setting the stage of this concept, we can identify as creative a system characterized by a collection of processes, natural or automatic, which are capable of achieving or simulating behavior that humans would consider as creative. Therefore, research boundaries of AI application could be extended towards the areas concerning the higher cognitive function, as they reflect most the previous definition of creative systems (e.g., mathematical reasoning, construction of language semantics, artistic pursuits, painting, and music). Anyway, to overcome possible over-restrictive limitations to our research, we set a concept of a creative system that is not strict to the concept of "creating something new from scratch" but rather, aligned with the standard definition embraced by scholars, consider a broad interpretation of "system which create something novel and useful" starting from an already existing knowledge base. This broad interpretation is also typically a human behavior. Namely, *(i)* intuitive creation – i.e. starting from scratch – and *(ii)* starting from existing knowledge coming from past experiences and then, collecting, analyzing, combining and creating an outcome that represents something that new and useful, or whose knowledge was not widespread inside the context of reference. This interpretation key allows us to analyze the beneficial aspects that the recent technology development is leading, grasping the shadow of the impact on the innovation process that otherwise a more closed interpretation would have prevented.

To briefly summarize the literature, artificial intelligence is said to provide its contribution to creative tasks in both direct and indirect ways:

- Direct impact through generative AI and creative recombination of knowledge (Shneiderman, 2002, 2007).
- Indirect impact by freeing up humans from operating tasks, supporting data gathering and data visualization, and enabling data sharing among actors (Dewett, 2003; Lubart, 2005; Siau, 1995).

However, an important aspect that deserves dedicated studies is how, according to the way in which a firm adopts AI to support the creative process, the tasks and the roles associated with such process change in their configuration and skill requirement. Indeed, if on the one hand, the enormous potential of these new tools could lead to reshaping the competition, on the other hand, it is equally true that understating how to use them, how the human-machine relationship changes, and how such tools communicate with the other interdependent component of the creative system is fundamental to maximize their contribution. Hence, with our work, we want to investigate and determine these new paradigms of interaction between humans and AI and which are their main determinants, considering the different applications of technology and any other variables which might be relevant.

Hence, we detailed the following two research questions:

**RQ1:** ***How does the application of artificial intelligence change the phases and the determinants of the innovation process?***

**RQ2:** ***How are humans' role and human-machine interactions changing in light of the application of artificial intelligence in the innovation process?***

To answer these questions, our analysis consisted of a multiple case study approach based on semi-structured interviews with a pool of Italian startups which, although in different ways, based their entire business model on the exploitation of artificial intelligence. The rationale behind our choice is that startups in the technology sector appear to value the potential for gathering and analyzing data in order to establish new businesses. These new market entrants frequently adopt a distinct organizational design strategy, which makes their business models more successful and nimbler than those of established organizations. Compared to established businesses, they are better able to utilize new technologies and try out novel ideas. They profit from chances brought by a continually shifting worldwide market. Knowing how these firms operate could aid incumbents in fending off competition from emerging digital platform companies and disruptive technology (van Rijmenam, 2019).

The present research is structured as follows. Chapter 2 explains in detail the methods of our research work, concerning both the systematic literature review and the interviews. Chapter 3 presents the results of the systematic literature review according to a structure in sub-chapters which facilitate their comprehension and conclude with some final discussion on them. In chapter 4, we present our multiple case study analysis and discuss our findings in relation to the extant studies, highlighting how our work contributes to filling the gap identified in the literature. Lastly, in chapter 5, we provide some final considerations and comments about our research question, point out the limitations of our work, and propose an agenda for the future development of studies on these themes.

# 2 Methodology

Our academic research work was based on two fundamental phases *(i)* systematic literature review and *(ii)* multiple case studies with semi-structured interviews. They both have been conducted by the two authors in a joint or complementary way, in order to be as methodic, systematic and structured as possible and to limit the procedural biases at the minimum.

## 2.1. Systematic literature review

The systematic literature review (SLR) work was conducted to pursue three main objectives: *(i)* to systematize all the scientific empirical evidence produced on the impact of artificial intelligence on innovation and entrepreneurship up to now, *(ii)* to critically appraise the current state of the literature, and *(iii)* to guide an agenda that reports the gap and the new avenue for future research. In order to be systematic and rigorous, we followed the principles suggested by Tranfield et al. (2003). This approach allows us to establish a list of all the peer-reviewed studies as complete as possible (Cronin et al., 2008) – being sure to cover the preponderance of existing works in the field. We did not set any temporal limitation in order to avoid losing possible milestones written back in the years but still a fundamental knowledge base of the topic. The research was conducted according to the adherence to the protocol in a methodological way in order to produce as output a SLR which has to be trustworthy and solid. Therefore, a strict step procedure was followed. The search and readings of papers took place from March to June 2022.

First of all, we decided to conduct the scrutiny on Scopus, one of the largest databases available, based on keyword research through a query. The first query was based on the keywords *"AI"* or *"Artificial Intelligence"* or *"Machine Learning"* and *"Innovat*"* or *"Creat*"* or *"Entrepreneur*"* and *"Human*"* or *"Manage*"* or *"People*"* or *"Labor"* or *"Employee*"* or *"Workforce"*. 3,339 results were found but from the first screening, we understood that our query needed some adjustments in order to be stricter on the topic.

After some adaptations (e.g., we decided to eliminate the category *Human* - and the relative synonyms - as too broad and not peculiar), we structured our final query around two blocks (linked by the AND operator): *(i) Artificial Intelligence,* the technology to be applied, and *(ii)* the application fields, *entrepreneurship, creativity and innovation.* Compared to the first query, we focused on the interaction between two blocks – rather than three – with a larger selection of key terms, but at the same time avoiding terms too much broad like *"innovation"* and *"creat*"*. As the last restrictions, we excluded conference proceedings from the search and limited the academic fields to *business management and accounting, decision science*, and *economics, econometrics and finance* and the language to English. The final query is attached below:

*TITLE-ABS-KEY(("AI" OR "artificial intelligence " OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("creativity" OR "innovative capability" OR "digital revolution" OR "human machine interaction" OR "entrepreneur*" OR "startup" OR "new venture" OR "knowledge discovery" or "intuition")) AND ( LIMIT-TO ( srctype,"j" ) OR LIMIT-TO ( srctype,"k" ) OR LIMIT-TO ( srctype,"b" ) OR LIMIT-TO ( srctype,"d" ) ) AND ( LIMIT-TO ( doctype,"ar" ) OR LIMIT-TO ( doctype,"ch" ) OR LIMIT-TO ( doctype,"re" ) OR LIMIT-TO ( doctype,"ed" ) OR LIMIT-TO ( doctype,"bk" ) OR LIMIT-TO ( doctype,"no" ) ) AND ( LIMIT-TO ( subjarea,"busi" ) OR LIMIT-TO ( subjarea,"econ" ) OR LIMIT-TO ( subjarea,"deci" ) ) AND ( LIMIT-TO ( language,"english" ) )*

660 articles resulted from the query, which has been considered a good trade-off between inclusivity and specificity. Figure 1 shows the number of articles per year found by the query. As we can deduct from it, it is a research field which is gaining momentum, as the number of publications has grown exponentially since 2017.

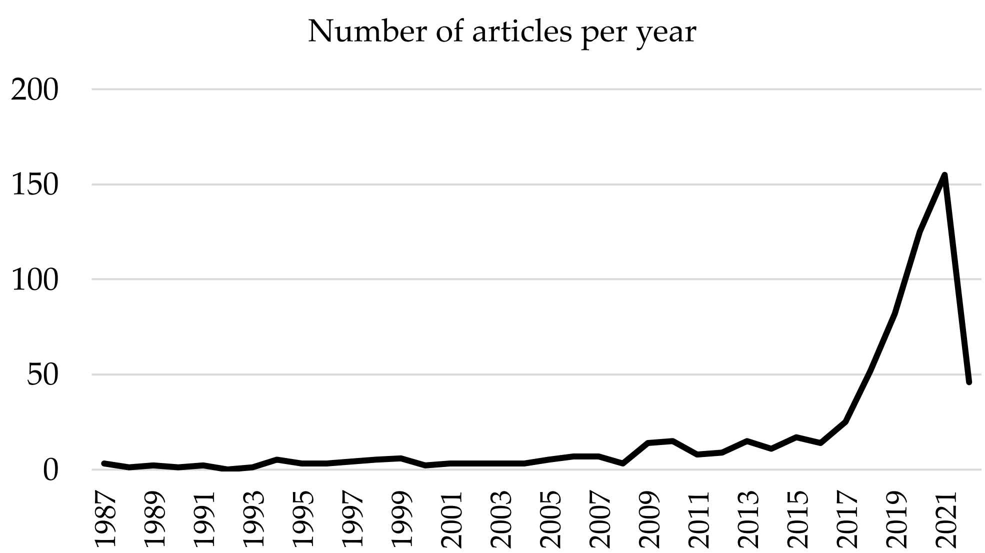


Figure 1 - Number of articles per year

The second phase started with a pure abstract screening based on the following inclusion criteria:

*(i)* Include articles which focus on the application of artificial intelligence as a business tool to spur entrepreneurship, and are not excessively concentrated on the technical functioning of algorithms

*(ii)* Include the qualitative and quantitative (i.e. empirical) articles that actually provide novel and concrete evidence on the topic.

All the abstracts have been carefully read by both authors in an independent way, in order to avoid possible biases (no major disagreement emerged), and all of them have been labeled into three categories: green (i.e. approved), yellow (i.e. to be further discussed) and red (i.e. out of scope). By putting together the two assessments on each paper with a conservativism principle – i.e., keeping the most positive valuation – we obtained 36 green articles, 72 yellow ones, and 552 red ones. After further analysis and a joint discussion on the 72 yellow ones, 35 of them were approved, resulting in a total of 71 articles as the final output of the abstract screening phase. In the same manner, the 27 articles passed to the following phase, which consisted of the article screening based on a full-text reading. The inclusion or exclusion of the articles was based on strict predefined inclusion criteria in line with the final goals of the research.

Moreover, to such a pool of articles, 6 articles were added, coming from parallel search conducted by keywords on Google Scholar that emerged during the full-text screening of the original sample of articles. This additional pool was separately analyzed in detail by the two authors, who assessed whether the articles should (or should not) be included in the review through a full-text analysis based on the same inclusion criteria of the initial larger pool of articles. All of them have been considered "green" articles by both authors based on their relevance to the survey. Finally, we employed an additional technique called snowballing (Greenhalgh & Peacock, 2005) by examining the cited contributions by the selected articles. Among these, we have identified some articles that were not included in our query but, at the same time, represented an excellent source of findings on the subject. After an analysis by both authors, based on the relevance and occurrence of the cited articles, 9 papers were added to the sample. The process, summarized in figure 2, gives a final output of 42 articles (27 from Scopus initial pool, 6 from Google Scholar keywords research and 9 from snowballing) to constitute the basis of our SLR.

For showing the results of the review, we initially selected a framework that was constituted by the following themes: *(i)* human-machine relationships, *(ii)* creativity,

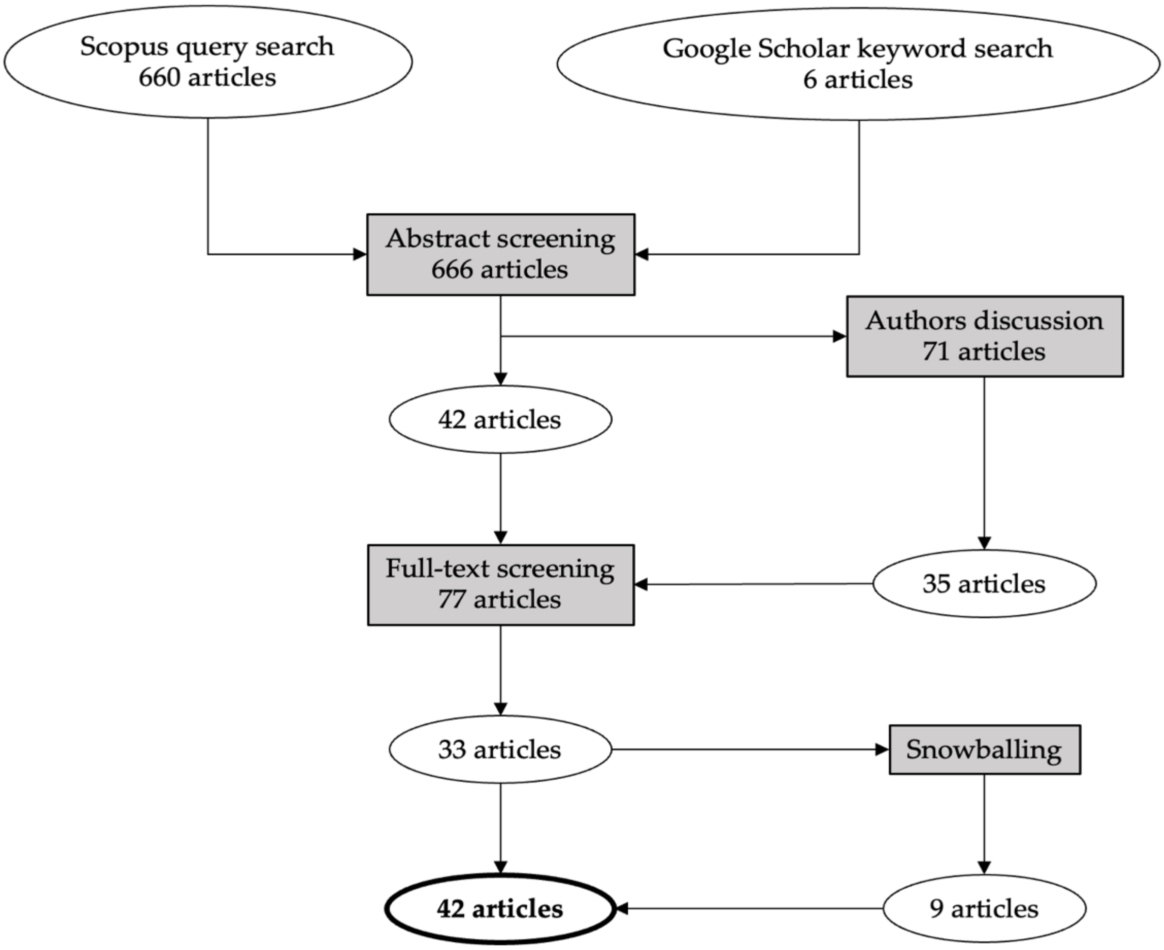


Figure 2 - Prisma flow diagram of the Systematic Literature Review

and *(iii)* barriers and facilitators. However, after another reading session of the all sample of selected papers in order to rationalize the key findings that emerged from the analysis, both the authors convey that a more suitable framework was needed, to give a better illustration and interpretation of the extant literature. Hence, we ended up with a reclassification, with the choice of a new framework that classifies the impact of artificial intelligence on business according to three distinct areas: daily operations, decision-making, and innovative and creative processes. Accordingly, the three clusters of literature (non-mutually exclusive since several articles present insights about many of them) have been labeled *(i) Process improvements*, *(ii) Decision-making*, and *(iii) Creativity and Innovation* (see chapter 3 for further details about the rationale of the classification).

## 2.2. Multiple case studies

Bearing in mind the goal of analysis and the issue addressed in the empirical work, it was felt that the best method to approach the topic was a qualitative analysis.

"Qualitative researchers attempt to describe and interpret some human phenomenon, often in the words of selected individuals. These researchers try to be clear about their biases, presuppositions and interpretations so that others can decide what they think about it all" (Heath, 1997). Thus, qualitative research encompasses any type of research that yields results that are not obtained through statistical procedures or other methods of quantification. It draws on a variety of data sources, including observations, documents, films, and even quantitative data. The data collection process in qualitative research requires intensive data on human phenomena, collected from multiple sources of evidence and analyzed in a non-statistical manner.

Among the different techniques which can be classified as qualitative research, we choose a multiple exploratory case-study approach, used to investigate complex phenomena observed in the field and can be applied any time a given phenomenon is mostly unknown and there is a lack of theories to formulate hypothesis ex-ante the investigation (Eisenhardt, 1989; Yin, 2009). That said, in our analysis we are dealing with a quickly changing topic with a high degree of novelty, still at a primordial stage of research. Therefore, this method was deemed appropriate since allows to collect and interpret the sentiments of a number of experts in an extensive way, allowing the generation of rich information and a deep understanding of the phenomenon of interest.

### 2.2.1. Research design

Through our interviews, we want to *(i)* gather evidence about the impact of AI on creativity and innovation, but also to *(ii)* analyzed them in a structured way, highlighting not only the presence of impacts but also gathering information to provide support for the emergent theory and extend it by identifying "polar types" that will depict and embedded a given phenomenon or implication. The final scope of our analysis is to identify findings that can be generalized and abstracted from the mere concept of "evidence" to express conclusions that can contribute to the enrichment of the existing literature on the impact of AI on business.

After having identified the best research strategies, the definition companies on which conducting the research became the first priority. Considering the fit with our research question our choice was based on investigating companies appropriately chosen among different industries. This allows us to slightly readapt our research questions and detect different sides of the same coin but at the same time, considering the goal of our research just exposed before, we wanted that the outcomes that came out from the interviews were as much comparable as possible, to enable patterns recognition and cross-analysis. For these reasons, we adopt the following criteria in the choice of the sample of analysis.

#### 2.2.1.1. Business model

A pool of startups has been selected to constitute our sample. We want to investigate how are characterized the process of innovation and creativity with the advent of AI and all the consequent impact that it has led, focusing also in particular on how the human-machine relationship is articulated. Hence, the best theoretical research sample has come out to be composed of companies which natively take use of AI as "the linchpin" of their business model. The choice was driven by the awareness that the innovation process and the creative process are at the baseline of building a solid and sustainable competitive advantage. Therefore, we need firms that do not employ AI as a mere support tool but rather companies which innervate AI as the funding element of their business model. In order to be rigorous and perform a consistent analysis, we provide the boundaries of the definition of *startup* which we strictly followed in the companies' sample choice. We considered as a *startup* a company that:

- *(i)* has not performed an exit strategy yet, the founder has not personally sold his/her own share and he/she is still the owner of the company;
- *(ii)* is organized by a flexible and agile strategy and has a business model that could allow it to potentially scale up easily;
- *(iii)* has a turnover of less than 5 million;
- *(iv)* has the social aim of developing innovative products or services, with high technological content (Colombelli et al., 2016).

#### 2.2.1.2. Geographic scope

The companies were all chosen from the Italian context. This choice was driven by a matter of comparability but also given the academic relevance that the "Italian case" has assumed. Indeed, studies conducted in the field have demonstrated an increase in incubating initiatives over the last years (Colombo & Delmastro, 2002). Since incubators and science parks are key players in the start-up support system, the expansion of such initiatives is an important indicator of the development of the Italian ecosystem. The Italian government, through Decree Law 221/2012, known as the "Italian Start-up Act," recognized the critical role of entrepreneurship and innovation as drivers of long-term economic growth in 2012. A separate section of the firm's Register was established to collect information about innovative new ventures (also known as 'innovative start-ups,' as well as a number of policies to support those initiatives. As a result, according to Registro Imprese, over 6000 innovative start-ups had registered and claimed to be innovative (Cavallo et al., 2020).

#### 2.2.1.3. Industries' choice

The choice of industries has been another key point of attention, considering the Italian market heterogeneity. In order to be systematic and as rigorous as possible in our methods, we have considered a qualitative evaluation of three key variables to understand the most fitting and emblematic industries for our research goal, starting from the main AI characteristics:

*(i)* Structure of information available, related to the nature of the data gathered from clients, and processes. From the more structured (quantitative and objective data) to the less structured one (qualitative and subjective data). This first variable has a direct link to the capability of artificial intelligence of gathering and processing a massive amount of data.

*(ii)* Relevance of prediction to provide an effective service, acting proactively to anticipate customers' needs and unpredictable events. This second variable has a direct link to the predictive capability of artificial intelligence, particularly in the case of ML algorithms.

*(iii)* Role of human intuition in creating a new and valuable solution to existing needs. This third variable has a direct link to generativity (i.e., creating something novel and useful from scratch) and recombination capability (i.e., creating new knowledge through a new combination of existing knowledge) of artificial intelligence.

Considering these variables together and applying a trade-off logic with the final aim to identify the best fit with our research agenda we choose three different industries: Healthcare, Finance and Content Making. The choice was based on the different way they addressed the variables introduced before, which increase the possibility to derive relevant insights from the analysis and the solidity of our work contribution. Moreover, we found confirmations of our choice in many economic and STEM sector newspapers such as Forbes, in which 14 tech experts agreed in appointing healthcare, finance and content-making industries as part of the sectors that will benefit most from AI (Forbes Technology Council, 2021).

#### Healthcare industry

The HC industry is characterized by many data about patients, drugs, and medical devices, which are often difficult to be analyzed in a comprehensive way. The application of AI in this field is massive, as AI can derive the meaning and context of the structured (such as clinical notes) and unstructured data (relevant reports) that might be critical for selecting a treatment plan. And then, combine different attributes from patients' medical records to identify potential treatment plans for a particular patient. In short, it works like a human doctor. Through the power of predictive analytics, AI can help doctors make proactive moves towards ensuring their patients' health by identifying diagnostic paths and exploiting the correlation of different data overcoming human local searching routines. This is a much better approach to healthcare than the reactive approach taken today. AI can also enable easier analysis of scan results through image recognition. This has already been used to help doctors diagnose symptoms at a much higher rate, as AI can comb speed and depth in the analysis through multiple scans in a very good level of trade-off. All in all, the main focus is on prediction, medical prevention, drug discovery and image recognition, areas in which AI and ML can definitely contribute to the wellness of the patient, empowering physicians with new powerful tools. To rationalize the three variables of our assessment:

*(i)* Structure of information available: *low*

*(ii)* Importance of prediction: *high*

*(iii)*Role of human intuition: *medium-low*

### Financial sector

The financial sector is one of the most impacted by Artificial Intelligence since companies have collected and organized data for decades. The areas of application are several, from the credit risk assessment to the Robo Advisor. The core of the application is the capability to gather and analyze data coming from different sources and recombine them in a predictive way. AI not only speeds up many processes but also enhances effectiveness and customer experience. It is useful to identify high-value customers through data mining and parsing text online, to provide additional services to the existing ones based on their spending or financial activities, and to look at the customer's credit history, thus predicting the individual defaulting tendency. The key interpretation here could be investigating the AI potentiality to overcome existing barriers, improve the *know-your-customer* factor, democratize existing restricted services, enlarge the current industry offer, and rethink the traditional approach to already existing challenges such as risk assessment. In our framework:

*(i)* Structure of information available: *medium*

*(ii)* Importance of prediction: *mid-high*

*(iii)*Role of human intuition: *low*

### Content Creation industry

Nowadays, the content creation industry cannot rely anymore on being informative or posting on social media: the critical success factors in the market have crossed these boundaries. The capability of establishing or improving the narrative of any business has become a key success factor. AI tools and software are strongly impacting the industry since are able to automatically create contents for a set of different parameters or for specific sectors and topics. The enormous data gathered and processed by artificial intelligence allows not only to improve the efficiency of the processes but might lead also to improve the content quality by offering ideas, suggestions, samples, and assistance with editing. Applications such as AI copywriting software help businesses write better copy with less time investment. That's why they have become a go-to solution for many markets to build content at scale. In our assessment:

*(i)* Structure of information available: *low*

*(ii)* Importance of prediction: *low*

*(iii)*Role of human intuition: *high*

### AI solution providers

In addition, based on what emerged from the first interviews, we decided to add two startups whose core business is designing and developing AI-based solutions for their customers. Even if they do not belong to the above-mentioned sectors, they could provide us with valuable insights for different reasons. As emerged from the first two interviews we conducted, sometimes even AI-based startups do not own vertical knowledge of AI and leverage the support of third-party companies which develop solutions customized for their specific needs. This has a double implication: these providers work with different clients, each with different needs and operating in different industries, consequently, they can depict an overall view of the Italian scenario. Moreover, they are updated on the most recent progress on AI applications and perform constant research in order to develop new solutions. All these contribute to making these two firms an appealing target for our research.

The type of companies selected constitutes a promising starting point, as it has the potential of allowing the collection of complementary insights about the topic. The financial and healthcare sectors are significant since they both operate in a data-rich environment, where AI can impact the most. Still, they are characterized by different dynamics and can provide insights from different perspectives about the impact of AI on innovation: the financial sector about the exploitation of structured data to enrich the value proposition and enable AI-driven financial risk management, while healthcare in enhancing predictive medicine thanks to algorithms of image recognition and other analysis of non-structured data. On the other side, content making industry is the most suitable choice to explore the latest development in computational creativity, such as generative AI and synthetic data, and AI solution providers – as mentioned previously – can offer the broadest view about the new emerging trends in artificial intelligence.

The companies have been selected through research conducted on the web portal about the most innovative emerging AI-based startups. In the second phase, the companies have been contacted via email or LinkedIn. We can sum up the steps of the process as follows:

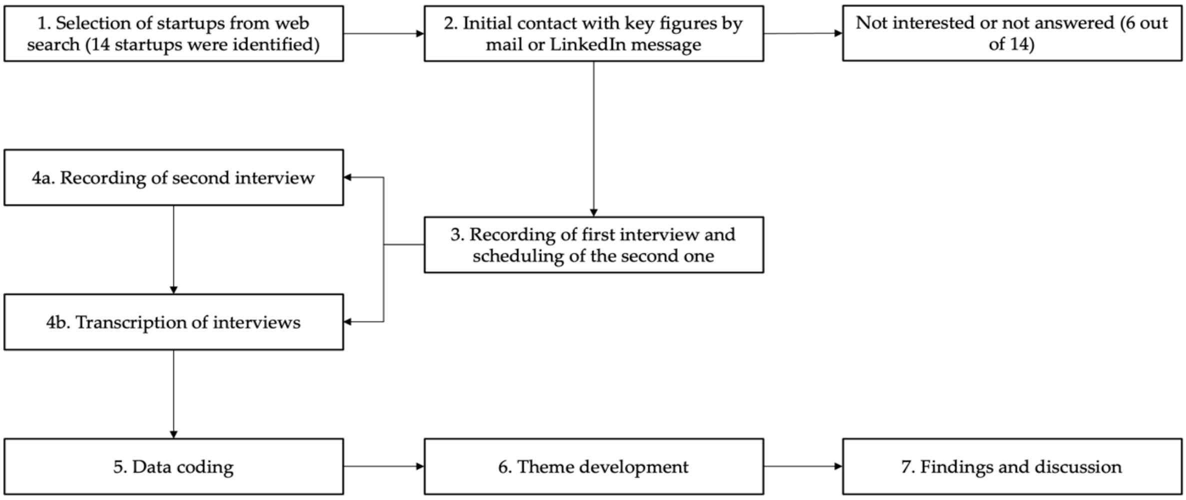


Figure 3 - Qualitative research main steps

In order to obtain more consistent results, in compliance with the data triangulation principle, we conducted two interviews per startup, for a total of 16 interviews. Specifically, for every startup, we selected two distinct profiles to be interviewed: a business expert (e.g., CEOs, heads of innovation, product owners) and a technological expert (CTOs, heads of scientific department, data scientist). In this manner, we were able to triangulate data but also gather complementary insights about the use of technology and the way in which startups manage their processes, with a business-side view combined with a more technical one. Every interview followed a semi-structured protocol of questions as a starting point (see Annex A for the complete set of questions), to which we added extra questions based on what emerged during the interviews, and slightly adapted the protocol to the background of the interviewees. The basic structure of the questions protocol was the following:

*(i)* profiling of interviewees and of the company, useful to contextualize the company in the Italian market, the peculiarity of the industry, the use of technologies in business, and the structure of the innovation processes;

*(ii)* uses of artificial intelligence, justifying the choice of AI as core technology and contextualizing its use according to the literature;

*(iii)* impact on innovation and creativity highlighting the use of AI as a source of competitive advantage and its contribution as an enabler for incremental or radical innovations;

*(iv)* role of humans and human-machine collaboration, focusing on which are the tasks in the innovation process that can be delegated to the machine.

All interviews, with the exception of company ε with whom there was an in-person meeting, were conducted via Microsoft Teams or Google Meet. Every interview lasted about one hour, it has been conducted by both authors and has been registered and transcript manually into Word documents for the coding phase.

### 2.2.2. Coding phase

Once the data collection has been concluded, we started to interpret and analyze the data asset. The text has been analyzed through the traditional coding approach, with the software support of NVivo. Coding refers to the analytical process of reading through data line by line or paragraph by paragraph in search of meaningful experiences, events, feelings (Glaser & Strauss, 2017). We use the "in-vivo codes" for the first stage, which are the actual words that interviewees used. An inductive – or "open coded" – approach has been followed, beginning from the text and determining the codes and categories of codification as a result of the analysis.

After the contents of the interviews were coded, we started the second phase, the axial coding, with the aim of analyzing and interpreting them. The grouping into categories took place on the basis of the commonality of content and pattern matching. That is, we grouped first-order codes which, if alienated from the specificity of the example of the company interviewed, brought coherent and aligned insights towards the same concepts. For instance, codes like *The algorithm signals an unexpected pattern to the development team, which interpret it in the light of their experience* and *The output is always checked by editors that verify the alignment to the objective and its quality* were clustered in the same category *Domain expert in interpreting result.*

In the third phase, we considered as a starting point for the third-order themes the theoretical framework about the stage and gate process proposed by Cooper (1983). We interpreted the main findings by adopting a dependent variables design approach, starting from predicting variables corresponding to the stages of the innovation funnel presented by Cooper's model. Hence, categories which refer to a specific phase of the process were grouped into a theme, labeled as the name of the phase itself. For instance, categories like *Synthetic data as primary input* and *Applicability to new domains* were clustered in the same category *Ideas identification*

Despite the identification of themes started from a consolidated framework in the extant literature, according to the open coding approach methodology, the predetermined variables have been adjusted, adding new ones according to the main relevance that emerged from the analysis. Indeed, categories which can be associated with the same concept without being directly linked just to one phase of the innovation process constituted additional themes, considered as enablers of the innovation process as a whole. For instance, categories like *Knowledge codification* and *Knowledge sharing* were clustered in the same theme *Support for knowledge management.*

The analysis of the results consists of two separate phases. First, the vertical analysis of the themes, in which the insights that emerged were deepened systematically, highlighting the link between the categories. To support the arguments, quotations from the interviewees were included, translated from Italian by the authors. Within this analysis, some concepts are even presented from according to a further angle, that is, from the point of view of the factors that were considered in the research design to select the industries for the interviews (*structure of data available*, *importance of prediction* and *role of human intuition*). Lastly, the analysis ends with the development of a framework that supports the graphic visualization of all the identified themes and facilitates the understanding of the reasoning behind their interactions.

# 3 Systematic Literature Review

## 3.1. Introduction

Through our query and screening, we were able to identify vast streams of literature concerning the application of AI in entrepreneurial activity. However, specific topics analyzed and key findings in each paper are characterized by a high degree of heterogeneity. This is mainly due to the complexity and multitude of factors that impact entrepreneurship, which combined with the rapid evolution of artificial intelligence result in a broad investigative framework and an incalculable number of subplots to be studied.

Hence, to facilitate and guide our line of reasoning, we grouped the findings of papers according to three different levels describing the impact of artificial intelligence on entrepreneurial activity: *(i) Process improvements*, *(ii) Decision-making* and *(iii) Innovation and Creativity*. Note that the classification of papers, shown in table 2, is not mutually exclusive, as several of them present insights regarding more than one cluster identified (such papers are highlighted in bold).

The rationale behind the classification is the following:

*(i)* *Process improvements*: articles which focus on how the entrepreneur, working as an ally alongside intelligent machines, takes advantage of the improvements in the productivity of business processes and the new paradigm which characterizes labor force, enabled by AI and human-machine collaboration. Key findings about this cluster are about the performance-enhancer role of artificial intelligence in daily operations.

*(ii)* *Decision-making*: articles which provide insights on how AI could help entrepreneurs to process and transform available data into more accurate and valuable decisions. Key findings about this cluster are about the support of AI in gathering and processing information, patterns discovery and clustering analysis, overcoming humans' limits across all the phases of the decisional process.

(iii)*Innovation and Creativity*: articles which provide insights on how an entrepreneur is engaged in operating digital transformation through AI, which helps in identifying new business opportunities, in terms of venture creation, innovation, and creativity. Key findings about this cluster are about AI-enabled tasks such as opportunities scanning and ideas development and the latest advancement in the fields of generative AI and self-innovating AI.

| Process improvements | Decision Making | Innovation and Creativity |
|---|---|---|
| *Botha (2019)* | ***Brem et al. (2021)*** | *Anantrasirichai & Bull (2022)* |
| ***Chalmers et al. (2020)*** | ***Chalmers et al. (2020)*** | ***Brem et al. (2021)*** |
| ***Ferràs-Hernàndez (2018)*** | *Choi et al. (2006)* | ***Chalmers et al. (2020)*** |
| *Gashenko et al. (2020)* | ***Dellermann et al. (2019)*** | ***Dellermann et al. (2019)*** |
| ***Giuggioli & Pellegrini (2022)*** | *Diamond (2020)* | *Elia et al. (2020)* |
| ***Holford (2019)*** | ***Eriksson et al. (2020)*** | ***Eriksson et al. (2020)*** |
| ***Popkova & Sergi (2020)*** | ***Giuggioli & Pellegrini (2022)*** | ***Ferràs-Hernàndez (2018)*** |
| *Upadhyay et al. (2022)* | *Janiesh et al. (2021)* | *Fossen & Sorgner (2021)* |
| *van der Zande et al. (2018)* | *Kalantari (2010)* | ***Giuggioli & Pellegrini (2022)*** |
| ***Wodecki (2019)*** | ***Makridakis (2017)*** | *Griebel et al. (2020)* |
| | ***Obschonka & Audretsch (2020)*** | *Haefner et al. (2021)* |
| | ***Popkova & Sergi (2020)*** | ***Holford (2019)*** |
| | ***Paesano (2021)*** | *Hutchinson (2021)* |
| | *Tabesh (2021)* | *Li et al. (2022)* |
| | ***Townsend & Hunt (2019)*** | ***Makridakis (2017)*** |
| | *Shrestha et al. (2019)* | *Mikalef & Gupta (2021)* |
| | *Vincent (2021)* | *Lubart (2005)* |
| | ***Wodecki (2019)*** | ***Obschonka & Audretsch (2020)*** |
| | | ***Paesano (2021)*** |
| | | *Schiavone et al. (2022)* |
| | | ***Townsend & Hunt (2019)*** |
| | | *van Rijmenam (2019)* |

Table 2 - Systematic Literature Review clusters

## 3.2. Process improvements

The first area of impact that emerges from the literature is how the entrepreneur can benefit from the operational advantages and the opportunities that AI enables in terms of job automation and performance enhancement.

To properly analyze such impacts, it is useful to start reasoning about the reshaping of the labor market. First of all, we have to define the boundaries of the impact by investigating which jobs are affected most by the advent of artificial intelligence, how they are changing, which are the new required skills, and how AI is reshaping the traditional balance between humans and machines. According to a 2017 McKinsey and Company report (Manyika et al., 2017), about half of the tasks performed by workers can be potentially automated. However "for most occupations, partial automation is more likely than full automation in the medium term, and the technologies will provide new opportunities for job creation" (Holford, 2019). Over the past few decades, digital computers have revolutionized labor across almost all sectors of the economy. Recent developments in ML are further speeding up this process, as companies are experiencing a faster and disruptive shift. Indeed, entrepreneurs will look to replace people with computers whenever is more efficient than humans at a task (Giuggioli & Pellegrini, 2022).

The figures below show the results of consulting firms about the forecasted impact of AI on job automation.

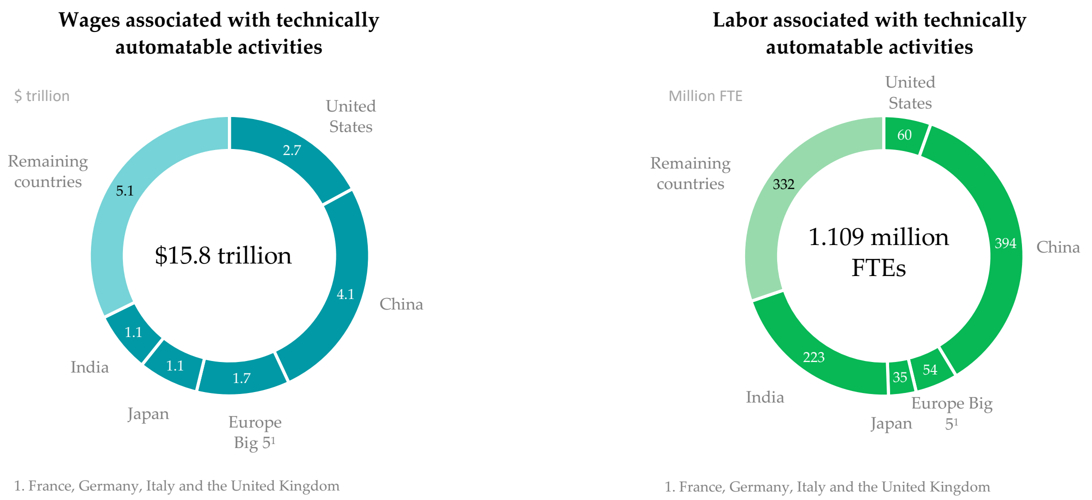


Figure 4 - Types of AI systems (Kaplan & Haelein, 2018)

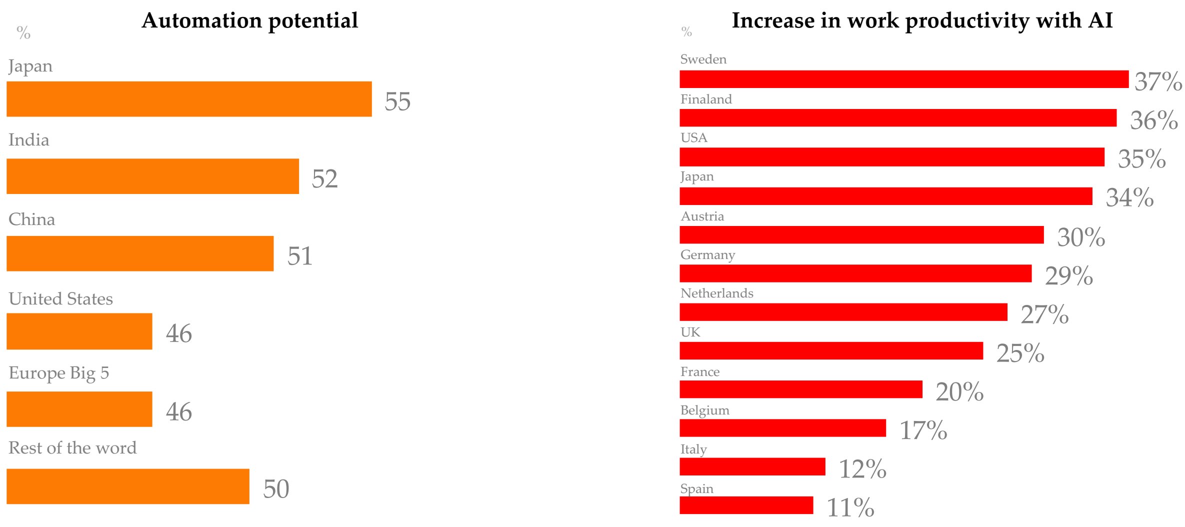


Figure 5 - Automaition potential and improvements (Frey & Osborne, 2013)

Generally speaking, we can distinguish between routine and non-routine tasks, with the first category of jobs more subjected to automation, while for the second one, automatization is not that straightforward since the human component is still fundamental and essential, as they often refer to value-added and customer-facing tasks (Davenport & Ronanki, 2018). More specifically, we can define routine tasks as those tasks that adhere to precise criteria that can be exhaustively specified and, therefore, converted into precise codes and procedures. On the other side, we refer to non-routine tasks when these criteria are significantly harder to codify as they are not widely understood and/or due to a difficult formalization (van der Zande et al., 2018).

Talking about job automation within the shift towards Industry 4.0, two directions can be recognized (Gashenko et al., 2020):

*(i)* *Automation of production*: in this direction, machine labor replaces human labor in industrial production. Companies develop their organizational set-up, creating separate intellectual departments (the so-called "smart plants") where all the technical gadgets are interoperable and controlled by AI. They follow a precise algorithm for the manufacturing or creation of industrial goods and the inspection of their quality.

*(ii)* *Automation of supply chain*: this course calls for the automation of supply chain management, sales, marketing, and distribution. Automation typically affects only a small portion of processes, such as the formation of business information systems or the management of knowledge databases, through neural networks and the processing of large amounts of data. Human intellectual capital continues to play the primary role in distribution accepting orders, creating the

logic and content of marketing messages and making the final judgment in light of machine recommendations and the elements that AI ignores.

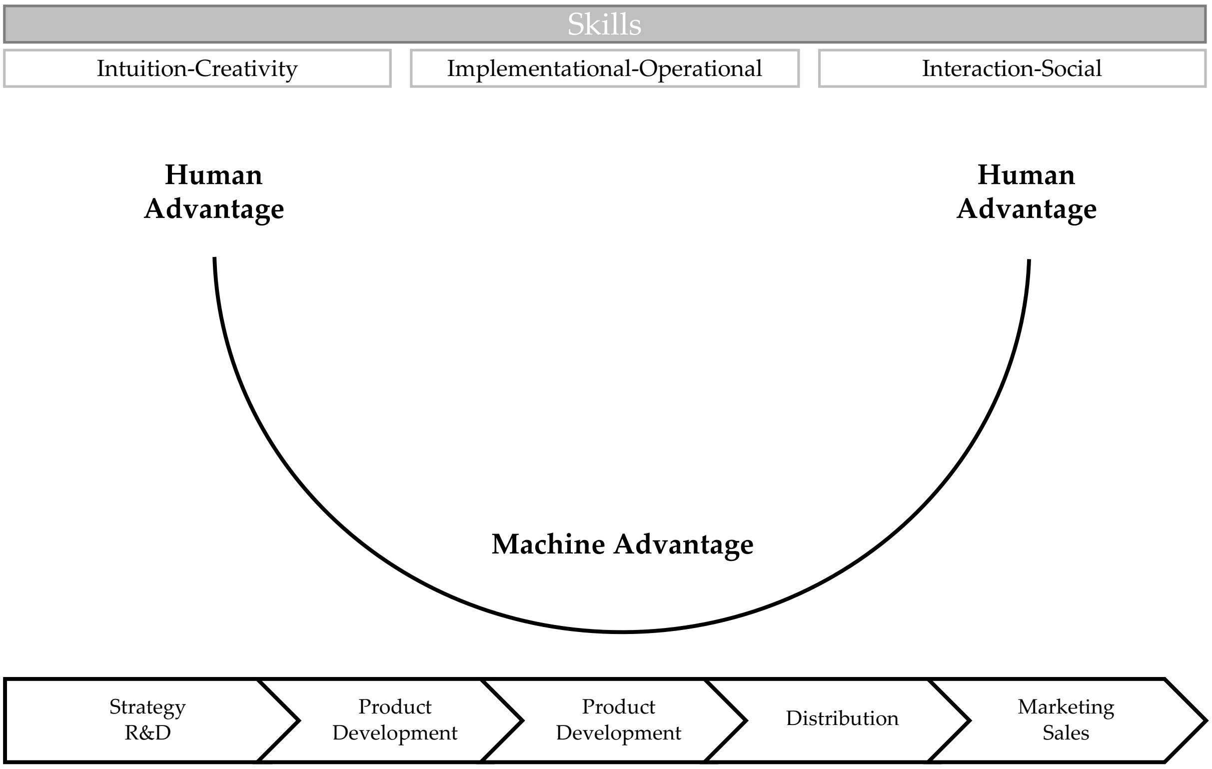


Figure 6 - Human versus machine advantage in the value chain (elaboration from Ferràs-Hernandez, 2018)

Anyway, the automation of repetitive tasks is a widespread practice across every industry, and it is not limited to the industrial sector. Boustani (2022) shows how AI is used in the banking industry and how it affects bank staff and customer behavior. He claimed that when it comes to customer contact with bank staff, AI cannot replace the role of humans. He supports the thesis that on the one hand AI is useful and has been proven to be a performance enhancer from an operative point of view, improving the quality of banking transactions and managing fundamental skill sets successfully. On the other hand, however, it is unable to replace emotional intelligence, which is necessary for front-end activities, managing client and staff relationships. As a first key finding, humans are called to advance to higher-order and sophisticated activities, where they still have a comparative advantage with respect to machines (Jaiswal et al., 2022).The findings of a recent study on the effect of AI on the future of work and the division of labor between humans and machines, conducted by the Fraunhofer Institute for Industrial Engineering, confirm that simple and analytical activities in the data field are likely to be subjected to automation (Paesano, 2021). However, in the future, human beings will continue to be primarily responsible for intuitive and empathic tasks, such as the perception and processing of emotion (Bauer & Vocke, 2020). One of the main reasons behind the inability of machines in performing such tasks is their lack of explainability, which makes it difficult to fully understand and codify the dynamics which regulate emotional-based activities (Ferràs-Hernàndez, 2018). However, the literature presents also a more groundbreaking vision, mentioned as "Digital Taylorism". This theory argues the existence of a framework that allows the organization of the "knowledge labor" which entails subjective intellectual tasks (i.e., which could be categorized as "non-routine tasks") equal to the procedure as chain labor (i.e. "routine tasks, Brown et al., 2012). Brown, Lauder, and Ashton in their paper claim that once the jobs are defined and digitalized and the decision rules can be computerized, the technology is able to carry them out, replacing human judgments and decisions. The procedure, according to the framework, makes it simple to translate them into computerized international connections. In other words, Digital Taylorism adheres to several of Taylor's founding principles which can be summed up in three main pillars: *(i)* converting complicated operations into straightforward, standardized ones, *(ii)* monitoring/measuring everything employees do, and *(iii)* connecting compensation to performance.

That said, will AI be able to impact management as a profession? Since it is closely entwined with interpersonal relationships, it is regarded as a branch of social science, which examines how people interact within the context of organizations, where people at all levels are subjected to incentives and pressure to meet organizational objectives. In terms of technology, nowadays machines can have impressive contributions just by watching a phenomenon and gathering data about it. However, persuasion, leadership, institutional ties and ownership-based processes are likely to be more resistant to the "AI invasion" (Ferràs-Hernàndez, 2018). Where AI can make the difference – and in many cases, it is already doing it – is in intermediate processes of the value chain (figure 6), such as operations management, logistics, manufacturing, finance, and quality control. Here, computer management can actually outperform human management since the required skills are connected to data processing and analytical optimization. Recent artificial intelligence advancements allow robots to handle large unstructured datasets through intricate and adaptable algorithms (Choudhury et al., 2020; Peter Stone et al., 2016). Still, even in these stages, the greatest potential of AI is not to substitute completely human abilities - both in routing and non-routine tasks - but rather to extend and boost them. Indeed, optimal results are obtained by combining machine speed, precision, repetition, predictive abilities, and scalability with human creativity, improvisation, dexterity, judgment, and social and leadership skills. Applied properly, AI allows people to operate more naturally and less robotically and it represents a win-win solution: it increases productivity and provides more time to focus on value-adding activities, freeing up the creative part of the human skillset (Wilson & Daughery, 2018). As a result of these new tools and procedures, the labor market may evolve quickly in a scenario in which prices drop, productivity increases and industries need to be restructured (Brynjolffson & Mtchell, 2017). As many ordinary tasks have been mechanized given the development of new technology, medium-skilled professional employees are beginning to be threatened by AI. Therefore, it makes sense to promote a viable alternative to re-organize workers in a set-up that fits better with this dynamic environment. In this context, entrepreneurship is growing as the main opportunity and answer to the reshaping of the labor market and exploiting all the new opportunities enabled by technological advancements (Giuggioli & Pellegrini, 2022).

AI has a positive impact on the economy promoting the growth of entrepreneurship, which helps to accelerate the development of productive power in society. Indeed, private research and development, as well as state investments in AI, all have a significant impact on economic growth most of all in terms of productivity enhancement (Mamedov et al., 2018). ML is precious to evaluate the startups' grade of innovation that is proven to be connected to the chance of surviving of the firm in the sense that creative businesses have higher possibilities to survive compared to the less innovative ones (Guerzoni et al., 2021). Anyway, digital entrepreneurship has also implications for how business owners set up and run their companies since they modify how they leverage emerging technologies (Fisch, 2019). For this reason, we can say that one of the key drivers of the growth of digital entrepreneurship is that "it has led to increasingly fluid and porous spatial and temporal limits for entrepreneurial activity" (Nambisan, 2017), breaking down traditional entrepreneurship barriers by offering accessible tools to virtually anyone.

Having defined the context of impact in the labor market, it is interesting to deepen the benefits and the main advantages linked to AI, which also represent the main reasons that have led the technology to be adopted as a performance enhancer. Starting from today's neoliberal ideology, it is argued that efficiency is still a dominant "cultural logic" that "values the quickest and least expensive production and distribution of any product, as well as fast and inexpensive modes, technologies, and behaviors" (Holford, 2018). Basically, the concepts of efficiency and maximization are integrated into the neoliberal ideology, and the main means to achieve these goals are technology and techniques. The authors (Marcuse, 1964) and (Ellul, 2018) explicitly demonstrated the ongoing relationship between technical efficiency and the economic pursuit of profit maximization and economic growth. Hence, it is not surprising that many technological efficiencies are present and incorporated in different workplaces and environments, keeping "to do more with less" as a company mantra (Autor, 2015). Technologies and AI, in particular, are heavily emphasized in current and upcoming organizational strategies with the overall goal of enhancing productivity and maximizing profitability (Holford, 2018). This has shown up, as explained before, in automating repetitive jobs, the digitalization of the workforce to increase productivity, and the valuable contribution of AI to more dependable and productive professional work. Machines have demonstrated to be better at interpreting large amounts of data, identifying patterns, preventing errors, and coordinating subsystems. As a consequence, processes which are heavily dependent on logic, statistics, and logical decision-making will be more likely to be replaced by machines which can assure superior performance. For instance, it can be the case of the operation management fields (concerning stock management, procurement, supply chain, production planning, quality control and logistics) or financial management, where the implementation of the plan can be performed by machines once the company objectives and the strategy have been established and determined (Ferràs-Hernàndez, 2018). We can look at some practical applications to move from the realm of ideas to the realm of empirical contexts. Every industry 4.0 technological paradigm relies on AI (Giuggioli & Pellegrini, 2022). It is adopted in the so-called "smart factories" which do not rely on human intervention for their operations but primarily operate in a fully connected manufacturing systems modality enabled by the detection, analysis, and transfer of data (Lasi et al., 2014). AI controls intelligently all systems, signaling the need of maintenance intervention, designing the operational workflows, and controlling the quality of the outcomes (Meziane et al., 2000; Murray, 1999). Moreover, it is an essential component of the internet of things (IoT) to manage or monitor remotely the interconnections between different physical devices which communicate with one another (Ashton, 2009). Indeed, AI processes and transform massive amounts of data to produce useful results, connecting different software languages of all IoT devices (Ahmad et al., 2020). Looking at the benefits that smart factories and AI can bring, we can mention efficiency in terms of resource savings, assurance of a certain level of goods quality, increased life of the machine devices, full transparency, and control of the production process. A stricter control over production enables predictive maintenance, more adherence to the parameters and conditions set at the beginning, and a higher level of safety conditions inside the factory thanks to decreased human involvement Gashenko et al. (2020). Another important advantage that AI solutions provide is that they enable process upgrades, helping firms to pursue the logic of constant improvement in terms of productivity and efficiency (Szalavetz, 2019).

On the other side, the main disadvantages consist for sure in the large capex required for building a smart factory and the high level of energy needed. In the same way, job automation is supposed to impact distribution. This path implies the automation of marketing, sales, logistics, and supply chain management. As said before, automation is much more difficult, and it is possible only to a limited extent given the current technologies. The highest level of automation is achieved in production, as in the case of fully automated "smart" plants and production departments. The central point in the full automation of the distribution is the disadvantage related to the imperfection of AI, in particular concerning communication. Indeed, this represents a severe limitation that crashes into the entrepreneur's interest and logic and explains the limited (or absent) presence of concrete applications in scientific papers. To some extent, AI in distribution can be useful as intelligent decision support in terms of information systems or knowledge databases, but it cannot be a strong performance enhancer since it doesn't consider key factors such as corporate, social and ecological responsibility.

So far, we have discussed the effect of the technological revolution on the labor market, which reshapes the *as-is* equilibrium and creates new opportunities and challenges, requiring new skills and expertise. According to the literature, entrepreneurship can be considered a valuable answer to these challenges, making it a promising field when investigating the impact of AI. Starting from the product-market fit and the idea validation, the traditional and current methods are the lean start-up approach and the business model canvas which emphasized customer engagement as a means of searching for ideas and proving assumptions. Chalmers et al. (2020) argue that these models are clearly useful but are subject to various biases (called social biases) and have limited generalizability.

The incorporation of AI in this process may have benefits in terms of research costs as well as failure reduction with time-consuming products/services. Their idea is that many entrepreneurial ventures don't fail due to a lack of product-market fit, but rather in underperforming sales capability, or better the capability to capture value from the venture idea. The main issues which are marking the sales functions in today's organizations are high turnover and "burnout" as a result of the emotional labor involved in routine activities. Since it is frequently repetitive and difficult work, salespeople can demand relatively high salaries, depleting venture capital and having a significant contribution to burn rates (Bande et al., 2015). For these reasons, AI can have an important impact in facing these challenges, enabling the selling activity to be automated. Among startups which are attempting to improve sales activity, this can help them to improve the proposed solution and provide a supplement to the existing ones like freeing-up time for the high-value customer or even replacing the salespeople. For instance, some firms are using ML approaches to help human salespeople in identifying warm leads, classifying and routing them to the right salesperson at the right time. Meanwhile, other ventures are going even further by capitalizing on the recent development in natural language processing and DNNs, replacing humans with "bots" (Chalmers et al., 2020). Examples of further development can be exploiting the technology to assess customer reactions to product features or prices, allowing companies to adapt their value proposition according to customer segments. The possibility to replace some human figure brings other important advantages which deserve our attention. It is demonstrated that the scaling costs can be reduced significantly (to zero marginal costs) as they are decoupled from human labor. This allows firms an easier and faster scale-up since they face lower marginal costs and don't have to search for new personnel. Furthermore, increasing the number of "bots" which substitute people in the interaction with customers can result in an increase in productivity. As data volume increases, ML algorithm improve their performance thanks to self-training (Esteva et al., 2019), thus resulting in higher effectiveness (enhanced output) and productivity (intended as a ratio between output and input).

More in general, entrepreneurs benefit greatly from the support of AI because it creates unique opportunities for business growth and supports the improvement of business operations at a very low cost, as well as reaching a high level of efficiency that helps the business scalability even in the global market (Darwish et al., 2020).

Furthermore, AI can have an impact also to another sphere of the entrepreneurial process: the decision-making systems, increasing the quality of the decisions made in terms of efficiency and efficacy, and improving operational performance. The ability of deep learning networks to improve operative performance has been validated since it is a powerful method able to outperform traditional data analytics methods in terms of prediction performance. AI collects an enormous amount of data that can be analyzed to provide quick solutions for practices. If all the procedures rely on software and automated procedures as a guideline for a different sphere of the business, this results in an impact on the performance and may result in an optimization of the production in terms of scale, with innovative procedures that are not currently available. Indeed, some of the most significant potential benefits of ML algorithms concern the translation of insights from data into sales opportunities, excluding improved planning and inventory management (Giuggioli, Pellegrini, 2022). As a result, most businesses discovered that these algorithms had a significant impact on their key performance indicator for the sales department (Ramesh et al., 2018). For example, it demonstrated that customer group predictions have direct involvement in the firm's total revenues (Suguna et al., 2019).

Another important impact is related to the argument that individual task substitution on a large scale will almost certainly change the nature of work and jobs, which we already marked previously (Frey & Osborne, 2017). AI freed up time and employees will be able to spend more time on more value-adding tasks or complementary activities, where the human presence is still essential like the activity involving creativity or human interaction, as the machine manages the routine manual and the cognitive routine tasks (Arntz et al., 2016; Autor, 2015). Human performance will be improved by machines for most of these tasks and the strict collaboration between humans and machines is expected to be more and more pervasive (International Federation of Robotics, 2017). One possible example is the work of doctors, where the human ability to make patient's final diagnosis still remain essential and cannot be replaced since it requires skills and a set of knowledge that the machine does not have, but they will be able, thanks to AI, to base a diagnosis on data from other sources, hence, to take more conscious decision and decrease the margin of error van der Zande et al. (2018).

About the effect of AI to re-humanize work by freeing up time and allowing people to work in a less automated manner (Wilson & Daugherty, 2018), we can mention another important argument regarding AI impacts. In fact, this potentiality of AI may lead to increase in inequality and unemployment. As a result, without a process that considers the plurality of voices in a democratic society, AI risks becoming a tool for resolving disparities, where software enable uncontrolled monitoring, facial recognition systems lead to discrimination, and algorithms could lead to behavior manipulation (Chalmers et al., 2020; Whittaker et al., 2018). According to this interpretation, the results of an AI-related entrepreneurship should be assessed in a broader sense, considering even the impact also in terms of equity (Giuggioli & Pellegrini, 2022).

The economic benefits deserve a deeper analysis since a new technology can be considered a solid business case based on the profitability assessment of its adoption: companies will adopt new technologies into their operations only if the benefits outweigh costs. The first and the most intuitive economic benefit of implementing technology automation is the reduction of the labor force cost since there is human substitution (van der Zande et al., 2018). As previously stated, it is unlikely that entire jobs will be replaced, but rather, to achieve the same output less employees will need thanks to productivity enhancements. Still, the economics however are not limited to workforce substitution but can be pointed out also in terms of new value creation. An increase in throughput and productivity, safety, quality or a reduction in waste can increase profit as well, even outweighing the advantages of labor replacement (van der Zande et al., 2018). Some examples in this sense could be the autonomous trucks, which would not decrease only the labor costs but also productivity and safety: is no driver who needs to stop, and these enhancements result in increased profit. Google, with DeepMind ML in its data centres, reduced energy consumption by 40%, resulting in a profit increase (Grosz et al., 2016; Manyika et al., 2017). As robotics has advanced, machines have become a useful solution even for tasks that were previously thought to be too expensive or difficult to be automated, such as surgery assistance. In terms of value creation, AI enables companies also to open new channels with customers and develop new insights, leading to the creation of value for both customers and firms, and allowing employees to devote more time to high-value tasks (Wellers, Elliot and Noga, 2017). This argument can be generalized to many industries that have been heavily digitalized and exhibit higher productivity and wage growth, like the financial sector, compared to less heavily digitalized ones, like education or retail (van der Zande et al., 2018).

## 3.3. Decision-making

This second section aims to summarize evidence gathered from the literature concerning the impact of AI on the decision-making process of firms. Through our query, we found plenty of papers that deeply discuss the topic, adopting different approaches and points of view and focusing on several aspects of this phenomenon. For this reason, to clarify our line of reasoning, we will structure this paragraph as follow: after a brief discussion on why it is relevant for us to analyze decision-making implication, we will present the main features of AI that firms exploit in their decision-making, how they organize their process and the co-existence of humans and machines, and some final consideration about the consequences of the application of AI in the decision-making according to the extant literature.

Decision-making is one of the critical success factors that allow outperforming competitors (Blenko et al., 2010) and thus it is worth for us to investigate whether and how these processes have been impacted by contingent factors. Figure 7 illustrates the so-called big data analytics cycle (Tabesh et al., 2019), which can be considered a reference point for all the following reasonings.

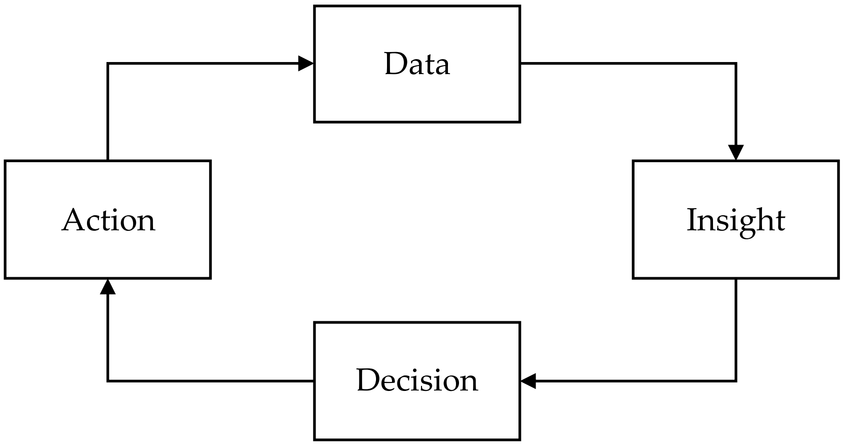


Figure 7 - Big data analytics cycle (Tabesj et al., 2019)

Bearing this framework in mind, it appears clear that digital technologies represent a variable that disrupts the entire process. When it comes to AI, Wilson and Daugherty (2018) list decision-making among the main areas of business process improvement where AI and people can work together, and this is even more true in the age of big data (Duan et al., 2019; Popkova & Sergi, 2020). Being based on statistical models, AI can provide an output which is "unbiased, free of social or affective contingence, able to consistently integrate empirical evidence and weigh them optimally, and not constrained by cognitive re- source limitations" (Blattberg and Hoch 1990).

AI applications generally rely on statistical models, which are applied to historical data. From these models, an AI algorithm learns a decision model for a specific task, which is then applied to new input data. Among the applications and features of AI, the literature emphasizes its impact on the decision-making process by supporting several phases (Brem et al., 2021).

Predictive capability is for sure one of the most frequent applications of AI, and ML algorithms particularly. Examples of applications have been studied by Vincent (2021), which reports how AI has been increasingly prevalent in predictive jobs in recent years, such as predicting the weather based on historical weather trends or predicting companies' financial distress (Agrawal et al., 2019). This development in prediction technology undoubtedly helps humans make better decisions since it makes it easier for them to analyze the pros and cons of the scenarios. Moreover, the literature stresses the strong link between predictive capability and the concept of uncertainty. The latter is a critical barrier to entrepreneurial action (Eriksson et al., 2020), and AI can impact decision-making by reducing uncertainty thus taking better decisions with low costs.

This is because AI does not provide firms with intelligence but instead with a critical component of it – prediction, and "better prediction reduces uncertainty" (Agrawal et al., 2018). This has led to both fresh opportunities for entrepreneurship theory development as well as challenges to existing entrepreneurship (van Burg & Romme, 2014). However, the stream of skepticism derives from the reliance of algorithms on past data and/or past decisions to build their knowledge and protocol to solve problems, which opens several doubts among scholars. Obschonka & Audretsch (2020) describe an uncertain environment as characterized by "no reliable and complete preexisting data available", and then ask whether an AI algorithm, in this context, is able tocan provide effective support or not, but then suggest that intelligent machines are not suitable to re-create the intuitive decision-making which characterizes entrepreneurs. Vincent (2021) agrees with that, questioning the capability to make accurate decisions in circumstances with scarce data and with no past decisions.

Aside from pattern recognition, ML can also be used for trend analysis and analytical decision-making, helping in predicting future states and occurrences based on historical and present-day company data, gathering and elaborating data from various sources to forecast financial decisions, (Yuan et al., 2016), stock return (Creamer et al., 2016), bankruptcy risk (Olson et al., 2012), and more. In this context, it is evident that the recent data abundance, which has characterized the last years, makes AI a tool more and more useful, even becoming "crucial in improving innovation, trend prediction, and decision support for entrepreneurs (Giuggioli & Pellegrini, 2022).

That said, AI is also able to make a step further concerning a data-driven approach. While the current approach incorporates applications that summarize complex data to generate inputs for some type of human judgment, AI may make automatic decisions and proposed actions based on all available data, removing judgment biases and the requirement to aggregate data to make it understandable to humans (Colson, 2019). Accordingly, although the cost of this prediction will decrease, the value of human judgment will increase as the other fundamental input to decision-making (Agrawal et al., 2018). A point of attention to be carefully checked is the possibility that the algorithm presents indirect biases which are embedded into the training dataset and the previous decisions from which the algorithm learns. The most famous and emblematic example is the case of Amazon, which abandoned an AI-based recruiting algorithm that was created to find promising candidates. Due to the male predominance in the IT field at the time the computer model was trained on resumes received by the company in the prior 10 years, the model inherently favoured male applicants (Dastin, 2018). As a result, female candidates faced discrimination under the system.

Another feature widely present in the literature is the classification and clustering capabilities of AI. This is strongly linked, and somehow enabled by pattern identification, thanks to the ability to employ AI for data gathering and analysis, as well as to successfully detect patterns and underlying signals that humans often overlook (Eriksson et al., 2020). Customer group prediction while examining sales data continues to be a difficult issue for all businesses (Giuggioli & Pellegrini, 2022). In this regard, ML algorithms are used to group consumer segments and forecast client needs, assisting decision-making processes in product manufacture and marketing. As a result, there is an increase in manufacturing design decision-making processes based on the prediction and clustering of client behavior (Saguna et al., 2019).

As a last application field, we present findings from the SLR that specifically address how AI can help entrepreneurs concerning the first stages of the life of startups. These are challenging very phases, mainly due to the need to gather data and constantly analyze, assess and adjust business models to be successful (Ojala, 2016). Collecting data to support decisions is therefore crucial: market data, financial data, feedback from every stakeholder, advisory from incubators and business angels, and everything which can help them in validating their business model and all their key assumptions. When facing these tasks, entrepreneurs deal with high degrees of uncertainty regarding market and technology advancements. Additionally, business owners are unsure about whether their skills and internal resources will be sufficient to successfully handle the new enterprise (Andries & Debackere, 2007; Timmers, 1998).

AI proved to be a valuable partner supporting business model validation thanks to the exploitation of data. To this extent, a hybrid intelligence decision support system (i.e. merging humans and machines in decision-making) can help with the iterative validation of a business model by combining insights from stakeholders (such as partners, investors, mentors, and customers) and analysis of the unclear degrees of business model development in early-stage businesses (Giuggioli & Pellegrini, 2022). These processes go beyond tools like business model simulations and financial scenarios by identifying intricate patterns and the relationships between individual components. Hence, this new class of decision support systems may help assist entrepreneurs in uncertain contexts (Derrlermann et al., 2019).

Concerning entrepreneurship, another notable impact is on fundraising, with a particular focus on crowdfunding, which has grown in importance as a means for business owners to raise money for their ventures (Giuggioli & Pellegrini, 2022). AI, ML particularly, can forecast the financial success of a crowdfunding project in advance, with significant ramifications for creators, investors, and crowdfunding platforms. Founders can concentrate on these elements to improve their financial performance and lower opportunity costs if they are aware of the factors that may increase their funding success rate in advance. Through projections, investors can steer clear of high-risk or failure-prone initiatives and allocate their limited resources to projects with better chances of success, boosting their chance of profiting from their investment (Wang et al., 2020).

Even in this cluster of the SLR, as for what concerned performance improvements, a critical barrier that prevents the reach of optimal solutions is the limited explainability and difficulty in codifying a key asset of companies – their knowledge. In this regard, Tabesh (2021) introduces the impact of AI on intuitive decision-making by human experts. In particular, it argues how even intuitive human experts' decision-making can be enhanced thanks to the new relationships and insights that AI discovers, new knowledge which becomes part of the tacit knowledge (if not explicit one) of decision-makers in their future intuitive decision processes. Moreover, AI tools can provide a visual representation of complex systems, showing every interdependence among each element clearly and powerfully (e.g. visualization map) which can have an indirect contribution to intuitive decision-making fostering knowledge sharing and visualization: "decision-makers gain a more holistic understanding of the realities surrounding the decision that could contribute to a generation of implicit inferences used in intuitive decision-making" (Tabesh, 2021).

Having understood which AI functionalities can provide their valuable contribution to decision-makers, the extant literature offers a branch of studies about how to integrate AI-enabled decision-making into the current process. The results comprehend a vast range of solutions which describe the interaction between humans and machines, from a full human-AI delegation to a much less invasive intervention of AI. In the middle, there is plenty of hybrid AI-human or human-AI sequential decision-making. The letters particularly interest entrepreneurs thanks to the possibility to "optimize open innovation strategies that are being used to source and select innovation ideas" (Obschonka & Audretsch, 2020), thus moving the focus from the generation of alternatives to their assessment and selection (Shrestha et al., 2019).

The starting point of every framework is that machines and humans are different and, to maximize their contribution, *collaboration* is the watchword. The very first reasonings about that go back to 1957, when Herbert Simon, talking about analytic and intuitive decision-making, wrote "it is a fallacy to contrast analytic and intuitive styles of management" (Simon, 1987). Broadly speaking, intuitive decision-making is more suitable in uncertain and ill-defined situations. On the other hand, analytical decision-making should be preferred when dealing with a structured and analytical environment, in which the main problem can be decomposed into several sub-tasks(Denhardt & Dugan, 1978; Friedman et al., 1985; Hammond et al., 1987). The latter is the field in which the literature undoubtedly agrees that AI can provide great support. Indeed, Tabesh (2021) when describing analytical decision-making talks about the need for "a systematic and intentional process for data collection and analysis before making a choice […] devising alternative courses of action and comparing the alternatives based on specific criteria" (Fredrickson, 1984). That said, when dealing with big data, human decision-making struggles in completing this task due to limitations in cognitive and elaborative capacity and attention limits (Provost & Fawcett, 2013).

Besides this task-related criterion (i.e. degree of objectivity and structure of the problem) another parameter to be considered in the choice for the most appropriate decision-making approach is the expertise of the human decision-maker, which should come even before the characteristics of the problem (Vincent, 2021). According to this criterion, indeed, if the decision maker has little experience, he/she is not able to provide a valuable contribution or correction to the output of the machine, therefore decisions should be delegated to AI both in case of structured and non-structured problems. In the case of structured tasks and expert decision-makers, two different decisional approaches rise from the literature, both of them considering a synergic contribution of AI and humans: the confirmatory method and the explanatory method. Whether to choose the former or the latter depends on the number of available solutions to be undertaken.

- Confirmatory method (human-to-AI sequence): when there are few alternatives, the authors suggest first using the intuition of the expert decision-maker about how to solve the problem. After having identified the possible answers to a given problem, he/she selects one of them based on his/her intuition and experience. Without giving the machine this latter information to guarantee unbiasedness, the AI tool is then asked to evaluate the alternatives according to a given utility function. In this approach, AI acts as a counterbalance to expert intuition and lessens the impact of decision-maker bias, a serious drawback of intuitive decision-making.

- Exploratory method (AI-to-human sequence): when there are many alternatives, the authors suggest first exploiting the capability of AI to reduce them, then going for the expert valuation. In this way, the computational capability of AI can optimize the process by quickly analyzing the possible solutions and performing a screening task, to provide a shortlist to the decision-maker and a first optimal solution. Intelligent machines with fast processing speeds and deep learning algorithms may be able to reduce information costs that are prohibitively expensive for individual actors to a negligible level (Bughin et al., 2017). Then, the expert can employ his/her time focusing just on a few possibilities and selecting the best one. With this approach, AI lessens information overload-related errors in human judgment.

So far, both approaches end up with a comparison between the AI solution and the expert one. The output of this analysis can be:

- Confirm the choice (of human decision-maker in the confirmatory method and ofAI in the exploratory method): in this case, the following step is simply to undertake that path.
- Differ from the choice (of human decision-maker in the confirmatory method and AI in the exploratory method): in this case, the author suggests considering another crucial variable – time. If there is no strict time constraint, the decision-maker should go back to the previous stage, re-consider the possible alternatives and iteratively fine-tune the decision process until he/she arrives at a solution which is accepted by AI (in doing so, the authors also emphasize that as the humans are involved more and more in the process, the process itself becomes slower and less replicable). Otherwise, when there’s not enough time to correct the process, the intuitive decision has been proven to outperform the machine-based one, always under the assumption to deal with an unstructured problem faced by an expert decision maker (Dane et al., 2012).

Figure 8 summarized the two methods and provides a clear visualization of the main “gates” which determine the correct approach that should be implemented.

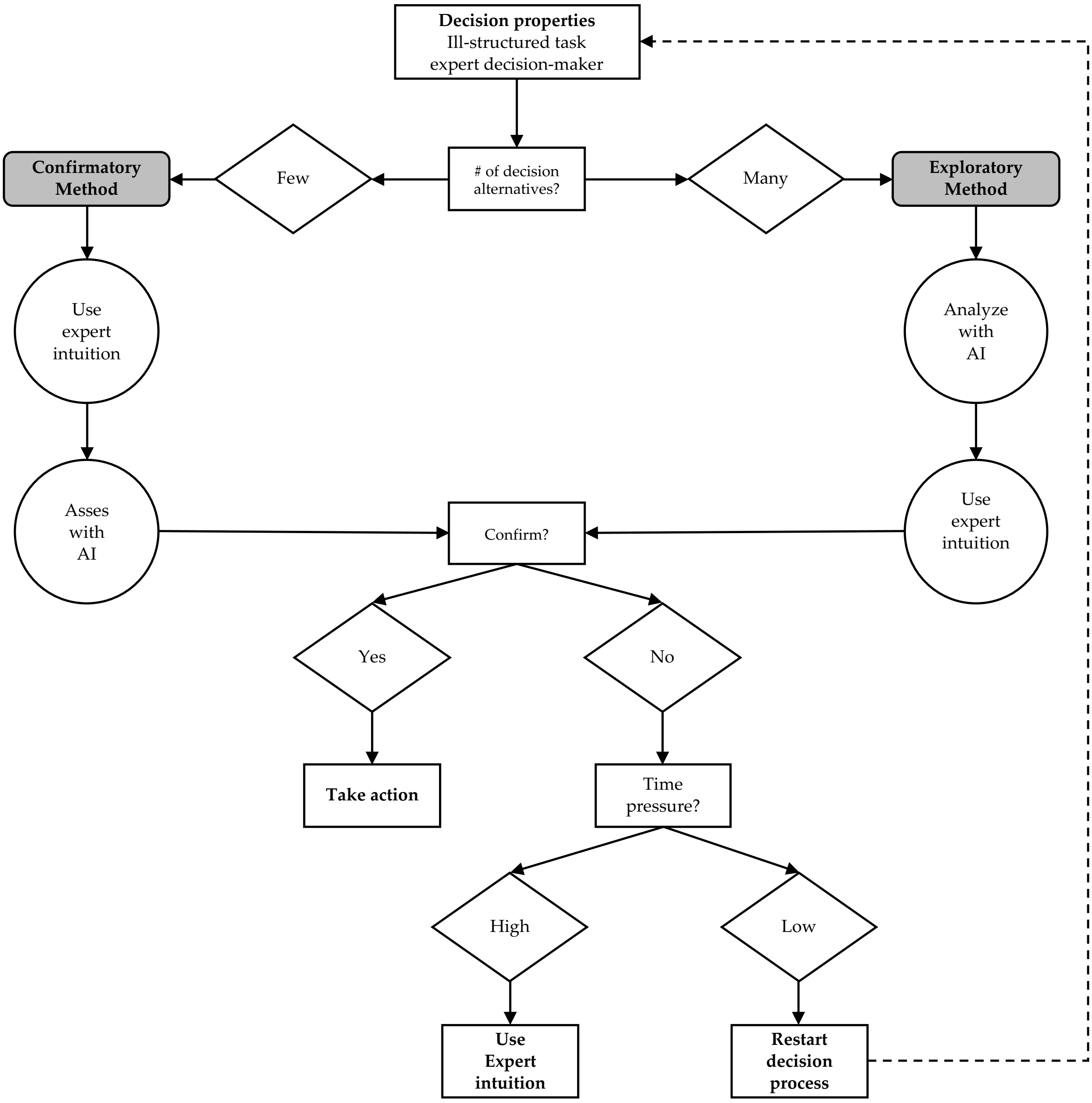


Figure 8 - Confirmatory and explanatory methods (Vincent, 2021)

In some circumstances, it could be beneficial to take a different course of action than what was initially chosen. For instance, a business challenge that was initially believed to have a few decision alternatives may have numerous decision options that the decision-maker had not considered due to the uncertain and dynamic character of many poorly organized situations. Therefore, utilizing the exploratory method may reveal some previously unconsidered choices if the confirmatory method did not yield a suitable outcome (i.e., a human decision that was confirmed by AI).

Two factors are identified as key conditions under which the model can be actually useful for firms and decision makers, namely the expertise of humans and the characteristics of the problem. Starting from the former, a stream of the literature agrees that a person reaches a sufficient level of expertise after 10 years in a particular domain (Dane & Pratt, 2007), while other scholars consider, besides time, the breadth and depth of knowledge as a key metrics for this kind of evaluation. Moving to the characteristics of the problem, the model is particularly useful when "decision cues are vague and there is ambiguity surrounding the best course of action" (Vincent, 2021), and not when dealing with recurring and programmed decisions with well-established practices. As a concluding remark about these models, we can make a direct association between the frequency of use of the model and the level of decision-making: from the operational level, where most of the decisions to be made are programmed, to the strategic one, with uncertain, unstructured and non-programmed decisions.

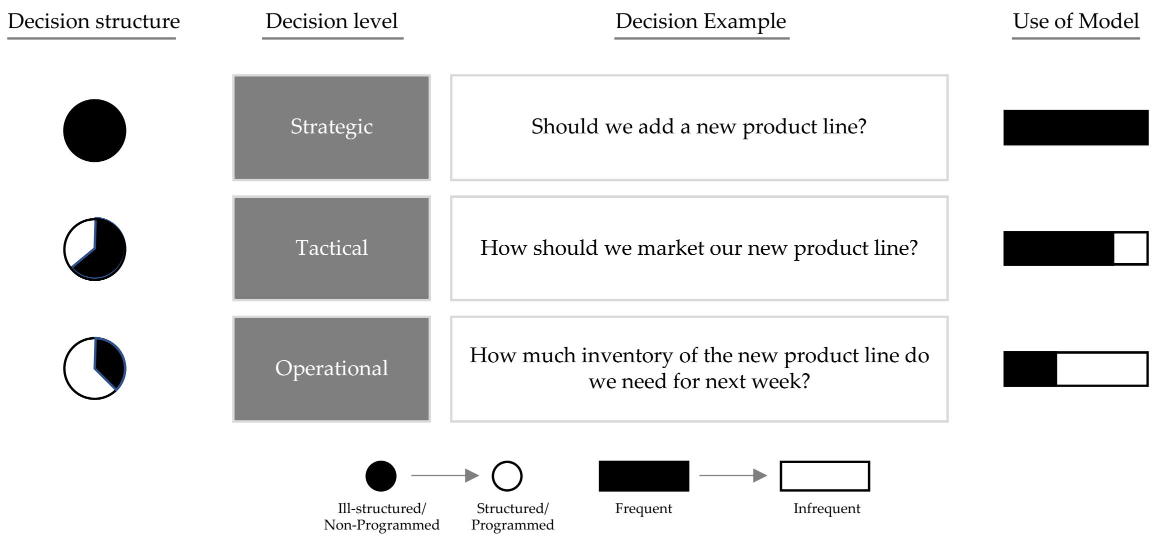


Figure 9 - Use of intuition and AI integrated model (Vincent, 2021)

Therefore, the strategic level, with its complex and uncertain environment, seems to be the most suitable for the application of a mixed approach – i.e., AI and the intuition of experts. The role of experts in the decision-making process continues to play a crucial role even for an important barrier that needs to be addressed, concerning the communication between humans and machines. Particularly, we can refer to the lack of explainability as the difficulty in translating formally some data, tacit knowledge, the objective to maximize and some human reasonings and ideas. When dealing with unconscious and instinctive processes, it is hard to articulate how the intuitive conclusion has come out, the elements they took into consideration and the decision process. Considering a well-known example, the one about the AI-based chess player, the machine is said to act in a well-determined environment in which both the rules and the were clearly defined (Townsend and Hunt, 2019). Hence, thanks to the computational capabilities, it is easy to identify which moves are more valuable and undertake the optimal decision. However, it is important to stress that entrepreneurs must deal with a more intricate collection of knowledge issues than only modal uncertainty issues (Townsend et al., 2018). These issues include determining customers' likes and value preferences in the face of uncertainty, which is still a decision problem that needs to be solved by human actors (Cyert & March, 1963). Identifying what is "valuable" involves human judgment and cannot be formalized into decision rules, therefore the necessity of agentic choice and human judgment is significant. In these circumstances, AI technologies support entrepreneurial actors' search capacities to handle modal uncertainty issues, but human judgment is still needed to address issues with taste, motivation, and preference.

Bounded explainability raises concerns over the justice and fairness of AI-based decision-making (Tambe et al., 2019). Vincent (2021) makes this argument by using the example of human resources (HR), where hiring and firing choices can have a big influence on people and communities. If the decision-making procedure cannot be precisely stated, these worries will grow. Additionally, the inability to explain something seriously impedes organizational growth and development. A decision-making process cannot be established as a prototype or a decision aid for further decision-making if it cannot be described explicitly. It is possible that improvements in explainable AI intelligence (Guidotti et al., 2018) will assist to resolve this problem, but organizational decision-makers must be informed of the negative effects of this restriction. It is important to notice that the lack of explainability can represent a problem even switching roles, becoming a problem of interpretability: a decision made by a multilayered ML algorithm is based on weighted combinations of a wide range of factors (Tambe et al., 2019). This kind of mystery surrounding the decision-making processes breeds skepticism and fairness concerns and also impedes organizational learning and development.

The role of humans is still required because of the ethical and legal implications that a purely AI-based system would lead to (Vincent, 2021). In the future, it will be crucial to not only address ethical issues but also to permit and control access to data and technology infrastructure. Researchers point out, for instance, that AI may not always produce the most trustworthy and practical answers (such as the “Clever Hans effect”, (Lapuschkin et al., 2019), and it is crucial to ensure openness and rigorous evaluation of AI performance. The example of the healthcare sector is of particular interest, in which researchers caution that the disadvantages of easy access to data and computer tools for data analysis include the potential for clinical interpretation, understanding the source of the data, and external validation to be separated from the scientific process of data mining (Belgrave et al., 2017). There appears to be a general risk associated with blind faith in algorithms (Logg et al., 2019). Entrepreneurs may therefore make biased decisions and suffer bad effects, or at the very least, the waste potential for their particular business, if they rely on AI outcomes without challenging and critically evaluating them. Similar reasonings are made by Vincent (2021) when talking about possible downsides of overreliance on machines by decision-makers: reduced physician-patient engagement, reduced physician compensation due to a decline in relative value, and the possibility of clinical judgment and diagnostic skill erosion are some of the issues with the integration of AI in the area (Miller & Brown, 2018). Many other businesses also have similar worries about AI. Finding the ideal balance between the application of AI and human talents in organizational operations is therefore crucial.

What we can conclude about AI's impact on the decision-making process is that from the literature a collaboratory approach emerged as the best solution, enhancing decision accuracy while reducing the limitations of each strategy used alone. According to robot expert Ken Goldberg of Berkeley, intelligent machines will be most valuable when working alongside people rather than in direct conflict with them (Markoff, 2016). In addition to Licklider (1960), Isaacson (2014), and Peter Thiel, many other experts on computers, software, computability, and neurology concur with Goldberg (Thiel & Masters, 2014). Wilson and Daugherty (2018) discovered that organizations obtain the greatest notable performance increases when humans and AI combine, with a sample size of 1,500 companies. Bringing together AI with human decision-making, firms address AI's vulnerabilities, such as those related to ethical issues, unfavorable employee reactions to decisions made by machines, and special events for which there is insufficient historical data to allow algorithms to be effectively trained to predict the future. Combining AI and human decision-making on a bigger scale will also help allay society's growing anxiety that machines will replace people in the workforce (Vincent, 2021). When describing this kind of synergic interaction between decision-makers and AI, Derrermann et al. (2019) define Hybrid Intelligence Decision Support Systems (HI-DSS) as "a computerized decisional guidance to enhance the outcomes of an individual's decision-making activities by combining the complementary capabilities of human and machines to collectively achieve superior results and continuously improve by learning from each other". The authors identify three main reasons behind the effectiveness of HI-DSS.

*(i)* In analytical processes, AI can manage even unstructured data and still deliver accurate decisions and insights (Einhorn 1972). Particularly, entrepreneurs can take advantage of this, exploiting AI capabilities in their business model

validation, which concerns the analysis of many ill-structured data regarding markets and customers.

*(ii)* In providing a critical assessment of ideas, interpretations and judgements related to soft information, humans can still provide a valuable contribution thanks to their intuition and their ability to see the big picture (Colton and Wiggins 2012).

*(iii)* In challenging and non-deterministic tasks, the combination of human intuitions and statistical models leads to the best and most consistent results. In this sense, collective intelligence is used to maximize human advantages while concurrently minimizing human disadvantages, such as prejudice or random errors, in individual decision-makers (Larrick et al., 2012).

Moreover, by exploiting this collaboration with machines, we can "augment our skills and always stay a step ahead of AI, or at least not be at a disadvantage" (Makridakis, 2017). Considering probably the most famous case of AI versus humans, the defeat of the chess master Garry Kasparov at the hands of the IBM Deep Blue algorithm, this means that a chess champion would be a human utilizing a machine tool rather than a human or a machine (Baraniuk, 2015). And actually, it is: even when using humans who weren't grandmasters and computers that weren't supercomputers, human-computer collaborators consistently came out on top in a tournament that allowed human-only, computer-only, and human-computer collaboration participants (Brynjolfsson & McAfee, 2014). Transposing this to the business field, the result is that given the capabilities of such new AI and ML tools, what will happen is that AI will not overtake managers, but that managers who use AI will overtake managers who don't (Brynjolfsson & Mcafee, 2017).

## 3.4. Innovation and Creativity

This third section presents results found in the literature about the contribution that AI provides to entrepreneurs regarding innovation and creativity through the identification of business opportunities. By business opportunities, we considered both ideas for new venture creation (i.e. startup foundation) and insights for driving innovation of already existing businesses. The link between AI and creativity is a widely discussed theme in the literature, but still divisive and characterized by conflicting opinions.

Nowadays, with the dynamic and unpredictable context in which firms operate, creative capabilities represent one of the very first drivers of their growth, survival and success (Anderson et al., 2014). Recent advancements in AI allow robots to handle vast unstructured data sets using intricate, adaptable algorithms to carry out activities that would typically require human intelligence (Choudhury et al., 2020; Peter Stone et al., 2016). This has caused some to consider AI as a tool which not only increases efficiency and productivity but also as a fundamental innovation to the methods through which humans innovate (Amabile, 2019, Cockburn et al., 2018). Hence, the concept of generative AI raises as a "revolutionary technology, capable of generating artefacts that were previously based on human creativity, guaranteeing innovative results without those prejudices typical of human experience and its thought processes" (Gartner, 2022). Generativity refers to the "overall ability of a technology to produce unanticipated change driven by a large, diverse, and uncoordinated audience" (Zittrain, 2006). Schiavone et al., (2022) define generativity as one of the two possibilities concerning computational creativity, namely the generativity mechanism – i.e. creating new artefacts by modifying existing ones – and the combination mechanisms – i.e. creating new artifacts by grouping resources. Additionally, according to Gartner, "by 2025, generative AI will account for 10% of all data produced, up from less than 1% today, and by 2027, 30% of manufacturers will employ generative AI to increase the efficiency of the development process." It should come as no surprise that according to Gartner, "IT leaders worldwide must apply effective governance to maximize its remarkable creative potential."

Generative AI is one of the latest topics in the field of computational creativity, defined by Boden and Wiggins as "The study and support, through computational means and methods, of behavior exhibited by natural and artificial systems, which would be deemed creative if exhibited by humans" (Wiggins, 2006). The concept of valuable assumes several connotations, such as intriguing, useful, beautiful, straightforward, richly complex, and many others. AI has been developed to produce concepts in the field of sculptures, houses, arts, and many more (Boden, 2004). When people alter their conceptual framework, they become capable of coming up with new concepts that were not previously possible for them to consider. The act of modifying one's conceptual framework to generate ideas that the previous framework was unable to generate is what is known as creativity (Turner, 1995).

In an early review of the state of AI creativity research, (Boden, 1998) identified three main categories of creativity in the generation of novel ideas: combinations of familiar ideas to generate novelty, analysis of structured conceptual spaces to generate new solutions, and transformational creativity to create novelty by changing the structures or constraints of the decision environment.

Considering the GAAM framework (Eriksson et al., 2020), which describes the questions which drive the different areas of impact of AI, the "creative-possibility" perspective has been recently added by scholars. After some interviews, Erikkson positions all the responses about the capability of AI to enhance human creativity in the strategy formulation process, providing its contribution to answering the question "what innovation can we imagine?" in the stage of the strategy creation process.

There is a lot of potential in studying how AI may help with the development of marketing strategies. (Martínez-López & Casillas, 2013) presented major study areas from a business marketing perspective, compounding also innovation and creativity, to advance the whole agenda. The idea that B2B organizations use AI to turn huge data into useful input for developing efficient marketing and sales strategies was recently emphasized by (Paschen et al., 2019).

The results showed that managers believed the hybrid system's guidance to be accurate and reflect managerial judgment. When examined by a small number of managers in field research, another hybrid technique that combines AI with human decision-making for marketing strategy generation demonstrated efficiency and efficacy in improving the strategy-building process (S. Li & Li, 2009).

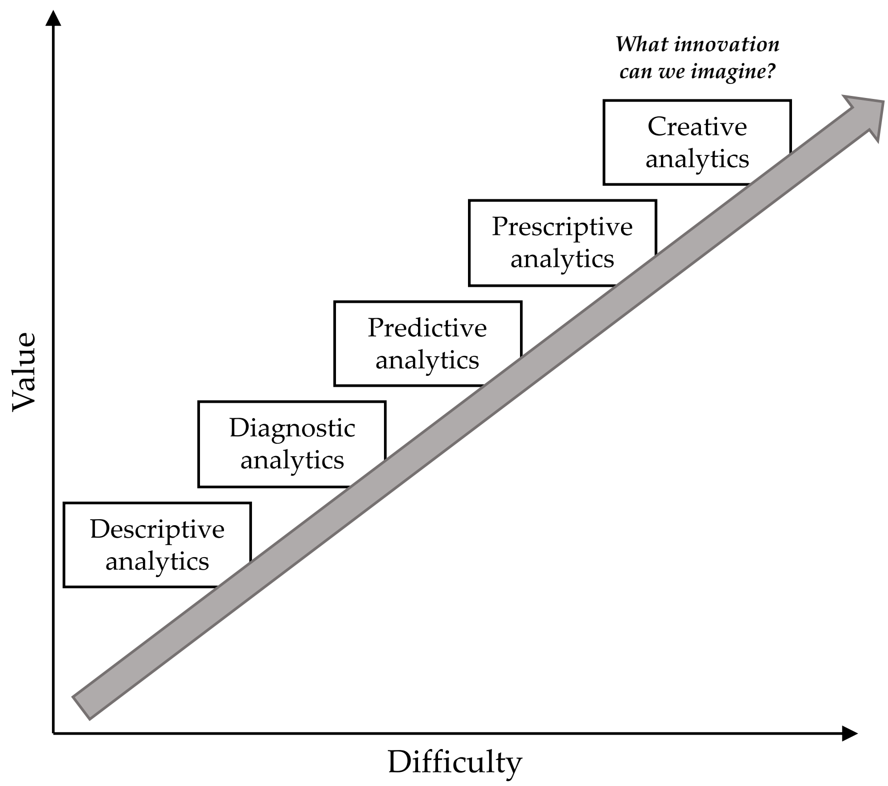


Figure 10 - Gartner Analytics Ascendancy Model (GAAM, Maoz, 2013)

The role of AI in the search and recombination function is deemed to be a game-changer in innovation management. AI enables businesses to expand their search space because of its capacity to gather and process enormous amounts of data from multiple sources (Mühlroth & Grottke, 2020). Companies can now develop more exploratory concepts because of this additional information (Haefner et al., 2021). Additionally, comparable to earlier general-purpose technologies like microchips and the internet, such as robotics, AI and related domains like these allow for the development of completely original solutions. Specifically, Brem et al. (2021) see AI as the originator and facilitator of business opportunities. The former leverage the generation and exploration of plenty of possibilities and the reduction of perceived uncertainty. The latter, instead, exploits the processing capability of AI, which helps in re-designing processes based on data. Concerning the innovation process and archetypes (source), we can detail the specific contribution that AI can provide in:

- Technology push approach: AI can help in identifying the hottest topic on the market, by screening and analyzing data about recent patents and publications available. Applications in the literature such as Kölbl et al. (2019) present case studies in robot surgery in which AI helped in finding empty areas of investigation which were not considered initially.
- Market pull approach: through the analysis of trends on social media, blogs, etc. AI can spot opportunities related to customers' needs, providing companies with lists of possibilities, which for a human would require massive work (Kakatkar, 2020; Paschen et al., 2019). As an illustration, Kakatkar, Bilgram, and Füller (Kakatkar, 2020) employed this strategy to find creative users in the semiconductor sector. Townsend and Hunt (2019) agree with this and describe AI as a useful tool to solve the problem of lack of awareness of a business opportunity in a certain market environment.
- Advancement in the innovation funnel (stage-gate process): AI helps in spotting the best features to match customers' needs. This allows companies to select among several options and filter them, thus enabling continuous improvements in customer satisfaction thanks to empathic products and services (Hyve, 2019; Tao & Tan, 2005). Considering the very first stages of the innovation process, case studies reported and discussed by Townsend and Hunt (2019) focus their attention on the contribution of AI in the exploration of business opportunities, reducing modal uncertainty. Examples such as Autodesk's AI-powered design tool (Autodesk, 2019), and Insilico Medicine AI-powered tool to discover new therapeutics (Insilico, 2019) demonstrate how AI can enable the pursuit of new

opportunities. These cases, according to Townsend and Hunt (2019), prove that entrepreneurs which exploit AI will improve their ability to manage modal uncertainty exponentially.

- Development of new product: generative AI can use several data sources as inputs for developing new products. Goodfellow et al. (2014) illustrate how AI can act with a double role simultaneously: generator of contents and discriminator between real and fake information, thus offering an output with a great number of possibilities. The limits and qualities of designs might then be changed when designers have identified unique and inventive designs. Alternative business prospects can be found fast and easily using this technique.
- Development of new business model: Giuggioli and Pellegrini (2022) argue that AI also enables new business models for firms, which can rely on tools such as data mining and predictive analytics to deliver value to their customers

Over the last years, the literature has made a step even further, arguing that AI is not only able to support humans in creative tasks through making recommendations but even – partially - replace them. An opportunity, rather than a threat takes place in three ways, namely recombination, exploration and transformation (Paesano, 2021).

AI-derived concepts can be used to describe conceptual environments as well as methods for exploring and modifying them. Computer models can be creative, which can be useful for understanding creativity. They can at least look to be creative, or something close to creativity. Computers and creativity are closely related in many ways AI. Computers can help individuals think of new ideas and also generate them for them (Boden, 2009). Some of the very first examples of applications of creative AI can be found in the fields of publishing or art, with the book "Lithium-Ion Batteries" written by the algorithm Beta Writer through the recombination of scientific materials (Beta Writer, 2019), and in the art sector, in which AI helps artists to think out of the box and to generate visual contents (Chamberlain et al., 2021).

One of the latest contributions to the literature on AI and innovation is the work of Hutchinson on the concept of self-innovating AI (SAI), an approach which aims at the continuous improvement of products and/or the launch of new ones based on several data sources (Hutchinson, 2021). Hence, the distinctive element of SAI is that innovation happens almost autonomously, with the intensity of human interventions based on the complexity of the products. Here, AI is presented as a method of inventing - i.e. an innovation which is not stand-alone but can enable a broad range of innovations (Griliches, 1957). Indeed, the authors stress that SAI does not refer to a specific tool or a product with embedded AI, but rather an AI-based approach to the development or improvements of products, enabling innovation in different fields by acting dynamically "as an active ingredient in fueling innovative initiatives" (Nambisan, 2013). Once again, the basis of SAI consists of data gathered from multiple actors and processes, but differently from generic *innovating from data*, "a centralized, firm-led process in which firms use digital tools to acquire, analyze, and act on consumer data to enhance their innovative offerings" (Rindfleisch et al., 2017), SAI specifically refers to AI as a digital tool, and extend the data sources not only to customers but also other external and internal data, such as innovation capabilities. According to Feigenbaum (1977), the performance of an intelligent agent is directly related to his specialist knowledge. Therefore, since SAI relies upon specialists' knowledge and on many other data sources such as lead users, patents, market trends and many others, it dramatically outperforms any other intelligent agent. Since lead users are at the cutting edge of the market and describe th(Mahr & Lievens, 2012)ishes, Mahr and Lievens (Mahr & Lievens, 2012) demonstrate how data acquired through virtual lead user communities can improve a firm's innovativeness. Consumers, on the other hand, could support SAI without being conscious that they are doing so. Numerous publications have demonstrated how consumer-generated data, such as online product reviews and social media posts that often attempt to grade existing items rather than build new ones, maybe methodically studied to learn more about how satisfied consumers are with their purchases (Humphreys & Wang, 2018). For instance, concerning incremental innovation, the author presents the case of Titan Company, a manufacturer of luxury goods which through SAI obtained a competitive advantage due to its responsiveness to the change in consumer preferences regarding colours. An important distinction is made between simple and complex products, concerning the required knowledge about each interdependent component, design and customization of products. The paper argues that currently, SAI can provide its support most in simple products, in which it works synergically with humans. However, given its recognized potential, SAI is expected to assume a primary role in the process even regarding complex products, at least in the design and development of the isolated components. All in all, the paper identifies three key success factors which enable a source of competitive advantage for firms adopting SAI:

- More effective resource allocation in R&D, with the algorithm developing the simple products and humans, focused on complex ones
- First-mover advantage enabled by responsive trend analysis

- Better knowledge management and data processing, addressing the limitations of the cognitive biases which affect the analysis of data gathered

At the same time, a stream of literature argues that, at the current stage, AI's contribution to creativity is still very limited, if not a utopia. AI applications can be distinguished between weak AI and strong AI: the former is referred to those algorithms which replicate human logic by processing big data, while the latter refers to the capability to think consciously. However, if weak AI is very widespread with many applications such as NLP (Jarrahi, 2018) and ML (Brynjolfsson and McAfee, 2014), strong AI does not exist yet, hence Erikkson et al. argue we are still far from a possible substitution of humans concerning creativity, conscience and critical thinking (Eriksson et al., 2020).

Jarrahi, Brynjolfsson and McAfee agree that despite the rapid technological advancements, humans still have a clear comparative advantage toover machines with respect to imagination, intuition and creativity (Jarrahi, 2018; Brynjolfsson and McAfee, 2014). David Autor (reported in Diamond, 2020), is skeptical about AI's creative capability when he says that computers are very unlikely to reach humans' common sense, adaptability and creativity. In the same article, even other MIT scholars and entrepreneurs, Rodney Brooks and Gary Marcus agree with this, considering AI programs as excellent tools to perform simple tasks but not appropriate to replicate human intuition, experience and flexible thinking (Marcus, 2014). Creativity and innovation are considered processes that require intuition and judgment, which at the current stage AI is not able to provide with the same efficacy as humans. That is mainly because "computers and robotics are only capable of solving tasks within established matrices or existing practices in which rules can be specified or patterns found in datasets" while creativity and innovation would require thinking out-of-the-box, out of those established matrices (Hammershøj, 2019). Moreover, as the environment is evolving more and more dynamically, intelligence, judgment, and will, all of which are founded on emotions and mood, will guide and drive creative and innovative processes, thus increasing the dependence on humans

Another element that limits the creative capabilities of AI is that machines, differently from humans, are not able to fully identify what is valuable and significant (Holford, 2019). This is due to the lack of explainability of many social beliefs, values and practices that constitute a form of tacit knowledge that AI cannot detect (Collins, 2010). What AI is actually able to do is defined by Holford as "pseudo-creativity", and it involves just a combination of given structures that have strong and clear links. Paesano (2021) groups several criticisms about AI and creativity, arguing that this one is only a human competence since humans will always have the big picture and the strategic view that confers meaning to what humans learn, w(Bauer & Vocke, 2020)lligence is meaningless" (Bauer & Vocke, 2020). Other reported results talk about collaboration at best, in which however humans continue focusing on creativity, while machines will do the rest, thus having just an indirect contribution by freeing up managers and entrepreneurs which, on their side, will continue to be the first responsible for intuitive activities like creativity.

All in all, going back to our initial concept of business opportunities we can argue that the literature assessment about the impact of AI is definitely positive. However, we also see a clear distinction between the impact concerning the exploitation of big data in exploring business opportunities and the impact on creativity. The literature on the former is well-established and aligned with a common result which sees AI as one of the most powerful tools in the hand of entrepreneurs to find opportunities to improve and/or launch products, services and ventures. On the latter, instead, we find more opaqueness and some criticism. However, the main reason behind that consists in the initial definition and boundaries that different authors set to concepts such as creativity, and once again we can identify two sub-categories:

*(i)* The first considers a broader definition of creativity and creative system which embraces the impact concerning the new recombination of data and knowledge provided by the machine.

*(ii)* The second considers a concept of creativity which is more strictly aligned with the intuitive process, typical of human nature, of creating something new, and it refers to the new concept of generative AI.

If for the first category we find consolidated results and a common view, the second is for sure the most debated also among scholars since it is the novelty which refers to the very last advancement in the field of computational creativity and therefore, despite its potential, still find few applications to allow the assessment of its actual capabilities and impacts.

## 3.5. Conclusions

The SLR highlighted how AI is impacting entrepreneurial activity at different levels, with a contribution which is more and more valuable thanks to the recent advancements of this technology. We can wrap up the main findings that arise from the literature as follow:

*(i)* **Process improvements:** this cluster of papers presents the benefits of AI from an operative point of view, highlighting how machines can replace humans, especially when dealing with routine tasks, freeing them up to focus on value-added activities. The main advantage is related to efficiency, both from an operating and an economical point of view. AI act as a performance-enhancing role, where the technology operates in a deterministic context with well-defined algorithms and data.

*(ii)* **Decision-making:** these papers highlight that AI can provide a significant contribution to the decision-making process of a company, thanks to its unique ability to analyze, combine and elaborate a large amount of data. By doing so, AI helps to overcome humans' bounded rationality and reduce uncertainty, one of the main barriers to entrepreneurship. Given these characteristics, many authors stress that AI-enabled decision-making is more effective when dealing with analytical and data-rich environments, in which AI has a remarkable comparative advantage concerning human decision capability. In particular, among the most useful skills of AI, the authors point out most frequently predictive analysis, clustering and pattern recognition. However, authors agree on the importance of humans in the decision-making process, leveraging their experience, critical judgements and intuitions, areas in which they still have a comparative advantage concerning machines, which, on the other side, strictly depend on past data and decisions.

*(iii)* **Innovation and creativity:** AI is not only about operating performance improvements and more accurate decision-making. The very last applications of AI in business want to move forward, but there is still an ongoing debate on whether AI is capable to perform creative tasks supporting the innovation process. The data processing capability is a powerful tool for fueling incremental innovation, and improving products and services based on market feedback and other external inputs. Concerning radical innovation and creativity, some authors argue that AI will never be capable to replicate human intuition and creativity in finding new solutions to market needs. Generative AI has the ambition to overcome these limitations, but its applications are still very limited, as well as the extant literature about it. However, on the other side, streams of literature bring attention to the supporting capability of AI in scouting and validating new products, services, and business ventures. This, in the last years, has led to a proliferation of AI-based startups, in which the

innovation process is completely integrated between AI and humans, interdependent and critical success factors.

All in all, the complementarity between humans and AI is the common factor that we can find at every stage of impact: from carrying out daily operations, passing to the tactical and strategic decisions, and even when dealing with innovation and creativity. The new paradigm of human-machine collaboration overcomes the traditional tradeoff between efficiency and effectiveness since as data volumes increase, the self-learning process of ML is triggered, and a quicker and more accurate outcome is obtained. At the same time, human actors are freed-up to dedicate themselves to value-added activities, thus maximizing their contribution. Humans and machines have different founding characteristics, and to allow entrepreneurs to obtain the best results a best-of-both paradigm is necessary. Therefore, understanding how to design such a collaborative paradigm is crucial, as well as properly describing how human-machine interactions take place.

# 4 Multiple case study results

The gap identified in the literature is about how the latest developments in AI impact the innovation and creativity of a company, and how the human-machine paradigm changes accordingly. To fill this gap, we conducted semi-structured interviews with AI-based startups, aiming at gaining a deep understanding of the topic and answering our research questions. Through data coding, from the specific empirical insights gathered we were able to obtain generalizable theoretical results, providing our contribution to this new research field.

## 4.1. Companies description

Before discussing in detail, the result of the cross-analysis of the interviews, we present an overview of each of them, briefly describing their business with a short focus on how they employ AI.

### Company $\alpha$

**Industry**: Healthcare

**Business description**: the company, founded in 2018, aims at improving the level of secondary prevention of several non-communicable diseases. It supports the early diagnosis of disorders to help early and effective treatments and reduce associated complications. Data collection consists of a saliva sample, analyzed by measuring values of specific biomarkers on a daily or weekly basis to gain statistically significant data. Such data becomes the core asset of the company, which carefully analyzes trends and patterns in the biomarkers to detect diseases such as Parkinson's and diabetes. The outcome of the analysis is aimed at drafting a report for the patient to be provided to actors in charge of the treatment.

**Use of artificial intelligence**: the biomarkers are analyzed through a POP (Point of Prevention) analyzer featuring a disposable cartridge and a set of tests. The results are processed through a ML algorithm which evaluates the data from each user, together with the dataset of the main parameters already included in the database and continuously updated, thus exploiting data abundance to maximize the accuracy of the analysis.

**Business interviewee**: Chief Executive Officer (CEO) and founder of the company.

**Technical interviewee**: Chief Technology Officer (CTO), responsible for the development of proprietary AI algorithms.

### Company ß

**Industry**: Finance

**Business description**: Found in 2009 and certified Fintech rating agency since 2016, the company is specialized in assessing the creditworthiness of companies and banks, providing transparent, verifiable and self-explanatory digital solutions to help companies prevent the risk of losses and insolvencies. By replicating the approach of a human financial analyst with algorithms, the company combines the evaluation of financial fundamentals with sector analysis and the macro context, to return a detailed and comprehensive credit assessment. Over the last few years, the company has enriched its service portfolio with algorithms for ESG rating and software-as-a-service (SaaS) solutions for risk management.

**Use of artificial intelligence**: the company employs artificial intelligence solutions for credit risk analysis and management. Most of the services provided are built upon a company's proprietary algorithm which, based on public data and statistics, assesses the insolvency risk of any company or credit institution, without geographical limits and distinction of sector and size.

**Business interviewee**: Head of Sales, responsible for the relationships with customers.

**Technical interviewee**: Head of Fintech, responsible for the development of customized solutions.

### Company γ

**Industry**: Content making

**Business description**: founded in 2020, the company aims at supporting the creative process of its clients (B2B and B2C), offering a list of content-making tools available as SaaS through its platform. Among its services, the company offers tools for content ideation (e.g., brainstorming, trend analysis), content creation (e.g., text generation, search engine optimization, e-commerce), and content transformation (e.g., translation, audio-text conversion).

**Use of artificial intelligence**: the company employs natural language generation (NLG) algorithms to develop its content and support the creative process of its customers, automatically scheduling the publication of content by inserting itself into your daily workflow and automating the main activities.

**Business interviewee**: Chief Product Officer (CPO), responsible for the quality of the process outcome.

**Technical interviewee**: Chief Technology Officer (CTO), responsible for the development of algorithms.

### Company δ

**Industry**: Finance

**Business description**: founded at the end of 2017, the company aims to develop an AI algorithm applied to risk management to investigate not presided operational risks. In particular, the company deals with risks related to business interruption causing indirect financial impact which statistically brings in financial default in 14 to 16 months. The main target companies are small-medium enterprises. The initial focus was based on financial and governance risks, but now the company's focus is extending to climate and infrastructural risks.

**Use of artificial intelligence**: The company developed software with calculation algorithm for analyzing and monitoring current risks and predicting their evolution through AI and ML techniques. It focused on at least 36 months of data and the type of risks covered is wide-ranging.

**Business interviewee**: Chief Risk Officer (CRO) and co-founder.

**Technical interviewee**: R&D director, responsible for the development of objective discretional systems who can work alongside the decision-maker.

### Company ε

**Industry**: Finance

**Business description**: founded in 2020, the company was born to exploit the "open banking" norm which obliged banking institutions throughout Europe to expose their customers' current account data to third parties, with the consent of the end customer. The company's goal was to exploit this transactional data to calculate value-added insight indicators to revolutionize the world of consumer credit and make it more inclusive.

**Use of artificial intelligence**: the company employs ML models to analyze transactional data to evaluate people credit worthiness through the development as the output of a scoring. This helps banks to take more aware decisions based not only on demographic data but enlarging the evaluation boundaries also to the transactional ones.

**Business interviewee**: Chief Product Officer (CPO), responsible for market analysis, industry benchmarking and the direct relationship with clients.

**Technical interviewee**: Chief Technology Officer (CTO), responsible for the development team.

### Company η

**Industry**: AI solution development

**Business description**: founded in 2013, the company designs and develops AI-based solutions in the B2B market through Saas mode. Initially focused on the Energy sector, the company has enlarged its business scope and its customer base to Manufacturing, Telco, Insurance, Banking, Automotive, Food, Sports and Retail industries. In recent years, the business division has been supported by an education project, paths to lead students, teachers, trainers and managers to discover AI and the conscious use of new technologies.

**Use of artificial intelligence**: the company leverages several technical algorithms which belong to the set of tools of AI and more traditional statistical models. Thanks to the competencies of its experts, the company exploits most of the context of data abundance to leverage customers' data to implement tailored solutions. Among the main solutions that the company designs, forecasting algorithms, optimization models, image analysis, robotic process automation and predictive control can be found.

**Business interviewee**: Chief Innovation Officer (CIO), responsible for product development and process improvement through the implementation of design thinking methodology.

**Technical interviewee**: Head of Analytic Translation, responsible for the architecture and the technical support in the problem set.

### Company θ

**Industry**: AI solution development

**Business description**: founded in 2018, the company is employed in the development and distribution of vertical solutions based on AI to support demanding and knowledge-intensive tasks such as planning, quality control, monitoring, forecasting and optimization. The solutions developed aim to help companies in uncovering the potential of their data, business knowledge and expertise.

**Use of artificial intelligence**: the company employs AI in the development of solutions as software platforms tailored to the customers' needs or as a consulting activity for companies who want to analyze complex problems and build their platforms.

**Business interviewee**: Founder and president, data scientist and software engineer with expertise in Natural Language Processing and Knowledge representation.

**Technical interviewee**: Founder and Chief Executive Officier (CEO), data scientist and software engineer with expertise in Natural Language Processing and user modeling.

### Company φ

**Industry**: Healthcare

**Business description**: founded in 2017, the company creates solutions for interpreting gynaecological ultrasound scans and aids clinicians in concentrating on what matters so they can make appropriate clinical judgments quickly and under any circumstance. Aside from diagnostic supportive algorithms, the company offers solutions to facilitate the digital transformation of the healthcare sector through telemedicine and offers interactive training courses for professionals in which it shows the latest developments in diagnostic image analysis.

**Use of artificial intelligence**: company's solutions are built on customized AI algorithms that are currently primarily targeted at ovarian cancer diagnosis, exploiting the capability of AI to scan and analyze images accurately.

**Business interviewee**: Chief Executive Officier (CEO) and founder of the company.

**Technical interviewee**: R&D Director, in charge of the technical development of algorithms.

Table 3 summarizes the sample involved in the research to make it easier to read the findings in light of the main characteristics of the companies.

| Company | Industry[2] | Services offered | Main use of AI |
|---|---|---|---|
| Company α | HC | Predictive medicine of non-communicable diseases | Predictive analysis |
| Company ß | F | Credit Rating, ESG rating, risk management advisor | Bigdata clustering and analysis |
| Company γ | CM | Tool for content ideation, content transformation and creativity | Content generation (text, images, audio) |
| Company δ | F | Not presided operational risks assess. | Predictive analysis and assessment |
| Company ε | F | Individual credit worthiness assess. | Predictive analysis and assessment |
| Company η | SD | AI solutions designer and developers | Tailored AI-powered solution |
| Company θ | SD | AI solutions designer and developers | Tailored AI-powered solution |
| Company φ | HC | Diagnostic support, telemedicine tool | Image recognition and predictive analysis |

Table 3 - Sample of the qualitative research

## 4.2. Starting point

When discussing innovation, the literature offers some milestones which represent a well-established starting point to ground further developments. In our case, discussing the innovation process led us to consider, first of all, *how* we can define and describe it in a structured way. In dealing with this preliminary task, we identified Cooper's stage-gate framework (Cooper, 1983) as our main reference to which our insights can be traced back, enriching the theory with our findings. Given the context of the present research (i.e., impacts of AI on innovation), the clearest way to establish a basis on which to frame our results is to describe the innovation process as a distinct sequence of stages, from idea generation to actual product launch. Thus, Cooper's model is particularly fitting to our purposes. Indeed, in his work, Cooper describes the innovation process as a structured sequence of stages and gates (i.e., the validation of the previous stage based on specific tests). After the *(i)* identification of ideas, the process consists of the following stages: *(ii)* preliminary assessment of the feasibility and attractiveness of the project, *(iii)* designing of the concept of the product, identifying the key success factors that must be achieved, *(iv)* actual technical

[2] Healthcare (HC), Finance (F), Content-making (CM), AI solution development (SD)

development and prototyping, *(v)* testing of the product within the company's boundaries, *(vi)* pilot test to assess the actual product-market fit, and finally *(vii)* full implementation and commercialization through the official launch.

That said, for our purposes, innovation identifies with the whole framework itself. On the other side, concerning creativity, the main area of interest is the very first step – i.e. the raising of ideas – which then triggers the entire process, thus, being a crucial part of it. Keeping Cooper's model as a reference point, we can contribute to understanding how AI is impacting it by recombining the insights gathered from our interviews.

## 4.3. Coding results

We started the abstraction process of our findings from the clustering of codes into categories according to pattern matching and similarity of the key concept pointed out. Following, some examples are provided. First-order codes like *the algorithm suggested unexpected associations which humans did not consider* and *signals of new patterns discovered come out from the process back to the solution designer* were both referred to the opportunity which came up from algorithm output, therefore, they were grouped under the second-order category *New patterns/solutions from the process.* Codes like *when knowledge is codified, then it can be shared among all the actors which participate in the process* and *algorithms speed up the training of experts by making knowledge a shared asset* both stressed the role of AI in contributing to the exportability of expertise, rules and best practices among the company, thus being grouped under the category *Knowledge sharing.*

In the third phase, we interpreted the main findings by adopting a dependent variables design approach, starting from initially predicting variables corresponding to the stages of the innovation funnel presented by Cooper. Our exploratory investigation aimed at gathering specific and detailed insights but, at the same time, able together to depict the scenario with a comprehensive view. Nonetheless, the coding phase highlights a dominant presence of themes relatable to the first two stages of Cooper's model. We might identify two main reasons behind this, one related to a conceptual bias and one due to the profile of the interviewees. Indeed, people associate the concept of innovation with the first stages of the process, the ones related to intuition and creativity, rather than the commercialization or launch of the product. Concerning the characteristics of the profiles, startups typically have an unstructured organizational setup and deal with innovation through agile methodologies, with a frequent overlapping of phases. Moreover, being some of them still in the infancy stage of life, they are more inclined to elaborate on their first steps of discovery and initial testing. Two themes have a direct association with a phase of Cooper's model, therefore, they have been labeled in the same way:

- *Ideas identification*: it is the very first step of the innovation process, the step from 0 to 1 which deals with the identification (or generation) of a business opportunity, might it refer to a product, a service or a new venture. Such ideas, in the traditional framework, are classified as a *market pull* when they come from the recognition of unsatisfied customers' needs or direct requests from them, and *technology push* when stem from a technology discovery (Dosi, 1982; Verganti, 2003). In this theme, categories referring to the generation of ideas input were grouped, such as *unexpected patterns and solutions* and *synthetic data as creative inputs*.
- *Preliminary assessment:* it is the early stage in which the company employ a lot of effort and resources to assess the attractiveness of the idea identified. During this phase, a crucial task is related to the gathering of data from multiple sources, to evaluate the product-market fitting and have an early, but comprehensive, view of the feasibility of the project. This theme grouped the categories which describe ways in which AI facilitates assessment analysis, like *simulation analysis through synthetic data.*

Despite the identification of themes is based on a consolidated framework in the extant literature, according to the open coding approach methodology, the predetermined variables have been adjusted, adding new ones according to the main relevance that emerged from the analysis. Indeed, additional themes referring to other kinds of AI impact emerged. Such themes, although not directly connected to a specific stage, have an impact across the entire process, acting as innovation and creativity enablers:

- *Support for knowledge management*: knowledge management (KM) refers to the techniques and practices according to which knowledge is collected, stored, accessed, and shared among the actors of the process. KM of a company is deemed to be a crucial driver of employees' creativity since it increases team members' repertoire that can be accessed through development (Amabile, 1997). The process of making people's expertise accessible to a wider audience constitutes the basis for knowledge sharing and recombination, providing an indirect contribution to innovation and creativity (Saulais & Ermine, 2012; Yeh et al., 2012; Bettiol et al., 2012; Shahzad et al., 2016). In particular, the theme grouped those insights related to the role of AI in spreading knowledge within the company, highlighting the consequent impact on innovation and creativity, like *knowledge codification* and *knowledge sharing*.

- *Role of organizational setup*: impact of the organizational structure, company culture and policies on innovation and creativity. Indeed, in addition to the specific competencies and core assets considered stand-alone, how they systemically manage the innovation process plays a crucial role in the effectiveness of such a process (Khazanchi et al., 2007; Laursen & Salter, 2006). In this theme, categories which stress the key role of organization, culture and company practices were grouped, such as *agility of innovation process* and *company's culture*.
- *Human-machine collaboration*: as our research aims at depicting how humans and machines interact in light of the newest potential of AI (the specific subject of *RQ2*), we dedicated a specific theme to group the insights that detail their interactions and complementarity. Within this theme, there were included categories that describe the complementary role of human experts and machines, with a focus on the key stages in which the human role is deemed to be more valuable. Among them, we can find *domain experts in the initial setting* and *domain experts in interpreting results.*

All in all, these five themes represented the last step of the coding procedures, to which every first-order code is traced back. Figure 12 shows the coding tree, exhaustive for what concerning categories and main themes, and with some examples of first-order codes for each category, while figure 11 illustrates a hierarchy chart provided by NVivo output analysis, to better figure out even the pervasiveness of each theme.

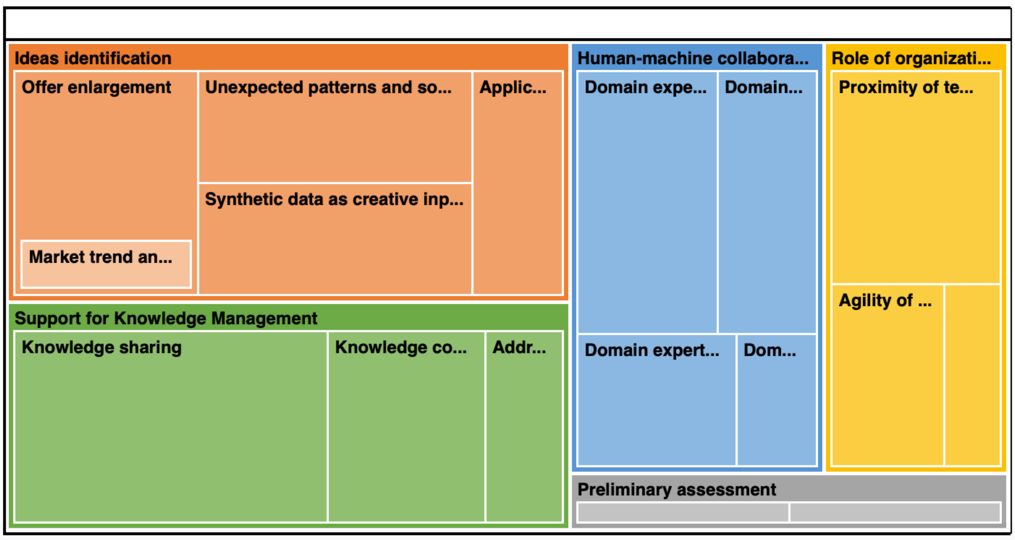


Figure 11 - NVivo hierarchy map of the themes

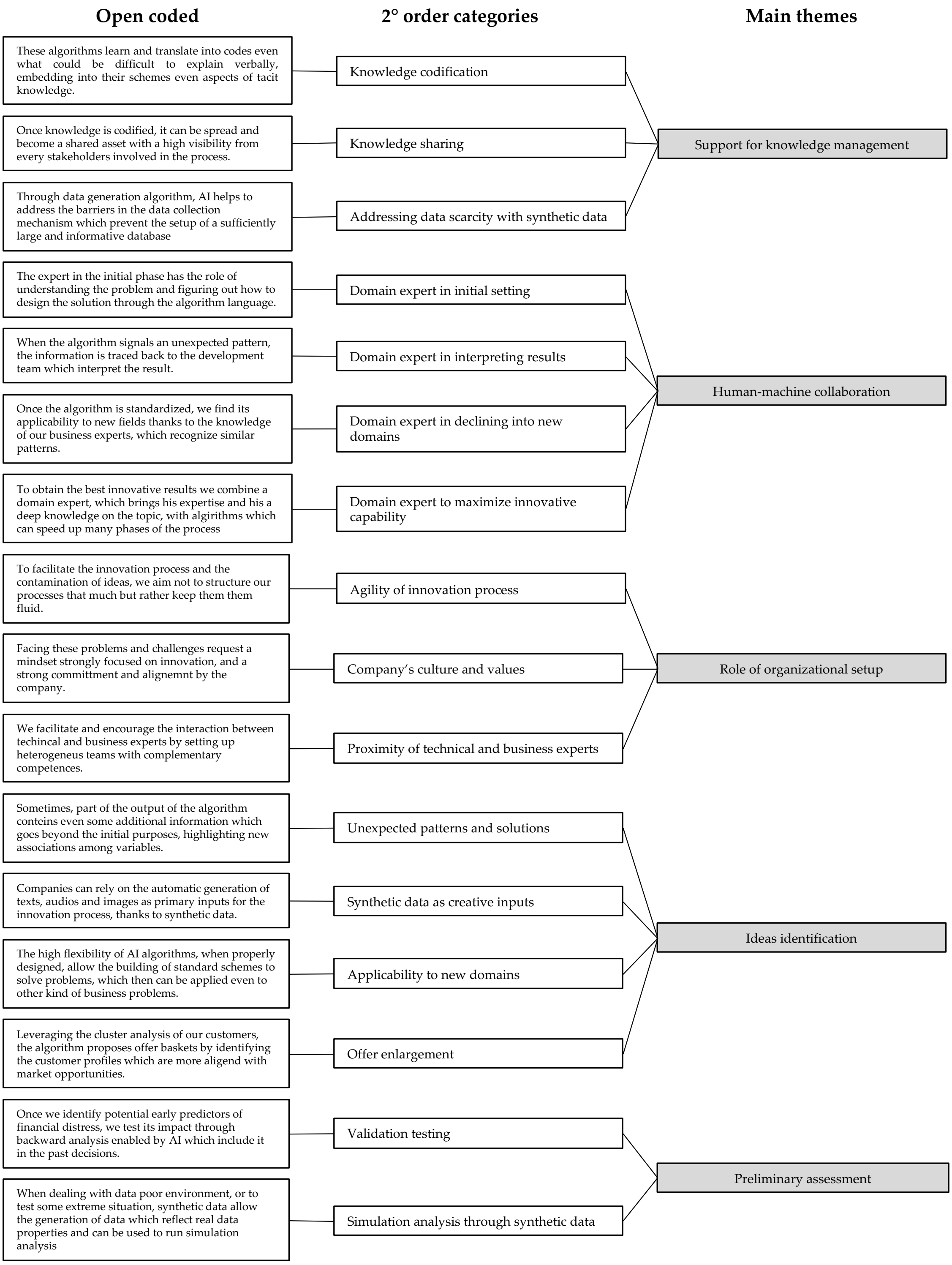


Figure 12 - Coding tree

### 4.3.1. Theme 1: impact on knowledge management

The first emerging theme we want to discuss is the impact of AI in knowledge management (KM), defined as the process of capturing, distributing, and effectively using knowledge (Davenport, 1994) and knowledge management system (KMS), the system of IT enablers developed to support and manage organizational knowledge

(Alavi & Leidner, 2001). As shown in figure 12, it has been one of the most pervasive themes, allowing a deep understanding of its implications. Its occurrence confirms *(i)* the relevance of KM as a fundamental prerequisite for innovation and creativity and *(ii)* the view of AI as a tool which disrupts traditional practices for KM. The facets of the topic are wide, many of which are already abundantly discussed in the literature, such as the ability of AI to contribute to the retrieval and processing of data in large quantities, enlarging the available data pool, and enabling more informed decisions throughout the process (Bettiol et al., 2012; Saulais & Ermine, 2012; Shahzad et al., 2016; Yeh et al., 2012).

That said, the most interesting insights are focused on some peculiar characteristics of AI, not just a powerful instrument for data collection but an exceptional enabler of knowledge exportability and sharing. Indeed, among the categories identified within this theme, there is a strict link between *knowledge codification* and *knowledge sharing*, as the latter is a direct consequence of the former.

Codification of knowledge can be defined as the process through which human knowledge is formalized as a set of explicit rules, logic schemes, patterns and well-defined concepts. The main barrier when discussing encoded knowledge concerns dealing with tacit knowledge – i.e., the knowledge that consists of intuitive association and rules, it is personal, specific to the context and sharable only through experience – which is often a determinant of a professional's success, distinguishing between experts and novices, and a crucial factor in solving certain business issues (Nonaka, 1991; Nonaka & Takeuchi, 1995).

However, AI is deemed to contribute to overcoming such barriers. A recurring concept that emerged from several interviews is how, during the training phase, algorithms are taught through the observation of past decisions of domain experts. In doing that, algorithms aim at capturing even those implicit aspects related to implicit associations and mental schemes, which usually are not transmitted during traditional training of human workers – e.g., verbally. Company δ provides a straightforward example to better understand the reasoning:

> *The process that involves knowledge can be rewritten thanks to these algorithms which learn and translate into codes even what could be difficult to explain […]. I often say, as an example, that it's easier to explain to a child what a cat is by showing him photos rather than defining it by rules, and he learns the concept faster and better. (Company δ, R&D director)*

In the like manner, coding mechanisms are a valuable ally even after the training phase, during the regular functioning, when the company faces an unprecedented event with a high degree of uncertainty. As stated by company ε:

> *Even in unpredictable scenarios, like the outbreak of coronavirus, in which the habits of people change dramatically […] our algorithm adapted surprisingly fast, giving its own interpretation to the new factors and how they would have impacted the process. For sure we had to check such interpretations, but as a matter of fact, most of them turn out to be reasonable and accurate. (Company ε, CTO)*

Combining its internal knowledge and logic, built upon company's data and past experience, with the external source of data, the algorithm allows greater flexibility and adaptability, as the novel elements are quickly embedded and encoded in its decisional schemes. Quickly adapting to a dynamic environment is a key enabler of sustainable competitive advantage (Fiegenbaum & Karnani, 1991), and such first interpretations provided by AI about exogenous events can represent even the foundation for a new opportunity.

Moreover, the aforementioned internalization of tacit knowledge allows moving forward in the direction of knowledge sharing. In turn, knowledge sharing facilitates knowledge recombination, a fundamental prerequisite for the solution of complex business issues – i.e., solutions which require the combined action of several domains. Once the training and testing phase is concluded, algorithms become a tool that, ideally, given the same inputs is deemed to replicate the output of the domain expert. However, differently from the latter, the algorithm is easily accessible as a knowledge skill tool to virtually countless actors in an efficient way. This provides them with the opportunity to combine their knowledge with other domain knowledge, which is no more of exclusive property of the domain expert, as it becomes an accessible asset even to people who cannot leverage his expertise. Hence, the use of algorithms facilitates the development of innovative and creative solutions, as it enriches the knowledge repository that can be accessed through development, which is among the determinants of individual creativity (Amabile, 1997). With respect to the variable of the research design, industries with unstructured data and with an important role played by human intuition are those which suffer most the low transferability of tacit knowledge. Hence, they are also those in which AI can provide a greater advantage since it allows for higher accessibility of such expertise.

Following are some examples which highlight the above-mentioned theme:

> *The information becomes truly useful only when shared. At that point I'm actually enhancing and leveraging medical knowledge. (Company α, CEO)*

> *Once the algorithm elaborates the knowledge, this knowledge can be shown to everyone, increasing transparency and aligning on the objectives. But there is more, if properly designed, they can also contribute to sharing the best practices about subjects which are typically hard to understand from non-experts. (Company δ, CRO)*

> *Knowledge belongs no more to business analysts or managers, it becomes an open-access resource which opens amazing opportunities that were previously closed due to the incalculable amount of time and resources needed. (Company γ, CTO)*

However, an important remark must be pointed out. Even if algorithms translate part of the tacit knowledge into a mathematical language, the level of complexity of the encoded information is such that it remains unintelligible to humans.

> *The AI learns from the best experts, but its brain is also difficult to explain. It's like opening the braincase and seeing deep neural networks that are difficult to understand. Some models are more explicable, such as decision trees, but others are much less so, uninterpretable levels of complexity are reached. Is it definable intelligence? It is still an open topic, there is still a lot of research [...] we are satisfied that they are actually useful. (Company θ, CEO)*

This phenomenon is referred to the well-known concept of limited explainability of AI algorithms (Tabesh, 2021), which leads some agents to use AI as a black box. Nevertheless, as company θ points out, the knowledge skill tool is still a valuable instrument, made available to a large set of stakeholders in practical and useful applications.

Another KM element pointed out by interviewees is the faster learning process of human agents. As far as we learned from interviews, this process is impacted in two distinct moments. First, during the early stage of algorithm training, when the company is forced to explicit some key concepts and rules which regulate the processes. In doing so, as reported by company θ, sometimes the beneficiaries are some employees themselves:

> *Helping our customers in setting up their algorithms, it has happened more than once that we asked them to write down some of their rules, key objectives […] and this turned out to be useful even for some workers inside the company itself! That's because before having written them, some of them were not completely clear and shared. (Company θ, CEO)*

Later on, during the regular functioning of the algorithm, some operators, although far from being considered an expert in a certain domain, aim at speeding up their training and they learn the rationale behind the decisions by interacting with the algorithm. The concept has been well-defined by company δ and company η, which also emphasizes the role of AI data visualization tool to make information accessible and interpretable by humans.

> *The actual value added is that once that information is codified, it can be shared and contributes to "building the expert", it speeds up the transmission of knowledge. (Company δ, CRO)*

> *[…] trying to export certain know-how and experience of a process to all the actors through our proprietary data visualization tool. Data are not more locked up in an SAP table, but it is shared and visualized thanks to a user-friendly interface through which the operators interact with the algorithm. (Company η, CIO)*

This is equally true and useful even for professionals which operate in sectors with a dynamic evolution of knowledge – such as the healthcare sector. Considering, for instance, knowledge sharing about the application of AI in image recognition for clinical purposes, healthcare professionals can keep up with the latest discoveries.

*The key point is to have aggregated information. It's the only way that leads to the design of solutions. There are few doctors that still study to be updated, even because most of them don't have the time to do so, and having the possibility to be informed is the key to think about innovative solutions (Company α, CEO)*

In this chapter, we have already introduced the role of AI in the first, and fundamental, building block of KM: the collection and aggregation of data in a structured way, functional to the analysis and interpretation. However, we still have to discuss a recent phenomenon of AI which has led to a further contribution to the building and initial setting of databases: the raise and proliferation of synthetic data. Synthetic data can be defined as data obtained from generative processes that assumes the properties of real data (Assefa et al., 2021). In the months and years to come, the diffusion of synthetic data is said to have a disruptive impact across industries, transforming the economics of data. According to a Gartner estimation, 60% of the data used for the development of AI and analytics projects will be synthetically generated by 2024, and synthetic data will completely overshadow real data in AI models by 2030.

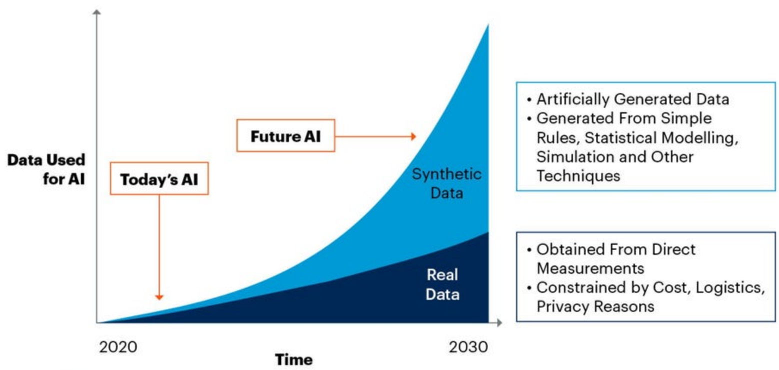


Figure 13 - Synthetic data diffusion (Gartner, 2022)

*In industries like financial one, there are privacy issues which prevent data availability […] but more generally, synthetic data can help in any kind of environment subjected to data scarcity, as you can generate thousands and thousands of data to built you artificial dataset, which is anyhow representative and useful as traditional ones (Company γ, CPO)*

When dealing with AI algorithms, their performance increases as the dataset becomes larger and more heterogeneous. In this regard, synthetic data represents a way out to overcome difficult and time-consuming data collection and data labeling processes. Indeed, synthetic data can enrich the database in terms of size and diversity, including the long-tail data – i.e. data which is not easily collected – and solving some typical problems of real-world data such as errors, missing data, inaccuracies and biases (e.g., limitations in the data collection process which prevent from collecting long-tail data, obtaining a biased distribution of the sample). According to companies' needs, through synthetic data it is possible to make punctual corrections to some missing or incorrect information, generating it artificially (partially synthetic data) or even enlarging the database through ready-to-use data. In other words, it makes data analysis process more efficient, reducing time and costs associated data collection and data cleaning, and more effective since they increase the accuracy of algorithms. Moreover, in some specific industries like financial and healthcare one, they address the barriers to data availability related to data privacy which prevent free access and use of data. In particular, the possibility of generating artificially long-tail data helps in two directions. First, it allows a better training of the algorithms, which is subjected to "stress tests" in which it must face artificially complex inputs which replicate extreme conditions that might happen even with real-world data, thus consolidating its performance. Secondly, the observation of algorithms in conveniently customized situations allows for gathering useful insights about the functioning of the algorithm itself, thus increasing its explainability and favoring knowledge extraction from it (Jaipuria et al., 2020; Nikolenko, 2021). To conclude, synthetic data represents a new instrument which can empower KM and thus, in ultimate analysis, the whole innovation process.

### 4.3.2. Theme 2: Human-machine collaboration

The second main theme that emerged as a research finding is Human-machine interaction and, as introduced before, we decided to reserve it a dedicated paragraph due to the strict connection with our *RQ2*.

The discussion about the human-machine relationship set is not new in the literature, since there is still an open debate about the technology's impact on the labor market. As we already discussed in the SLR, the vision according to which humans and machines have to operate in a collaboration regime is consolidated and the new paradigms shift from human or machine concept to human *plus* machine one – "AI will not overtake managers, but managers who use AI will overtake managers who don't" (Brynjolfsson & McAfee, 2017). The main findings that came out from our interviews follow this direction since all the companies interviewed are aware of technology's potential and the related advantages but still remarked on the human centrality in the creative and innovation processes that cannot be given up.

The categories related to this theme are strictly connected to each other since all refer to the "human-in-the-loop" (HITL) paradigm (Zanzotto, 2019), an approach that places human knowledge and experience at the center of AI application processes. Among them, we can find *Domain expert in initial setting*, *Domain expert in declining into new domains*, *Domain expert in interpreting the results*, and *Domain expert to maximize innovation capability*.

*Domain expert in the initial setting* refers to the importance of the presence of a human figure with a comprehensive view and deep knowledge of the business sector, customer characteristics, customer needs and requests, who therefore has clear in mind the final goals to pursue. Although it is a requirement common to every industry of our sample, it is even more relevant for those companies in which expertise and human intuition are core elements of differentiation and fundamental asset that contribute to business processes. As stated by company $\gamma$:

> *[...] for a goal-setting matter of fact, at time zero, a person who has a deep problem comprehension, who knows customers' requests and the peculiar characteristics the solution must to have is essential. (Company $\gamma$, CTO)*

The domain comprehension, the analysis of the available dataset, the understanding of which data represent a valuable asset, which ones lacked, and it is needed to collect, the awareness of which evidence is essential to detect, or which actions are necessary to pursue in data scarcity contexts, all these actions of "getting and cleaning data" assume a relevant weight in the process' success.

The key source of differentiation – thus, competitive advantage – does not lay in the modelling itself, but rather in the domain expert who is able to translate client needs into a programming language. Problem culture remains paramount, its main expressions, business verticalizing and personalization inescapably need the human component.

This concept has been pointed out clearly during the interviews of company θ:

> *Problem analysis, rational data use setting, data collection, evidence finding; [...] more in general the initial problem setting. [...] We need people knowledgeable about the domain comprehension which led to understand how the system will be used, what will be the point, which data you have, which data lacked, what happened where there is not possibility to collect the data. [...] we*

> *need someone who made clients requirements explicit in a programming language. (Company θ, President)*

Linked to this topic, a different shadow is provided by new domain applications that the expert could recognize in the problem-setting phase. This mainly happened during the statistic-mathematic modeling part, when working on a specific (custom) problem definition or for a peculiar industry need. The expert skill lies in recognizing the similarities between that specific application and another one that is theoretically far from this but requires the employment of the same technology and a solution that follows a similar pattern (technology recycling):

> *Image-video analysis is what it is: image classification, object detection or segmentation […]. The fact that you have to apply it in this contest, or another doesn't change the technology which still is the same (Company θ, CEO)*

> *These is a sort of sharing, there is is a general template over the deep learning is extremely knowledgeable and then the domain expert who thanks to his domain expertise is able to find it a perfect business application. (Company η, CIO)*

The importance of the presence of a domain expert who has a 360 degrees comprehension of the underlined field emerges in the same way during the interpretation and check of the results. AI can assume a key role in enhancing the capabilities and tools of the domain expert on whom, however, the last word and decision always fall. Without the presence of a domain expert, the actions performed would lose credibility, as well as reliability and solidity.

During our interview with the company η, the interviewee claimed how, for instance, customers can be clustered into different marketing profiles, connected to different offers baskets. Through an example, it emerged that the domain expert always has the last word, he then assumed a key role in the final decision concerning the offer to formulate:

> *I can take the example illustrated before, different mobile tariffs are sent to a different cluster of clients, 90% of the time, AI is employed as an "advisory instrument" but at the end of the story, there is the marketing manager of that business division, who looks to the algorithm advise and can finally modify the*

> *decision. It's him pushing the red button. (Company η, Head of Analytic Translation)*

This is common for each domain, independently from the structure and the innovation degree of the process. The same vision was argued by company ε, a company working in a completely different context:

> *For sure the expert verifies the machine learning model output, this happens both in the transactions categorization, where we look if the model actually was right or not, looking through how the single transactions have been categorized, rather than the result that we provide at the level of creditworthiness, the scoring is then close to what the bank expects. Or maybe by analyzing the customer's payment the model gave me an OK, then the customer turned out to be a bad payer or on the contrary, maybe it gave a knockout and then, going into more detail about the customer's economic situation, we realized that this customer was worthy. (Company ε, CTO)*

Another implication that came out from this concept is that the human expert brings the algorithm from a "black box" to a "grey box". This increases the explainability of the way in which AI is taking decisions since they have the expertise to interpret a pure data output and translate it into a business application.

Similar reasoning could also work when the machine comes out with a pure data input of correlation among variables, which can advise about the insurgence of a new pattern. However, it is still the domain expert who evaluates the solution as feasible or not and decides whether to actually implement it. This concept clearly came out from the cite extracted from the interview with the company δ:

> *The expert can build a story around the pure data output, starting from data to identify which could be the warning signals inside the company to evaluate conditions originally ignored by the human". (Company δ, R&D Director)*

The vision of the big picture is still a characteristic hardly attributable to the machine and is a key pillar of the processes of innovation and creativity. This can be read also under a vision of maximization of the entire innovation process. Whenever a creative person is involved in the process, a person who can define a creative, not engineering, out-of-the-box innovation, which does not follow a structured process, this typology of innovation is hardly replicable from the machine. Therefore, it is structured on a level of expertise and data sensitivity that the machine does not have. At this glance, can be remarked again the need to find a hybrid between the two words, human and machine, to maximize the innovation capability by merging the more engineering, mechanic, and process-based innovations with the more human-based ones which can define in under a certain perspective "artistic".

> *When there is a person, who can be define creative; in this context, that type of innovation developed cannot be replicable by the machine. This is a completely different scenario, where we play at quality level the machine cannot reach. This is the reason why it will be always essential to have a human component, who brings himself a sectoral expertise and a data sensibility which the machine does not have. (Company $\gamma$, CPO)*

### 4.3.3. Theme 3: Role of organizational setup

Organizational setup represents an important enabler for innovation (Khazanchi et al., 2007; Laursen & Salter, 2006). If this could sound like something already heard in the literature, our findings clearly point out how AI diffusion has marked its importance. The theme of innovation culture is embedded in the startup concept, which sees the development of new solutions as an "innovation mark" that characterizes startups, thus confirming the reasonable foundation of our research design. In order to pursue this strategy companies must adopt an agile structure that allows them to adapt rapidly to changes and exploit new opportunities instead of crashing into them. Compared to incumbents, their innovation-focused strategy brings them to avoid the adoption of a rigid and more structured organizational setup. Organizational setup represents the baseline of all the AI applications as emerged from the interview since the process of developing and sustaining a competitive advantage starts from the building of an organizational structure and processes capable of capturing and implementing the value created with the aid of AI through a structure suitable to innovation. For instance, possible new patterns, which would remain implicit with the traditional analysis, emerged with AI involvement or offer enlargement opportunities come out as expansion with complementary solutions. This, as remarked by our interviewees, could be fully exploited with an organizational agility that starts initially both from a cultural and an organizational setting. The capability of adapting rapidly at a strategic level to the opportunities that emerged from the interaction with the machine allows the companies to be always one step ahead of their competitor.

The creative application of AI starts firstly from the domain expert, and this is linked to the topic we introduced before of an expert domain in the initial setting who is able to discover latent market opportunities that the company must aspire to solve with a business solution. Data analysis involving AI allows the highlighting of unexplored solutions making evident the need to rely on the model. The latter could provide instructions useful to fine-tune the development of the solutions.

This allows us to introduce an important topic: the importance of the *proximity of technical and business experts* in the organizational setup. Context understanding is fundamental during the developing process of innovative solutions and often the effectiveness rate is measured on the capability to set a fruitful interaction of different experts.

> *Before I was talking about design thinking, but maybe we can enlarge the argument boundaries considering interaction design and x-design. These techniques allow to allocate on the same level professionals marked with different backgrounds, creating a contest of knowledge contamination, reaching results easily and developing higher potential solutions. (Company $\gamma$, CEO)*

"Knowledge contamination" allows the domain expert to set the problem in the best way possible and define the modality to solve it (Savino et al., 2017). The expert with deep technical competence highlights details and pain points which then come out to be fundamental during solution development and to fully exploit the machine-enhancing capabilities. As remarked before, talking about human-machine collaboration, one of the key arguments is that machines have many potentialities, which bear the risk to remain hidden if the human is not able to define clearly what to ask. The solution to this issue would be way easier by setting an organizational setup that provides the interaction between complementary experts as domain one with the technical one. Most of all, this is true for the R&D process that many times has been described as de-structured and managed in a fluid way with numerous overlaps with other processes:

> *There isn't a specific R&D unit, I think the main characteristic is that all the processes and all the services are close to R&D. When we developed a product or a service, can be considered an R&D process since prior knowledge does not exist. (Company $\gamma$, CPO)*

As stated in this example, the agile setup is extended pervasively to all the processes. This encourages and facilitates knowledge sharing, increasing interaction between experts belonging to different fields and building multidisciplinary teams. The importance of heterogeneity has been often stated as the key source of competitive advantage that companies benefit from with respect to their direct competitors (Adegbesan, 2009). Although this, on the one hand, allows the development of advantages in terms of personalization and tailor-made solutions development, the advantages in terms of efficiency and scalability cannot be neglected too, replicating solutions developed for other domains but characterized with managerial similarities.

> *The organizational setup is always central when we talk about key factors, the context where we work is dynamic [...] and if you are not able to adapt your organization with a dynamic setup in the same way you cannot compete. We, as a team of analytic translation, interface on a daily basis with the business area, we work together in the solution development and this allows us to see the big picture, complementing our vision. (Company η, Head of Analytic Translation)*

### 4.3.4. Theme 4: Ideas Identification

Ideas identification represents the first phase in Cooper's framework of the innovation process. Given the aim of our research work, this theme is one of the most relevant for us since *(i)* it is the factor that triggers the entire innovation process and *(ii)* it is the phase most relatable to the concept of creativity. For our purposes, we will intend *Idea identification* as the discovery of a set of different kinds of business opportunities, such as new product or service proposals, improvement of already existing products or services, designing of new business models, and ideas for venture creation. As a matter of fact, AI has proven to facilitate all these sources of opportunities that emerged from interviews. In particular, with respect to the traditional framework, our insights demonstrate how AI not only enhances the traditional channels of ideas scouting – market pull and technology push – but it actually adds new sources by leveraging internal and external data recombination, pattern recognition and generative AI.

The capability to process and recombine data from different sources could lead to the identification of unexpected patterns, thus, ideas directly suggested by the machine. This is an enabler of the development of innovative solutions. This concept could be rationalized as the improvement of product-market fit through offer enlargement. More in detail, we refer to incremental innovations enabled by the integration of external data – e.g., market data and sector analysis – with internal one – e.g., customers data. For instance, through AI companies are able to combine information about new product launch with cluster analysis of their customers, based on demographic data and historical consumption, to propose bundling offers and cross-selling of their services, thus innovating their business model. With the words of the interviewees:

> *Through AI we can aggregate even heterogeneous data and make them comparable [...]. This allows us to explore new opportunities for the enrichment of our offer with complementary services [...], customizing the offer for each of our customers. (Company α, CEO)*

> *Algorithms give us intuitions about new applications, and we discover how, for instance, certain financial profiles fit well with a certain kind of investment, and this is something that with the traditional methods would be prevented. (Company ε, CTO)*

> *Cluster analysis that we implement suggest our customers a certain basket of offers in a very effective way [...] and this enhances upselling and cross-selling possibilities and ideas for bundling offers. (Company η, Head of Analytic Translation)*

Therefore, data, if managed properly, also becomes one of the primary sources of innovative ideas. Sometimes even those data that apparently seem incompatible with any application or those ones that were stored since many years ago, actually unused.

> *At a certain point, we found out that data that was stored and left apart for years turned out to be compatible with a new line of product that anyone had ever thought about. (Company α, CTO)*

Another pragmatic example of unexpected pattern recognition through AI data recombination is the correlation identification and causality analysis between variables initially considered as independent. This could also lead to the development of innovative solutions interpreting appropriately the suggestions provided by the machine. For the sake of simplicity, we will consider such processes as a "black box" at the service of companies, as our aim is not to zoom into this box to elaborate on its technical aspects. Algorithms, during their functioning, receive data as input and, once it has been processed, return a certain output. As discussed in the *Human-machine collaboration* theme, this output is not completely under human control. Despite, to some extent, this can lead to interpretability problems, if faced with the proper competences it turns out to be a source of new and valuable opportunities. Among many others, company $\alpha$ provides evidence of this aspect when talking about unexpected but interesting output coming from AI pattern resolution capability:

> *What often happens is that during the analysis, artificial intelligence combines the results related to some biomarkers, which are "green" if considered stand-alone, and signal a possible red area related to another biomarker, which was not taken into account initially. (Company α, CEO)*

Once again, this feature is due to AI capability to analyze instantly all the possible associations among the available data, thus identifying solutions and patterns to which humans did not think, due to their bounded rationality and limited resources. This property is particularly suitable for data-rich environments, as a confirmation, we found a strong commonality between the healthcare and financial sector, both characterized by large and extensive databases. Moreover, these two sectors also present a high relevance of predictive capability, among the factors considered in the research design. For the healthcare sector, this translates into predictive medicine, while for the financial sector into better risk management. In this regard, the more the companies are aimed at detecting early predictors of a system, the more they might benefit from the pattern recognition ability of AI. Indeed, company ε talked about the role of AI in signaling new associations too:

> *In some scenarios, we had some intuitions coming from the algorithms [...]. In addition to the information that we were looking for, the model suggests a new variable to consider in our assessment, as it has reported a significant impact on this one. For instance, a personal habit of a person, or a hobby, which contributes to giving us useful insights for its profiling. [...] when a business problem arises from the process itself, we find ourselves in a position to use artificial intelligence even in fields and applications that we didn't imagine. (Company ε, CTO)*

This very last phenomenon pointed out by company ε, the applicability of AI in context initially not considered, leads us to discuss another key topic, that is, the high flexibility of AI algorithms. More in detail, in our coding procedure, the category *Applicability to new domains* refers to those insights that see AI as the main enabler of the business model scalability to new application domains. It is the case, for instance, of company η:

> *We started to understand that applied mathematic could work even outside our traditional boundaries, […] after five years of projects in the Energy sector, we found several themes that could be faced in a structured way with artificial intelligence algorithms […] because when you have certain algorithms, with consolidated schemes, it's much easier to extend it to new domains. (Company η, CIO)*

Therefore, by leveraging AI flexibility it is possible to enlarge companies' business scope, enhancing exponentially their growth opportunities. The basic concept which lays the foundation of this argument is the typical approach that AI-based startups and data scientists adopt to solve their business problems. Following is company θ in describing such an approach:

> *Regardless the industry from which we receive the request, we translate the problem into mathematic models that refer to our areas of video, texts, and structured data. This allow us a high replicability because artificial intelligence tools are very similar to themselves from the logic point of view. (Company θ, President)*

This method allows the establishment of algorithms based on highly standardized schemes which go beyond the specific application domain but rather refer to mathematical and statistical logic shared by many sectors. Hence, the algorithm assumes a modular structure with a "back-end" component shared by several verticals. Once this component is set, it is possible to identify business opportunities which stem from problems relatable to the same founding scheme of the initial algorithm. Such projects' replicability gives a remarkable push to a fast and efficient business scalability thanks to a "light" adaptation procedure. Indeed, in a like manner to the last-mile customization principle, the adaptation of the algorithm to the new domain is related to some detailed aspects but does not alter the core design of the solution. Company θ offers some examples that better clarify these dynamics:

> *[…] projects about the recognition of eye defects which have been in a large part replicated to work on the analysis of fabric defects or production defects in the steel industry. That's because the image analysis followed the same principles and steps […]. And the same works for text analysis, be they legal or medical, and many other fields. […] Working with artificial intelligence projects, overlapping abound! (Company θ, CEO)*

Considering the different industries that we considered in our sample, structured data availability is a factor which clearly facilitates the applicability into new domains. The more the new domain is characterized by the availability of ready-to-use data, the higher the flexibility of the process will be, easing the scalability. Not surprisingly, firms such as company η found the first opportunity of scalability towards financial sectors.

The last point we want to present in this theme is among the most innovative and hotly debated ones, which in the very recent period has been facing months of revolution, raising debates among commentators: generative AI. With generative AI, we intend programs that allow machines to produce their own content through the generation of synthetic data. Data generation algorithms have evolved towards neural network techniques, which extend data generation to images, texts and audio. Among the most innovative and widespread, generative adversarial networks (GANs) introduced by Goodfellow are gaining momentum, defined in 2016 by the AI expert and writer Yann LeCun as "the most interesting idea in the last ten years in machine learning". The brilliant intuition behind GANs is the combined – and adversarial – action of a generator algorithm, aimed at generating artificial data, and a discriminator algorithm, aimed at distinguishing between real and synthetic data. The generator performance is constantly improved through an iterative loop, until the ideal situation in which the discriminator reaches 50% confidence in detecting synthetic data (Goodfellow et al., 2020). The advent of generative AI potentially represents a disruptive element for every industry, that now sees machines as one of the main actors of the creative process by producing content – almost – from scratch. Company θ, talking about generative AI, reports how these applications will represent – to some extent, they already do – the new wave of AI.

> *There is a very rapid evolution of the development of creative algorithms, it's for sure the hottest topic when talking about innovation […] we see the huge opportunities enabled by image generation, audio, text […] we're having a boom*

> *of requests from the market for marketing applications, digital contents and many other field historically dominated by humans' creativity […] which is not replaced but rather augmented by machine, which provides a virtually infinite creative element. (Company $\theta$, CEO)*

When discussing the generativity of algorithms, the first industries that are typically mentioned are those in which creativity is a core component of the business, making them the natural target of these new applications. Company $\gamma$, a company belonging to the content-making industry, pointed out its current usage of generative tools:

> *We worked on projects about websites with meta-title and meta-description in which, almost starting from scratch, algorithms generate texts through a keyword analysis to make them catchy and aligned with the market trends […] which usually would take a person hours and hours of work. (Company $\gamma$, CTO)*

We can deduce how AI content generation on the one hand automates several tasks – which, even in a small portion, require a creativity component – and, on the other hand, enhance and enlarge the set of possibilities of content-creators. Indeed, generative AI provides additional inputs to the innovation process, with texts, images, audio and videos made available at a low cost, and in a short time. Hence, the role of humans is not replaced, but rather his set of creative building blocks is empowered with new opportunities. Machines have undoubtedly made remarkable steps ahead even in those industries in which human predominance has never been questioned, making the boundaries between human and machine tasks more blurred. Still, the differential aspect, where most of the competitive advantage actually takes place, is understanding how to leverage these opportunities and acting complementary to the algorithms, according to a best-of-both paradigm.

What is impacted, as a matter of fact, is the most operating part of content creation, which is often a set of non-core activities but at the same time necessary and – historically – requiring human intervention. It is the case, for instance, of social media management, which requires the constant development of engaging content on several social media, each with its specific requirements and specificity. Company θ told us about it:

> *[…] or copywriting: artificial intelligence writes contents which must be compliant with the requirements about engagement, marketing, social media policy, and so on. With the diffusion of the omnichannel paradigm, we are facing a growing demand due to the need for companies to be present online, on Facebook, Instagram, TikTok with daily posts […]. Something that might not seem to be the main problem but through artificial intelligence, they can guarantee a higher consistency in their presence without the employment of too many resources. (Company θ, President)*

AI generative process cannot be considered fully from scratch since it requires some human inputs, usually consisting in a written description of the desired content. Then, based of millions of data – e.g., image datasets, texts, audios, each of these categorized into pre-determined style – the algorithm recombines it and aims at generating what has been asked by users. As previously argued in *Human-machine collaboration*, human's role remains crucial – at least – in two key phases. First, in the initial setting, which is to say, the specification of the request to be submitted. This task, to be performed properly, requires human operators an adequate experience in terms of both the domain of application and the specific formulation to be used. In the case of image generators, for instance, it is required a well-specified description of what one might want to be drawn, and the specific style too. Secondly, humans always are in charge of the critical assessment of the output, implementing corrections or adjustments for the development of the contents. This second phase is equally important because of possible misinterpretation of the machine and lack of explainability in the command submitted, which makes the output of AI just a good starting point, but not suitable enough.

Therefore, despite the magnitude of this innovation, we are in a context of empowered creativity but still under human control. AI, although can be considered a source of creative suggestions generated semi-automatically, is still a tool in the hands of humans, the actual core of creativity. Indeed, this approach refers to the HITL paradigm, described by company $\gamma$ as follows:

> *There is a journalist which understands the request by the client and roughly designs the solution […] Then, the solution is implemented by algorithms, supervised by data scientists, and the output is verified by editors, and therefore there is often human intervention upstream and downstream. […] the treatment is always necessary: we need a person who explains very clearly*

> *to the machine what to do. And then a downstream person that controls, this is our system. Human-in-the-loop, that's the way we apply it. (Company $\gamma$, CPO)*

### 4.3.5. Theme 5: Preliminary assessment

The last theme we present is the impacts on Preliminary assessment stage, the second of Cooper's framework. It is the moment that signs the beginning of the converging phase of the innovation process, in which companies screen and assess ideas to have an early, but comprehensive, view of the feasibility and attractiveness of the alternatives. To perform this task, a lot of resources are employed to gather data from multiple sources. AI can be considered a valuable ally given its capability to process data and run simulation analysis on countless scenarios. This characteristic fits particularly well in business models in which predictive performances represent the core of the offer. Hence, considering the variable on which we based our research design, companies with a large availability of data and with a great relevance of prediction. Indeed, in our interviews, both company $\alpha$ and company ß discussed how algorithms represent not just the basis of the regular functioning of processes but even accelerators and facilitators of innovation:

> *Once new potential biomarkers are identified, the machine helps us through its capability of performing backwards testing […] that is to say: let's see how the same algorithm would have performed considering this new variable, or two of them, and so on. This helps us in identifying the most promising ones. (Company $\alpha$, CEO)*

> *Artificial intelligence offers us a good starting point for simulation with thousands and thousands of data. Even when we measure new unconventional soft data, we can give it to the algorithm to understand whether it is actually relevant. (Company ß, Head of Fintech)*

AI acts as a facilitator of innovation not only by providing inputs and suggestions but also enabling quick feedback about the feasibility and attractiveness when the initial idea comes from humans. This leads to better employment of effort, resulting in a more efficient and effective management of the screening phase.

However, not every innovation occurs in data abundance environments such as those described above by our interviewees. When dealing with preliminary assessment, one of the main barriers is linked to the scarcity of data, as important to run tests as difficult to collect. The product (or service) is at the very early stage of its life, and the entrepreneur works in a context of uncertainty, particularly when dealing with the launch of a completely new offer, if not a new venture itself. During the interview, company θ pointed out a possible tool to overcome, in some circumstances, this barrier: once again, synthetic data.

> *With data augmentation models companies can obtain in a fast way, after a few iterations with the expert who corrects the output, an accurate tool to address the data scarcity. Not just concerning the low availability of data but also the absence of data which describes extreme situations, particularly useful for simulation analysis. For instance, in a project for the optimization of energy consumption of a building, through data artificially generated it's possible to run simulations which involve the total shutdown or other scenarios which would not be depictable through real data. (Company θ, CEO)*

AI aims to enhance the preliminary assessment with predictive analysis and simulation scenarios in an efficient and automatic way. This allows the entrepreneur to gain an early, but accurate, view of the potential and the implications of developing the new idea. Under the uncertainty which characterizes the early stage of life of the process (Eriksson et al., 2020), AI has a positive impact on risk management and resource allocation of the company. Moreover, addressing the uncertainty barrier might represent a way to reduce information asymmetry with external stakeholders (Giuggioli & Pellegrini, 2022). Through the results of simulation analysis, the entrepreneur can bring a credible and solid argument that assesses the benefits of a business idea, increasing the opportunity of receiving funds to carry on his business.

As a concluding remark about *Preliminary assessment*, an important aspect is worth to be mentioned. Indeed, some interviewees point out industry-specific limitations to the use and impact of synthetic data. It is the case, for instance, of the healthcare sector:

> *Simulations with synthetic data in our case have limits [...] in our field we need an additional mandatory element which is clinical validation, [...] everything you go to develop and test must be tested on real data and no synthetic data can change that. (Company φ, CEO)*

## 4.4. Results discussion

In this chapter, we started from Cooper innovation model to trace back the insights of our interviews, thus identifying a direct impact on the first two phases (Identification of ideas and Preliminary assessment) plus three cross themes, as enablers of creativity and innovation (Knowledge Management, Organizational setup and Human-machine collaboration).

We can structure all the findings in a new theoretical framework, in which every impact, both direct and indirect, is depicted. Figure 14 summarizes the main findings and links the themes identified by the coding of the interviews.

Let's consider the three funding blocks of our framework:

- *External data* coming from market analysis, competitors, regulators, consumers and any other source of data coming from outside the company.
- *Company data*, referring to the database of the company with data about its customers, products, services and processes.
- *AI business process* that we model according to the human-in-the-loop paradigm (HITL), a cyclical sequence of activities which gravitate around human role and competence. In particular, domain experts design the algorithm and then verify and interpret its output. The algorithm, for the sake of simplicity, is described as a black box model which transforms inputs into output.

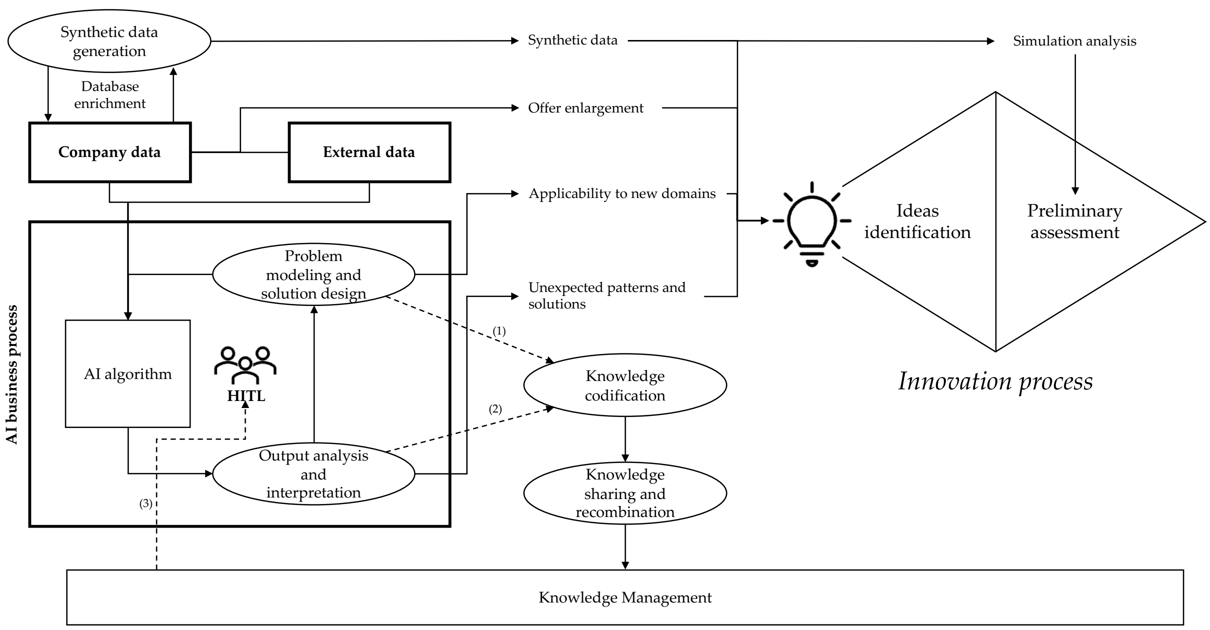


Figure 14 - Framework which allows for a systemic view of the findings

The second and third block act in a systemic way in an organizational environment which has certain practices, values and culture. AI is a potential game changer. However, getting the most out of these solutions is not simply a matter of technology: companies must embrace organizational changes to capture the full value from it. To maximize the contribution that AI can provide to innovation and creativity, our findings suggest an agile organization with values and a culture marked by an innovation mindset, and whose processes combine the synergic interactions between technical and business experts.

Our findings, which correspond to the direct and indirect impacts on the process, originate from these three building blocks. More in detail, the impacts on *Ideas identification* refers to the divergent phase of the innovation process, which aims to increase the opportunities for innovative ideas. On the other side, the impacts on *Preliminary assessment* refer to the convergent phase of the process, which deals with the screening and validation of the most promising ideas.

*Company data* fuel *synthetic data generation* providing inputs for generative algorithms. *Synthetic data* play multiple roles. First, they contribute to *database enrichment*, addressing data collection limitations and increasing the size and heterogeneity of data. Secondly, they can be considered a primary input for ideas identification (e.g., through the generation of synthetic texts, images and audio). Thirdly, dataset enlargement enables consistent and statistically relevant *simulations analysis*, which enhance *preliminary assessment* even in contexts of data scarcity in which barriers to data collection prevent the construction of solid and large databases.

Combining *company data* with *external data* leads to innovation opportunities that are generated automatically by matching emerging trends with cluster analysis of customers, resulting in an *offer enlargement* (e.g., cross-selling and bundling suggestions).

*Company data* and *external data* constitute the input for *AI-powered business processes*. These processes are characterized by the *HITL paradigm*, in which humans are the active protagonists, considering a strict interaction between business and technical experts. *Problem modeling and solution design* and *output analysis and interpretation* are based on their complementary competences and experience. Many opportunities for ideas identification stem from such processes. *Problem modeling and solution design*, deals with understanding of the customer's request and its translation into mathematical models. The high level of flexibility of AI models allows their *applicability to new domains* – i.e., new business cases, but still, referring to the same logic and dynamics. This fast and efficient adaptability enables the scalability of the solutions, with the possibility of enlarging the business scope of the company to new customers, domains and industries. Moving to *output analysis and interpretation*, it might include additional information beyond the initial purpose. Therefore, it is possible to identify *unexpected patterns and solutions* suggested by AI itself that, if properly interpreted, represent a source of new ideas.

Moreover, both *problem modeling and solution design* and *output analysis and interpretation* deal with data, information, and knowledge that is processed – or to be processed – by AI, with significant implications on knowledge exportability, namely, impacting *knowledge codification*, *knowledge sharing and recombination*. The algorithm, after the training phase, is deemed to embed into its decisional process even some tacit aspects of knowledge(1) that the limited human explainability would not be able to transmit directly. From *output analysis and interpretation*, it is possible to obtain useful insights(2) about such knowledge and even describe it through precise and formal rules. On the other hand, during *problem modeling and solution design*, the company is obliged to clearly define the final purpose and what exactly has to be asked the algorithm through a set of rules and models. This translation of the customer requests into codified languages further contributes to the formalization of knowledge, whose beneficiary is not just the algorithm but even the company itself, thanks to greater awareness and alignment of all the stakeholders involved in the process. Indeed, these dynamics have a direct impact on *knowledge management* of companies since the codification of knowledge is a fundamental prerequisite and enabler of knowledge sharing. The higher accessibility to knowledge represents a powerful tool that facilitates the recombination of knowledge of different domains to find valuable and innovative solutions to complex problems. KM is a cross-theme that constitutes the baseline of the entire innovation process, fueling the competences of people(3), the core asset in the HITL paradigm. Hence, impacts on such a pervasive theme directly affect the entire process of creativity and innovation.

# 5 Conclusions

## 5.1. Relevance of the topic

AI is among the digital technologies which have been disrupting every business field for the last decade. The distinctive feature of AI – i.e. its capability to process a virtually infinite amount of data – represents a powerful ally to entrepreneurs to overcome the limits of human rationality. Hence, the attractiveness of AI has led to a proliferation of algorithms-powered processes within companies, not just to enhance the operating performance but also to provide valuable support to the decision system (Ferràs-Hernàndez, 2018; Vincent, 2021). But the story does not end here. With the recent technological advancements, AI is pushed at the edges of computational creativity (Toivonen & Gross, 2015), as algorithms are deemed to carry out even creative tasks. Such a revolutionary breakthrough opened a great debate among both scholars and practitioners about whether AI is actually challenging the role of humans, even in industries in which their comparative advantage has always been clear and never questioned (Paesano, 2021; Weingarten et al., 2020).

## 5.2. Main goals

The extant literature about AI implications in entrepreneurship concerning innovation and creativity is vast but at the same time, zooming in on the most novelty aspects, is still at its infancy stage. On the one hand, more and more empirical evidence has been gathered about AI's consequences on creativity and the innovation process (Giuggioli & Pellegrini, 2022; Paesano, 2021; Townsend & Hunt, 2019). On the other hand, the literature lacks a consolidated framework that takes stock of a pragmatic and tangible narrative, identifying the actual impact of each entrepreneurship activity. Filling this gap has a triple purpose, that is, *(i)* to define the state of the art about applications of such a dynamic technology, *(ii)* to identify in a structured way its areas of impact, and *(iii)* to analyze the evolution of the relationship between humans and machines, stressing which specific skills and tasks remain in charge to the first.

The identified investigation area led us to formulate two research questions:

**RQ1:** *How does the application of artificial intelligence change the stages and the determinants of the innovation process?*

**RQ2:** *How are humans' role and human-machine interactions changing in light of the application of artificial intelligence in the innovation process?*

To address the research questions, the qualitative methodology of multiple case study has been chosen since it allows a deeper understanding of the matter. Indeed, the combination of business and technical interviewees from different industries led to the gathering of specific insights, still, comprehensive and complementary as a whole.

## 5.3. Main findings

The main findings of this work resulted from a detailed and structured analysis of the themes that emerged from the interview phase, highlighting the common traits, the difference and peculiarities with a critical point of view. From a general viewpoint, all the interviewees pointed out a strong implication of AI as a linchpin element, not only in the core processes but also as an innovation enabler from different perspectives.

From the coding procedure, five main themes have emerged. Among them, two are directly linked to Cooper's framework (Cooper, 1983), tracing its first two stages. Three of them, instead, are cross-thematic which can be defined as broad enablers of the entire innovation process. These five main themes lay the foundation for the analysis of the main findings and their interpretation in light of our research questions.

**[RQ1]** AI impacts different stages and in different ways the innovation process. Starting from the *Ideas identification* (which can be considered as the "divergent" stage of the process), AI acts as an enabler of business opportunities in different ways: *(i)* offer enrichment based on the client's characteristics and needs, *(ii)* generation of textual, visual or audio artifacts, *(iii)* scalability opportunities towards new business fields and solution replicability towards business issues characterized by common underlying traits, and *(iv)* recognition and suggestion of new associations between variables to be further investigated and embedded into the system to make the predictive model more accurate.

Moving to the *Preliminary assessment* phase (which can be considered as part of the "convergent" stage of the process), AI provides support in identifying the most valuable opportunities by enabling simulation analysis thanks to its capability to process big data. Moreover, in data scarcity scenarios, synthetic data represent a "way out", enabling simulations based on artificially generated data. According to the industries' characteristics, different aspects were stressed.

The content-making industry put a greater emphasis on the generative sphere of AI and the role of synthetic data. On the other side, the finance and healthcare sectors highlighted the AI capability to speed up the trial-and-error process, enhancing the possibility to test and fine-tune the solutions, thus increasing the probability of market validation (Giuggioli & Pellegrini, 2022).

As anticipated before, three main themes emerged as broad enablers of the process. As for any technological breakout, to facilitate a performing AI-powered innovation process the organizational setup has to follow some requisites in terms of practices, policies, and company organization (Khazanchi et al., 2007). In particular, the facilitation of knowledge contamination, the creation of heterogeneous teams with mixed business and technical backgrounds, and fluid management of the innovation process. Knowledge has emerged as a key underlying asset of the creative process. To this extent, AI arises as a facilitator and strengthener of the firm's knowledge asset, enabling knowledge accessibility from all the shareholders involved, thus allowing the recombination of competences, expertise, and know-how within the company boundaries.

**[RQ2]** The last theme, about human-machine relationships, addresses directly our second research question. Humans and machines collaborate according to the human-in-the-loop (HITL) paradigm (Zaznotto, 2019), which still sees human experience and critical thinking at the center of the process. Zooming into the HITL model, we can highlight the capability of the machine even in terms of creativity and innovation support. Still, the paradigm brings to light the role of humans in the initial setting and in the more value-added stages such as problem codification, the definition of the inputs to be submitted to the machine, the solution design, and the output interpretation as source opportunities suggested from the algorithm.

## 5.4. Scientific contributions

Our work contributes to the extant literature in several directions. At a general level, the qualitative nature of the research contributes to consolidating two streams of literature, both hotly debated. First, the role of AI in creativity and innovation, detailing it according to a well-known framework of the innovation process like Cooper's one. In this regard, this paper contributes to addressing future research suggested by Paesano (2021) and Schiavone et al. (2022) about further studies on AI roles and implications in the innovation process. Secondly, it elucidates the relationships between humans and machines, by describing new dynamics in a structured way. Moreover, the point of contact between the two research areas has been highlighted through the development of a visual framework that allows for a systemic representation of every theme. The novel component consists of the systemic portrait of findings and even some innovative aspects of those. More specifically, the enrichment of the literature about AI and creativity involves some recent developments based on features of AI that, to the best of our knowledge, were not evident in the extant literature. Of particular novelty are findings about synthetic data and the flexibility of algorithms. Indeed, synthetic data proved to affect innovation not only through primary inputs that trigger the process but also through data augmentation, by acting as a database enricher and simulation analysis enabler. This finding can be seen as a further development of the results of Brem et al. (2021) and Dellermann et al. (2019) about the role of AI in the screening phase. The flexibility of algorithms, when properly designed, leads to the development of highly standardized solutions which found fertile grounds for applicability into new domains. On the other side, pattern identification and contribution to ideas generations enforce more consolidated views of Eriksson et al. (2020) and Hutchinson (2021) with new insights.

Arguments about synthetic data also fuel the literature about the bond between creativity and knowledge management with findings from innovative angles, namely, knowledge generation enabled by the enrichment of databases through artificially generated data, and the role of algorithms to contribute to knowledge exportability through the availability of knowledge skill tools. In particular, this finding about a pragmatically useful application of algorithms goes against a stream of literature that sees humans as the only actors who can contribute to the innovation process given their irreplaceable intuition and expertise (Holford, 2019).

The design of the interviews integrates two perspectives about the subject often treated separately by the extant literature – thus, with a partial view. Our double interviews not only enabled information triangulation but also permitted a deep comprehension of the phenomenon by combining a technical perspective (e.g., interviews with CTOs, data scientists, and algorithm developers) with a business one (e.g., interviews with CEOs and CPOs).

As the last point, our work provides an overview of the state of art of the Italian scenario regarding the latest development of AI applications concerning innovation and creativity, among the key factors which drive the competitiveness of firms. Indeed, our research design allowed the identification of companies that are at the forefront of innovation for what concerns the Italian scenario, taking stock of the situation in such a dynamic field.

## 5.5. Social implications

The present work contributes to the currently open debate about AI and job replacement (Autor et al., 2003; Brynjolffson & Mtchell, 2017) in light of the recent sophistication of AI, contributing to addressing the questions proposed by scholars such as Brem et al. (2021). Our reasoning about the human-machine relationship consolidates the collaborative paradigm according to which AI still remains an extension and empowerment of human abilities (Fossen & Sorgner, 2021; Zanzotto, 2019). Concerning the hotly debated job replacement issue, our findings emphasize that even in creative industries machine is a supportive tool. The human actor still assumes a relevant role in the machine's initial setting, providing directions for analysis and interpreting the output. Even for the more creative application, algorithms are anyhow limited to executing whatever *we know how to order it to perform* (Turing, 1950). Hence, at the end of the story, it is the human figure that must understand how to exploit it and interpret the output to extract value from it. The HITL paradigm does not suggest job replacement, but rather it leads to employees upskilling and refocusing on the more actual value-adding phases of the process related to modeling and the problem coding, solution design, and critical assessment of the output.

## 5.6. Managerial implications

From a broad perspective, this work enforces the role of AI as an innovation and creativity enabler, providing both primary inputs which trigger the process, both supporting the process itself as a whole. From a managerial point of view, this work highlights some takeouts which can meet several needs directly connected with the innovation process, both at a general level and from a domain-specific or application-specific one.

One of the pervasive themes of the interviews is that the company must embrace an organizational setup that can allow for extracting the maximum value from AI. As explained before, AI adoption can be pointless if not backed by an organizational setup that facilitates the interaction between heterogeneous competencies and knowledge contamination. This is strictly connected with another implication, precisely, companies' awareness about the role of knowledge – and KM – as an enabler of the innovation process. This results in designing processes that imply interactions between different stakeholders inside the company with stages specifically dedicated to knowledge formalization and knowledge sharing, even leveraging the contribution of AI in this direction.

Coming to peculiar domains of application, our research claims the generative part of AI as a tool for the operative stages of content creation, such as supporting social media management efficiently and effectively. Indeed, machine adoption brings less time-consuming processes with more open opportunities for humans to focus on value-added activities and higher output quality, avoiding biases and errors which humans might crash into.

Moreover, we already highlighted the role of synthetic data to address the problems of data scarcity. This is followed also by two important practical implications. On the one hand, increasing data availability allows simulation analysis to reduce uncertainty, one of the main barriers to entrepreneurship during its first stages. On the other hand, generally speaking, synthetic data dramatically changes the rules of AI competitive scenario since the strength of proprietary data assets as a durable competitive advantage will be undercut. Historically, the identification of the owner of certain data has been the most important aspect to understand and evaluate an emerging AI opportunity, in terms of *who* and how might benefit from it. Synthetic data democratizes data availability, allowing even small players to challenge the dominance of big players such as the IT giants (Google, Amazon, Apple, Meta). Hence, synthetic data might serve as a key catalyst for an AI-driven generation of startups, addressing the data barriers to building AI-first products to unleash a wave of AI innovation. An opportunity for companies and entrepreneurs that cannot be missed.

## 5.7. Limitations

This research work does not lack some limitations, concerning both the research design and some intrinsic characteristics of the subject investigated at the current stage.

The companies and the sectors chosen for the interviews have been selected based on a qualitative assessment of three variables identified by the authors, which could be subjected to evaluation biases or lack of some other relevant elements for the aim of the research. Hence, the sample of startups chosen might have failed in capturing some additional insights that a broader and even more heterogeneous sample would have done. In a like manner, the choice of restricting the geographical scope, focusing on the Italian scenario, prevents a larger data collection and, potentially, a larger view.

The insights gathered from the interviews, as pointed out in chapter 4, turned out to be focused on the first two phases of the innovation process described by Cooper. The exclusion of the following phases (i.e., *Concept*, *Development*, *Testing*, *Trial*, *Launch*), equally important and potentially relevant for our research questions, prevent a complete view of the impact of AI on the entire innovation process, which includes by definition every step until the actual commercialization of the product or service. Moreover, some of our findings might be subjected to limited generalizability due to some industry-specific constraints. It is the case, for instance, of the limited applicability of synthetic data for assessing and testing a medical device, which requires clinical validation with real-world data.

The application of AI to business and entrepreneurship is an extremely dynamic topic, and the focus of this work, particularly regarding creativity, is among the newest directions of this technology. Indeed, at the current market maturity, there is still low availability of case studies and tangible projects about the creative use of AI such as generativity. However, this study could be useful in setting a benchmark for further research in such a promising field.

As a last limitation, we point out that we considered AI algorithms as a black box, a tool in the hand of companies. Despite we gathered a smattering of the technical point of view through the interviews with CTOs and data scientists, all the lines of our reasonings did not consider a deep analysis of the inside of the black box. Hence, we cannot detail that much the technical functioning and dynamics which constitute the baseline of our findings, thus reducing the robustness of our arguments.

## 5.8. Directions for future research

These shortcomings open directions for future research in different directions. A quantitative method could be useful to elaborate in depth on our main findings such as the link between AI adoption and the innovation capability of the firm, or the impact on knowledge management through correlation analysis. A promising direction could be conducting an empirical analysis with large data collection to assess whether companies adopting AI in their innovation process can outperform their competitors in innovation output and financial performances. From a company-specific perspective, assessing the performance improvements of the R&D resources and their output would enforce the capability of AI to increase the productivity of the innovation process.

In addition, further qualitative research could consolidate the results and the robustness of our analysis. A broader sample in terms of industries, geographical scope, and kind of companies involved could be selected, enhancing the probability of capturing all the main findings and providing greater solidity to the research. Considering a larger set of industries, a promising future development could be towards people-intensive industries such as consultancy companies, where talent management assumes a relevant role. HR management has a direct consequence on employees' involvement in their job, which is among the key drivers of individual creativity (Amabile, 1997). Recent applications of AI are deemed to impact talent acquisition and retention, leading to a better fit among demand and offers in the labor market. On the other side, enlarging the geographical scope could be also useful to detect the state of the art from a more panoramic point of view, identifying an international benchmark and allowing for comparison among countries. In this regard, of particular interest is the analysis of the US context, which is deemed to be at the forefront of innovation for digital technologies and whose market maturity represents an appealing field for future research. The research could also assume a different point of view by choosing a sample of companies different from our pool of startups. Indeed, considering a sample made up of incumbents (or, generally speaking, non-AI-based companies) could allow remarking on the different approaches adopted compared to startups, and facilitate analysis of how innovation and creativity processes change *before* e *after* AI adoption.

Some of our findings are suitable for being deepened from a technical point of view, opening the black box and driving new research insights. Grounding on our work, further and in-depth technical analysis of the knowledge codification process or the mechanism behind the generation of synthetic data (e.g., GANs process) might represent a promising field for future research.

Finally, future literature works could find a fertile field in the upcoming years, when generativity and the latest innovations will find higher applicability, thus allowing a better understanding of all the facets of the phenomenon.

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# A Appendix A: interview protocol

## Company and interviewee profiling

a) *When was your company found?*

b) *What is the business of the company and your role in the company?*

c) *How long have you been adopting artificial intelligence?*

d) *How are innovation and R&D managed in your company?*

## Use of artificial intelligence

e) *What is the business opportunity that you identified in the market?*

f) *Why did you chose artificial intelligence as the technology upon which your company was found?*

g) *Which are AI features that you leverage most?*

h) *Which are the advantages that AI brings in (i) knowledge collection, (ii) knowledge elaboration for predictive aim, and (iii) knowledge elaboration for creative aim*

i) *Do you think AI gives you a competitive advantage with respect to those competitors which do not use it?*

## Humans and artificial intelligence

j) *How do you manage the human-AI relationship?*

k) *Which are the tasks in which humans is not replaceable?*

l) *With respect to knowledge collection and elaboration, which are the tasks that AI can perform autonomously? Which are those in which AI and humans are complementary?*

m) *With respect to the generation of creative ideas, which are the tasks that AI can perform autonomously? Which are those in which AI and humans are complementary?*

n) *Which is the value added of AI in terms of craetivity and innovation?*

o) *Do you think that you were (and will be) able to increase your innovative capability (both incremental and radical) concerning your non-AI user competitors? Why?*

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