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ARTIFICIAL INTELLIGENCE PERCEPTION OF STRATEGIC DECISION-MAKERS: AN EXPLORATORY STUDY

PHD THESIS

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XXXVII CYCLE

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Introduction: purpose, conceptual background and structure of the dissertation

The topic of Artificial Intelligence (AI) has gained significant momentum in recent years, and it is at the forefront of academic debate in several disciplines for its technological peculiarities as well as for its multifaceted implications for society and for the business word.
The present doctoral dissertation is guided by the aim of investigating the role Artificial Intelligence can play in strategic decision-making contexts and how human-machines interactions and/or the related human expectations at the highest level of the decision hierarchy shape Artificial Intelligence perception.
Although the perspective adopted in this dissertation is managerial rather than technical, it is nevertheless deemed useful to introduce some key concepts from the broad and complex domain of Artificial Intelligence, in order to more effectively contextualise its potential for strategic decision-makers.

The origins of Artificial Intelligence trace back to the 1940s and in particular to Isaac Asimov's publication of "Runaround", the story of a robot that then gave rise to the first studies in the field of robotics (Haenlein & Kaplan, 2019). In the 1950s, the English mathematician Alan Turing published his article "Computing Machinery and Intelligence," in which he described how to create intelligent machines, specifically how to test their intelligence through the so-called "Turing Test". The test introduced the principle of behavioural indistinguishability as a criterion for evaluating Artificial Intelligence, establishing that a machine can be considered intelligent if a human interrogator cannot distinguish it from a human one in a text conversation (Turing, 1950). However, the first use of the term "Artificial Intelligence" traces back to John McCarthy, who coined it in the proposal he wrote with co-authors Marvin Minsky, Nathaniel Rochester, and Claude Shannon, presented to the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) (McCarthy et al., 1955). Numerous definitions of Artificial Intelligence have proliferated since its origins. A few of them are reported for illustrative purposes, as relevant concept of the dissertation.

"Artificial Intelligence is a system's ability to correctly interpret external data, learn from such data, and use those learnings to achieve specific goals through flexible adaptation" (Kaplan & Haenlein, 2019, p. 15). Longoni et al. (2019) define it as "any machine that uses any kind of algorithm or statistical model to perform perceptual, cognitive, and conversational functions typical of the human mind" (Longoni et al., 2019, p. 630). OECD proposes the following broad definition: "an Artificial Intelligence system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different Artificial Intelligence systems vary in their levels of autonomy and adaptiveness after deployment" (OECD, 2024, p. 4). An overlapping definition is also proposed in the Artificial Intelligence Act Explorer of the European Commission .

Various categorisations classify Artificial Intelligence systems in different ways. Two commonly cited approaches are those that distinguish Artificial Intelligence systems according to their capabilities and according to the type of learning.

The former distinguishes between Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI), reflecting the difference between systems designed to perform specific tasks, systems that are endowed with cognitive capabilities similar to human capabilities to perform different tasks that span across different domains, and systems that outperform human intelligence in all cognitive domains (Goertzel & Pennachin, 2007; Searle, 1980). However, based on the current state of technology, AGI and ASI still remain theoretical concepts.

Since learning is a key feature of many Artificial Intelligence systems, especially after the consolidation of machine learning approaches in the 1990s as those systems that improve through experience, another key categorisation is that between Supervised, Unsupervised, and Reinforcement learning Artificial Intelligence algorithms. In supervised learning, the model learns from a labelled dataset, in unsupervised learning it explores hidden patterns in unlabelled data, and in reinforcement learning it iteratively improves based on trial-and-error feedback (Mitchell, 1997).

Within the scope of machine learning, neural networks and, in particular, deep learning architectures, represent a major evolution. They are inspired by the biological functioning of the human brain and are able to learn from complex raw input data by constructing hierarchical representations (Goodfellow, 2016).
Another crucial development in the field is represented by the introduction of the so-called Large Language Models (LLMs), which are capable of performing tasks that require linguistic capabilities. They underpin many general-purpose systems commonly referred to as generative Artificial Intelligence. Being trained on vast amounts of input data, these systems are now able to go beyond analytical tasks (both descriptive and predictive) and engage in the generation of textual content. When combined with additional models they also engage with the creation of non-textual content (e.g. images) (Goodfellow, 2016).

This overview of the technical evolution of Artificial Intelligence provides insights that are useful to frame the overall scope of the dissertation of studying it in relation to strategic decision-making.

Strategic decision-making is positioned at the highest level of the decision hierarchy within organisations. Strategic decisions define the long-term direction of the firm, determining its competitiveness and survival (Ansoff, 1980; Eisenhardt & Zbaracki, 1992). Based on the definition proposed by Simon (1960), strategic decisions are those non-programmed decisions made in novel, ambiguous, and complex situations, for which no predefined standardised rules exist. Their nature therefore implies that decision-makers extensively rely on their judgement, creativity and intuition to identify the most appropriate course of action (Langley et al., 1995; Mintzberg et al., 1976).
Historically, Artificial Intelligence systems have been extensively employed in support of those decisions that are programmed in nature. Such decisions rely on clear sets of inputs and stable patterns on which Artificial Intelligence algorithms strongly perform to generate predictions (Brynjolfsson & McElheran, 2016). Artificial Intelligence has therefore become increasingly relevant for managerial decision-making at operational and tactical levels, for which decision-makers rely on increasingly larger datasets whose complexities exceed human cognitive capacity. In this perspective, Artificial

Intelligence offers the possibility to identify useful patterns and extract useful insights, as well as detailed recommendations on the course of action, which can also be fully automated.

The same logic hardly applies to strategic decisions, which are characterised by the need to complement predictions with human judgment, experience and creativity, as well as the ability to leverage contextual awareness and tacit knowledge (Brockmann & Simmonds, 1997; Nonaka & Takeuchi, 1995). In this perspective, it has been acknowledged that, for strategic decision-making tasks, Artificial Intelligence can only act to augment rather than replace human contribution (Raisch & Krakowski, 2021; Shrestha et al., 2019).

However, the ability of Artificial Intelligence to contribute to strategic decision-making evolved and expanded over time as a consequence of its increased sophistication and potential. In particular, the recent rise of generative Artificial Intelligence has broadened the scope of Artificial Intelligence applications, introducing the possibility to extend its use to exploratory and creative tasks that rely on ideation and interpretation capabilities, beyond purely analytical tasks. In this vein, a broader scope for Artificial Intelligence application at strategic level has been increasingly taken into consideration, as an opportunity to combine predictive and optimisation outputs with recently unlocked generative capabilities, thus offering personalised and contextualised insights potentially useful in support of complex strategic decisions.

This domain is relatively new and offers a compelling, yet inherently challenging, line of inquiry on how various Artificial Intelligence systems can effectively be integrated into strategic decision-making.

Given the high-stake nature, complexity and relevance of strategic decisions, the potential contribution of Artificial Intelligence's increasingly advanced capabilities needs to be examined beyond its technical aspects. This requires an in-depth exploration of the individual challenges strategic decision-makers encounter in imagining or attempting to integrate such systems in their strategic decisions, which are profoundly shaped by their perceptions, expectations and interpretations of Artificial Intelligence, ultimately influencing their willingness and ability to rely on it at the strategic level.

The dissertation is positioned in this area of inquiry, aiming to uncover perceptual and value-related mechanisms underlying strategic decision-makers' interaction with Artificial Intelligence, by employing an exploratory qualitative approach.
In light of the exploratory nature of the dissertation and its managerial rather than technical perspective, Artificial Intelligence is deliberately approached in a broad and comprehensive manner, without restricting the scope to specific systems, models or algorithms. This choice is consistent with a design focusing on overall perceptions and interpretations of Human-Artificial Intelligence interactions at the strategic level.

The dissertation is articulated into three chapters guided by the following logic. While the first chapter aims to provide some clarity on the state of the art of management literature, the second and third chapters consist of two empirical qualitative studies that investigate the strategic decision-makers perception of Artificial Intelligence in different contexts and under two different theoretical lenses.
Chapter 1, entitled *"The Adoption of Artificial Intelligence in Strategic Decision-Making: A Systematic Literature Review"* maps the emerging findings in management literature on Artificial Intelligence in strategic decision-making. This study establishes a foundation for the rest of the dissertation, identifying key thematic areas (antecedents, outcomes, and processes) and reveals the fragmentation of the field and the need for a more integrated and human-centred perspective.
Chapter 2, entitled *"How do strategic decision-makers make sense of Artificial Intelligence?"* is a qualitative study grounded in sensemaking theory that explores how managerial sensemaking of Artificial Intelligence is constructed and which sensemaking patterns determine strategic decision-makers' understanding and interpretation of Artificial Intelligence. The key contribution of this chapter is the development of a typology of four distinct sensemaking patterns: Sceptical Observers, Tentative Explorers, Pragmatic Experimenters, and Visionary Innovators. This typology provides a framework for understanding the diversity of managerial responses to such a disruptive technological solution.
Chapter 3, entitled *"Perceptions of the Artificial Intelligence Among Principal Investigators in Supporting Value Creation: The case of KM3NeT4RR Research Infrastructure",* is a single case study conducted in a knowledge-intensive large-scale

research infrastructure with the purpose of exploring, under the interpretative lens of value theory, Principal Investigators' and Co-Principal Investigators' perceptions of Artificial Intelligence in terms of value creation motives and value destruction risks.

The concluding remarks paragraph summarises the main contribution of the dissertation's findings.

1. The Adoption of Artificial Intelligence in Strategic Decision-Making: A Systematic Literature Review[1]

Abstract

The purpose of this work is to contribute to a comprehensive understanding of whether and how Artificial Intelligence is revolutionising the way strategic decisions are made in organisations. Indeed, despite the increasing use of Artificial Intelligence in business contexts, especially to perform operational and tactical tasks, its potential adoption at a more strategic level to support decision-making still requires further investigation. For this purpose, we conduct a systematic literature review of 68 papers drawn from Web of Science and Scopus databases. We identify three macro-thematic areas: *(1) Antecedents and Risks of Artificial Intelligence use in strategic decision-making, (2) Outcome orientation, (3) Process orientation*. Eventually, some insights on future avenues of research are provided.

1.2 Introduction

Effective decision-making is a crucial factor contributing to organizational success (Blenko et al., 2010). Several literature reviews have been conducted to investigate AI/human collaboration to perform some operational and repetitive tasks such as human resource training, recruitment and performance evaluation (Qamar et al., 2021; Votto et al., 2021; Vrontis et al., 2022) as well as advertising, promotion and pricing activities (Verma et al., 2021; Vlačić et al., 2021), smart manufacturing activities (Cioffi et al., 2020; Wang et al., 2021). These are indeed some of the areas in which Artificial Intelligence use has spread at an incredible pace in the last decades.

[1] This chapter is based on a research paper that was presented, in an initial short version, at the *British Academy of Management (BAM) 2024 Conference* and at the *Sinergie-Sima 2024 Management Conference*. The current full version of the paper has been submitted to the *Journal of Knowledge Management* and is currently under review (first round).

However, a major challenge to be explored is whether and how Artificial Intelligence can provide significant support to human decision-makers for more complex and impactful strategic decisions. Moreover, despite the growing popularity of Artificial Intelligence as a topic at the intersection of different research fields – information science, computer science, and management – its implications for management research in decision-making have been predominantly studied by exploring its use at an operational and tactical level (Niu et al., 2021; Rana et al., 2022). The purpose of this work is to review management literature concerning the adoption of the disruptive technology of Artificial Intelligence in strategic decision-making. Indeed, despite the rapid growth in Artificial Intelligence research, the focus on strategic decision-making is still fragmented. In particular, we aim to address the following questions: *to what extent is Artificial Intelligence now being used for strategic decision-making? to what extent is AI, if used in strategic decision-making, successful? What are the challenges that managers and leaders as Artificial Intelligence users face when using it in strategic decision-making? How does Human-Machine interaction take place in strategic decision-making?*

Our study contributes to extant literature on strategic decision-making by laying the foundations for a broader understanding of the support provided by Artificial Intelligence to decision-makers dealing with strategic choices, clarifying the related antecedents, risks, decision-making process dynamics, and outcomes, and eventually suggesting some future research directions. The study also has some managerial implications: it enhances awareness on the possible uses of such a disruptive technology in making strategic decisions and on the ways human decision-makers can interact with it to achieve better results.

The paper is organised as follows: a background section provides an overview of the concepts of strategic decisions and decision-making, and Artificial Intelligence. The methodology section presents the steps taken to conduct the review. The finding section presents the main thematic areas identified. The discussion section evidences some insights on our findings as well as some future research avenues, followed by a conclusion section.

1.3 Background considerations of literature

This section offers some literature considerations on strategic decisions and strategic decision-making, as well as on the emerging role of Artificial Intelligence in this regard. The purpose is to outline key conceptual foundations that frame the scope of investigation and support the design of the study.

Strategic decisions and strategic decision-making

Strategic decision-making is a core construct for the purpose of this study. Depending on the disciplinary perspective, there are different definitions of what is a strategic decision, based on its nature, characteristics and orientation. In the strategic management field, Mintzberg et al. (1976) propose to rely on the "importance" criterion to identify a decision as strategic. A decision is strategic if it is "important, in terms of the actions taken, the resources committed, or the precedents set" (Mintzberg et al., 1976, p. 246). Strategic decisions are "those infrequent decisions made by the top leaders of an organisation that centrally affect organisational health and survival" (Eisenhardt & Zbaracki, 1992, p. 17). In another view, a decision is strategic when it entails a choice between discretely different alternatives (Leiblein et al., 2018), such as differentiation or cost advantage (Porter, 1985a), or the selection of different organisational forms (Williamson, 1991). An additional definition leverages the idea of a long-term trajectory shaped by strategic decisions, which influence the sustainability of the business, despite the changes that may arise in the external context (Mintzberg & Quinn, 1991). Even the context in which the impact of the decision takes place has been used as a distinguishing criterion. Indeed, strategic decisions pertain to external issues rather than internal ones. Some examples are the identification of the industry in which the company operates or aspires to operate, as well as the definition of its long-term goals and objectives (Ansoff, 1965). Operational decisions have instead an internal focus and pertain to the day-to-day functioning of the organisation, such as resource allocation, scheduling, and performance monitoring (Ansoff, 1965).

Strategic decisions have also been defined based on commitment, irreversibility and reliability (Ghemawat, 1991; Van den Steen, 2017). A decision is strategic also depending on its ability to represent a core guide for other decisions (Van den Steen, 2018). Moreover, Leiblein et al. (2018) focus their definition on the concept of interdependence, claiming that there are three dimensions of interdependence that make a decision strategic: inter-temporal, inter-decision and inter-actor interdependence. The concept of commitment, along with the so-called "scope of the firm", is at the foundation of another framework to distinguish strategic from non-strategic decisions, proposed by Shivakumar (2014). Commitment is measured in terms of the costs arising from the idea of reversing a previously made decision. The scope of the firm is instead defined as the where (market) and the how (organisational activities) of the value created by the firm, respectively by means of the market and organisational transactions. Strategic decisions considerably impact both scope and commitment, neo-strategic decisions that only impact on the scope while leaving the commitment unchanged, tactical decisions mainly affect the level of commitment but not significantly the scope, operational decisions affect neither of the two (Shivakumar, 2014). We elaborate on the above-considered definitions to identify four main characteristics that constitute our guiding criterion for paper selcetion: *1)* the decision implies a long-term commitment, *2)* the decision impacts the where and how of value creation, *3)* the decision pertains to external issues rather than internal ones, *4)* the decision is characterized by a strong interdependence, *5)* the decision contributes to shaping the long-term trajectory that influences the sustainability of the business.

Strategic decisions are the end of a deliberation process that leads to the allocation and commitment of a set of resources to realize the chosen course of action (Davis et al., 1997). In strategic management literature with a focus on strategic decisions and decision-making, two main streams of literature emerged: *content research* and *process research* (Schwenk, 1995). Content research, focuses on the subject of the strategic decision-making process and on its impact on outcomes, with the aim to provide useful insights to improve organisational performance (e.g., (Porter, 1982)). Process research investigates decision processes for strategic purposes (Huff & Reger, 1987). In the stream of process research, the most important choice paradigms, as reported by Eisenhardt and Zbaracki (1992), are: rationality and bounded rationality (Simon, 1960; Simon, 1965), politics and power, and garbage can (Cohen et al., 1972). Another model is the one developed by Mintzberg et al. (1976). Building on Simon's Intelligence, Design, and Choice trichotomy, the authors provide an alternative representation of the process applying it to unprogrammed strategic decisions, renaming the three phases into Identification, Development and Selection, and identifying a set of subphases called routines. Unlike the original rational model, it rejects the idea that the three steps occur sequentially. It allows for the possibility that phases and routines take place in any possible sequence, subject to changes, repetitions, interruptions, revisit of previous phases and cycles (Mintzberg et al. 1976). However, even in recent literature, the interest in strategic management process research is still significant. An example of a more recent elaboration is the organizational decision-making process by Trunk et al. (2020).

Artificial Intelligence and Strategic Decision Making

The term Artificial Intelligence defines all those automated systems that leverage machines to mimic human brain functions, thus being able to think and learn (Russell & Norvig, 2010) and process extensive datasets (Jarrahi, 2018). This is referred to as Weak Artificial Intelligence. Strong Artificial Intelligence is instead supposed to emulate human thinking and possess a conscience, but it actually does not exist yet (Paschen et al., 2019). Common Artificial Intelligence applications based on advanced data analysis provide insights to interpret events, support and/or automate some decisions, and perform repeated actions. Artificial Intelligence is nowadays considered a key support tool for business decisions (Akerkar, 2019; Stone et al., 2020). However, despite its numerous applications in operational activities, its potential in supporting strategic decisions has only recently been acknowledged (Stone et al., 2020; Trunk et al., 2020).

1.4 Methodology

Our study focuses on analysing research on Artificial Intelligence adoption in strategic decision-making by means of a systematic literature review. Systematic literature reviews have become increasingly popular since they provide a rigorous scheme of the activities performed by scholars while conducting a literature review: "assembling, arranging, and assessing existing literature in a review domain (i.e., the 3 As)" producing as an outcome a "state-of-the-art understanding of existing literature and a stimulating agenda to advance understanding through new literature in the review domain (i.e., the 2 Ss)" (Paul et al., 2021, p. 2). A systematic review aims to select and map findings of research papers that meet specific inclusion criteria, consistently with previously defined research questions, applying a replicable and transparent protocol. The adoption of such a scientific method distinguishes systematic reviews from traditional narrative reviews and reduces biases during the review process, thus adding robustness to the findings and conclusions drawn by researchers (Snyder, 2019; Tranfield et al., 2003). The output generated is an overview of evidence in the research domain of interest (Petticrew & Roberts, 2008). This review has been conducted through the steps detailed below and represented in Figure 1.

1. The first step consisted in the identification of Scopus and Web of Science as research database of reference, as well as in the definition and application of a search strategy. The strategy entailed to apply the following search strings in the aforementioned databases: "Artificial Intelligence AND decision*"; "AI AND decision*".

   The identified keywords were deemed appropriate to conduct inclusive research, encompassing the possibility to narrow it down in the following steps of articles selection by applying some predefined criteria. Indeed, the inclusion of "strategic" as a keyword would have prevented from including articles which actually focus on strategic decisions, without necessarily specifying the nature of the decision in the title or abstract. In Web of Science, we repeated the search in both title and abstract fields, applying the following thematic filters: Operations Research Management Science; Management; Business; Economics, Social Science Interdisciplinary, Information Science Library Science; Business Finance. This resulted in a total of 1131 records, having removed duplicates due to the replication of the research in title and abstract. In Scopus we selected "title, abstract and keywords" as field and applied the following thematic filters: Business, Management and Accounting.

   We narrowed the search to English language articles, and we did not specify any date range. This returned 2657 articles, covering a time window between 1961 and 2023.

This procedure resulted in a merged dataset composed of 3788 records, which was reduced to a sample of 3247 after being cleaned from duplicate based on Digital Object Identifier (DOI) as well as on a subsequent manual check.

2. The 3257 articles were subject to a title and abstract screening guided by the general criterion of relevance for the objective of the study. The relevance was assessed based on the following criteria: presence of a management perspective, focus on decision-making and strategic nature of the decision addressed in the paper under evaluation. The first criterion led the authors to exclude all those papers lacking a management perspective, either because their core positioning was in other disciplines far from the business context (e.g. education, disaster management, urban planning) or because, despite their relevance for business purposes, their major aim was to propose new technical solutions or to improve existing ones. These "technical papers" are deeply concerned with technological aspects of the solutions (smart decision support system, specific algorithms, tools or models) while neglecting the managerial impact and implications of such solutions. Among the papers characterised by a management perspective, a selection was made based on the above mentioned second and third criteria. Some were excluded because their main focus was far from decision-making in general. Eventually, many of them were excluded because, although dealing with the topic via the lens of management theories, were focused on non-strategic decisions. To this aim, we employed the dimensions outlined for the identification of strategic decisions (commitment, impact on value creation, external focus, interdependence, impact on long-term sustainability of the business).

   We adopted as benchmark the concept of predominance, thus keeping only those whose object of analysis is represented by decisions with a strategic nature that can be stated based on at least 3 of the 5 dimensions. Following this guiding criterion, papers dealing with operational B2C marketing decisions (such as advertising, online advertising and search engine optimisation, targeting and contents personalisation) as well as with human resources decisions (personnel selection, CVs evaluation), supply chain management operational decisions and smart production decision were not included. On the contrary, other marketing paper with a strategic perspective were included (such as papers on marketing strategy or B2B marketing decisions). However, we decided to include also those papers dealing with both strategic and operational decisions. Furthermore, some papers whose focus was broader (neither exclusively on strategic decisions, nor on operational ones) were included. This second step generated a sample of 138 papers.

3. The sample resulting from the second step was then subject to a more accurate assessment based on full reading. This allowed to decide on the exclusion of some papers whose strategic nature had been previously considered doubtful, while conducting a quality assessment as well. The final sample resulting from this step included 68 papers.

1.5 Findings

Based on our analysis we grouped our themes into antecedents-based, outcome-based, process-based findings, evidencing how the literature until now has tried to shed light on the possible positive or negative antecedents of the adoption of Artificial Intelligence in strategic decision-making, the outcomes resulting from it and some aspects characterising human-machine interaction during the process.

1.5.1 Descriptive analysis

The sample was analysed and categorised to present its key features. This section includes some figures and tables that provide a general descriptive analysis of our sample, composed of the 68 selected papers. Figure 2 represents the sample distribution over time, showing a growing interest in the topic, especially in the last 3 years. Table 1, 2 and 3 respectively present the top journals, authors, and papers. Table 4 provides an overview of methodologies adopted by the papers analysed.

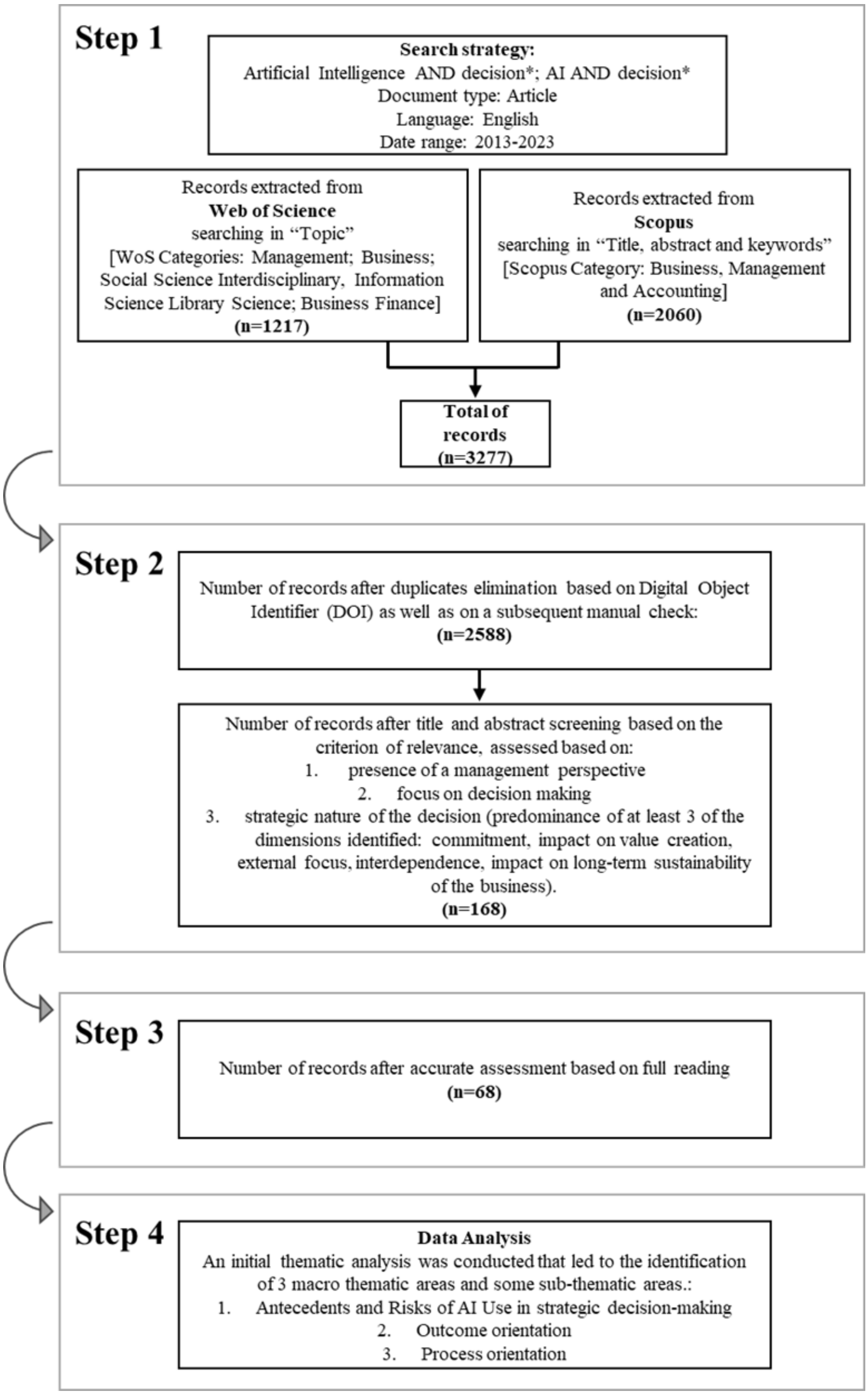

Figure 1: SRL Process (source: our elaboration)

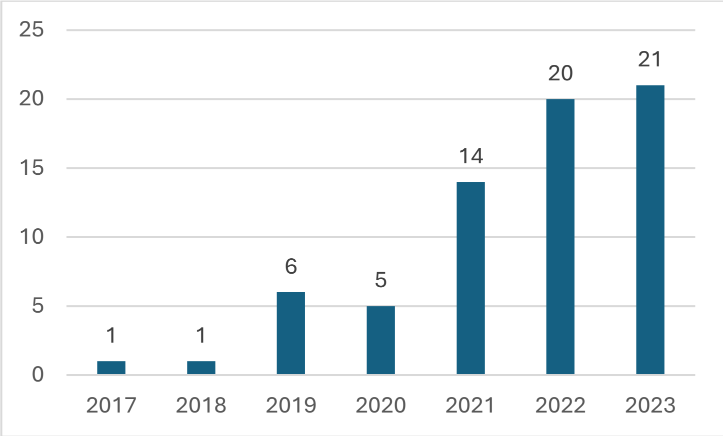

Figure 2: Sample distribution over time (source: our elaboration)

Journal	Publications
Industrial Marketing Management	5
Journal of Business Research	5
Technological Forecasting and Social Change	4
Business Horizons	3
California Management Review	3
International Journal of Information Management	3
Journal of Business & Industrial Marketing	2
Journal of Business Analytics	2
Journal of Business Strategy	2
Strategic Management Journal	2

Table 1: Top 10 Journals (source: our elaboration)

Author	Publications
Dwivedi, YK	2
Edwards, JS	2
Kumar, A	2
Rust, RT	2
Chatterjee, S	2
Huang, MH	2

Table 2: Top Authors (source: our elaboration)

Article Title	Citations
Artificial intelligence for decision making in the era of Big Data - evolution, challenges and research agenda	723
Artificial intelligence and the future of work: Human-Al symbiosis in organizational decision making	526
A strategic framework for artificial intelligence in marketing	236
Organizational Decision-Making Structures in the Age of Artificial Intelligence	177
Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research	108
An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance	107
Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making	88
What influences algorithmic decision-making? A systematic literature review on algorithm aversion	79
Patterns of business intelligence systems use in organizations	75
Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making	74
The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context	72
Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector	71
A Framework for Collaborative Artificial Intelligence in Marketing	56
On the current state of combining human and artificial intelligence for strategic organizational decision making	51
Business Intelligence Capabilities and Firm Performance: A Study in China	49
Artificial intelligence (AI) in strategic marketing decision-making: a research agenda	49

Table 3: Top 15 most cited papers (source: our elaboration)

Methodology	Publications
MIXED-METHOD	**3**
Interviews and Structural Equation Modelling	2
Delphi study, survey, and focus groups	1
QUALITATIVE	**27**
Case study	7
Focus group + in-depth interviews	1
Interviews	2
Literature review / Systematic literature review	16
Literature review and Focus group discussion	1
QUANTITATIVE	**22**
Analytical model development	1
Experiment	5
Hierarchical regression analysis	1
Logistic regression	2
SEM (PLS-SEM or CB-SEM)	12
AI test	1
THEORETICAL	**16**
Conceptual	16

Table 4: Methodological overview of the sample (source: our elaboration)

1.5.2 Antecedents and risks of Artificial Intelligence Usage in decision-making

Some scholars have investigated drivers and barriers to Artificial Intelligence adoption in strategic contexts (Kar et al., 2021), although the majority of the studies dealing with this topic in our sample do not explicitly refer to strategic level decisions but adopt a general perspective on decision-making.
Additionally, some of the studies that mainly deal with outcome and process-oriented factors, provide some useful insights on antecedents that have enriched the general understanding of this aspect of the topic.
Antecedents in terms of barriers and drivers, and risks can be mapped based on the stage they are linked to (design, development/implementation of AI solutions, usage), as well as the actor or factor they arise from (AI, input data, individual human decision-maker as Artificial Intelligence user, organisation, environment).

Design-related antecedents

The design of Artificial Intelligence solutions for decision-making may be hindered by *data-related issues* (data availability, source identification, ethical concerns), which are linked to external issues of information disclosure, as well as by issues at organisational level (difficulty in identifying assets and partners, in assessing risks and the quality of the solution) (Desouza et al., 2020).

Implementation-related antecedents

Some barriers and drivers arise according to the implementation of Artificial Intelligence and are linked to *individual* decision-makers and *organisational* openness towards the integration of Artificial Intelligence in organisations (Fares et al., 2022). First of all, what can significantly hinder Artificial Intelligence adoption even in strategic contexts is the lack of awareness of the need of Artificial Intelligence by decision-makers (Chen et al., 2021). What may also generate resistance toward its implementation is the actual existence of complex business problems that raise the need for Artificial Intelligence support (Chen et al., 2021). At an aggregate level, an overarching organisational culture is also considered a relevant factor in influencing the propensity toward Artificial Intelligence adoption (Eriksson et al., 2020; Fares et

al., 2022). However, even organisational structure and the allocation of resources as well as the overall organisational strategy play a key role in the choice of Artificial Intelligence applications for strategic decision-making (Trunk et al., 2020). Some possible organisational drivers of Artificial Intelligence adoption at a strategic level mapped by (Kar et al., 2021) are: sustainability, productivity, accuracy, speed, customer satisfaction, well-being, improved predictions and learning capabilities in decision-making tasks, cost reduction.
An important *external driver* is represented by information processing requirements, which have been boosted by the emergence of Big Data (Chen et al., 2021).

Usage-related antecedents
Concerning the usage phase, which entails the actual interaction between Artificial Intelligence and human decision-makers, even for those with a good understanding of Artificial Intelligence potentials, the individual attitude toward it can make the difference. The behavioural anomaly of algorithmic aversion as the reluctance of managers to rely on algorithms for their decisions (Mahmud et al., 2023) is undoubtedly a great barrier to adoption, especially in strategic contexts, and it is dependent on individual factors as well as on communication, training, explainability, transparency and participation in the process (the idea of "Humans in the loop" (Brink et al., 2023b; Volkmar et al., 2022)). It can also be influenced by what is referred to as the degree of digital/technological readiness (Eriksson et al., 2020; Kondapaka et al., 2023) and is strictly connected to the lack of trust in the decisions made by Artificial Intelligence solutions (Kar et al., 2021). General personality traits and specific personality traits (among which the propensity to trust) have been found to influence trust (Riedl, 2022). Cao et al. (2021) argue that the overall intention of managers to use Artificial Intelligence depends on some framework conditions but especially on their attitude toward AI, which is influenced by both their expectations and personal concerns, and by their perceived threats. Other barriers that occur at an individual level are threat to job security (Chen et al., 2021; Kar et al., 2021), perceived risk and reliance on AI, as well as perceived control over Artificial Intelligence (Solberg et al., 2022). Ethical concerns on the lack of moral responsibility of Artificial Intelligence algorithms for their decisions are also relevant in shaping human attitude (Trunk et al.,

2020). Relevant risks are represented by over-reliance on Artificial Intelligence decision-making (Jiang et al., 2023), and the lack of awareness by managers on the accountability and responsibility of their decisions, when based on Artificial Intelligence suggestions (Volkmar et al., 2022). Some barriers however arise at a higher *organisational level*. Examples are lack of Artificial Intelligence talent, lack of Artificial Intelligence strategy, lack of infrastructure, challenge in problem selection and lack of leadership commitment (Kar et al., 2021). The Artificial Intelligence literacy of those who are supposed to interact with it represents an important driver (Trunk et al., 2020); on the contrary, the lack of trained people may represent a barrier (Desouza et al., 2020). Potential risks are represented by the spread of a "Blame-AI" culture (humans indeed tend to be more tolerant with other humans than they are with AI) (Volkmar et al., 2022).

There are then some antecedents which have their roots in *Artificial Intelligence characteristics* and functioning as well as in the *input data*. The main factors extrapolated from the reviewed papers are the following: budding state of Artificial Intelligence (it may be too narrow-focused and not suitable to the type of company and its level of maturity); reliability and error tolerance, biases and accuracy; data and privacy concerns (Chen et al., 2021; Jiang et al., 2023; Kondapaka et al., 2023), data leakage, and unpredictable Artificial Intelligence behaviours (Jiang et al., 2023), lack of reusable algorithms, lack of usable data (Kar et al., 2021).

At an organisational level, a challenge is represented by the availability of tools to identify bias (Desouza et al., 2020). Some challenges may be linked to specific features of the implemented solution. For the adoption of Artificial Swarm Intelligence (ASI), Metcalf et al. (2019) evidence that synchronicity may represent an issue when applying this kind of Artificial Intelligence as well as the ability to collect participants with truly relevant knowledge for the task and issues concerning the response options. Data transparency is instead a driver of adoption (Trunk et al., 2020).

Some risks are unpredictable Artificial Intelligence behaviours (Jiang et al., 2023), risk of inaccuracy due to the training of Artificial Intelligence on different datasets, lack of transparency and exposure to hackers' attacks (Pietronudo et al., 2022).

1.5.3 Outcome Orientation

A large body of literature explores the outcomes generated by the implementation of Artificial Intelligence to make strategic decisions in different contexts (Anderson, 2019; Kinkel et al., 2023). These studies predominantly adopt quantitative approaches, mainly structural equation modelling methodology. However, some useful insights that enrich the overall understanding of outcomes also emerge from some mixed-method and qualitative papers. A consistent share of quantitative studies that address outcomes are grounded in the resource-based view of the firm (Barney, 2001) alone or combined with the dynamic capability view (Helfat & Peteraf, 2009; Teece, 2007), institutional theory (Scott, 2008) and knowledge management theory. Some of the contributions explicitly refer to specific decisions, while others do not. Many of them are positioned in the field of marketing. The outcome-oriented findings have been sub-categorized based on the outcome measures they focus on: performance measures and competitive advantage, specific decisions, capabilities, decision-related constructs and/or a combination of them. Figure 3 visually shows the outcome-based finding constructs and relationships, while Table 5 provides a detailed overview of hoe they are operationalised.

Impact of Artificial Intelligence on performance measures and competitive advantage
A subgroup identified includes all those studied that comprise an outcome variable linked to firm performance or competitive advantage on which Artificial Intelligence impacts. For example Behera et al. (2023) investigate how the implementation of Explainable Artificial Intelligence (XAI) solutions by a consumer packaged goods retailer can drive sustainable growth. Dawning on the idea that sustainable growth is a problem of decision-making, they conceptualise a model in which XAI, being able to enhance decision-making, positively influences information systems (IS) business value, measured in terms of ability to successfully attain financial goals (financial performance) and ability to accomplish strategic goals (strategic performance), by outperforming competitors in terms of acquiring market share, increasing brand recognition, and effectively addressing competitive challenges. IS business value therefore plays a positive role in possessing a sustainable competitive advantage,

which in turn eventually impacts sustainable growth. Moreover, Abrokwah-Larbi and Awuku-Larbi (2023) use the construct "Artificial Intelligence in marketing" (AIM) – composed of the Internet of Things, Collaborative decision-making systems, virtual and augmented reality and personalisation – and evaluate its impact on small and medium-sized enterprises performance, driven by the ability of Artificial Intelligence to process information and eventually generate previously unidentified insights. These insights provide SMEs with superior knowledge, thus guiding and enhancing the quality of their decisions. The operationalisation of performance made by the authors, along with the financial performance, also includes other measures ranging from a purely operational nature (*internal business process performance*) to a hybrid operational-strategic nature: *customer performance* is indeed dependent on operational decisions and actions but with strategic implications for a firm's competitiveness, while *learning and growth performance* integrates some employees-level learning outcomes to some higher level outcomes, such as the ability to gather and exploit information for new products or services. Focusing on a B2B context, where customer relationship management (CRM) is considered a strategic activity, Chatterjee et al. (2021) show how the shift from legacy to AI-CRM eventually leads to organisational performance and competitive advantage improvements, because it influences B2B engagements, employee experience and information processing. A focus on customer-related measures, again in a B2B context, characterises the work by Chatterjee et al. (2022). The authors show that the integration of Artificial Intelligence to automate some CRM decisions, improves B2B relationship satisfaction (with this relationship being negatively moderated by technology turbulence), and B2B in turn positively influences firm performance, with a positive moderating effect of leadership support. The impact on performance can also be considered in a broader sense, investigating the overall increase in the performance of an organisational function (i.e. increase in the performance of the purchasing function (Allal-Chérif et al., 2021)). AI-based CRM in B2B contexts is also though to drive the general success and growth in marketing, support online brand building and improve marketing performance in designing and managing customer experience and journey (Saura et al., 2021). The adoption of Artificial Intelligence practices influences both financial and non-financial performance, with the forms being measured as profitability, sales and ROI and the latter with some customers-related measures (satisfaction and loyalty) and competitive advantage.

Impact of Artificial Intelligence on specific decisions

The most common fields of study in this group are marketing and investment decisions. We found that some studies explore the role played by Artificial Intelligence in the process that leads to location decisions, concerning both production processes and headquarters. Kinkel et al. (2023) in cross-country research in the manufacturing industry found that Artificial Intelligence use – operationalised with an Artificial Intelligence use index measured in terms of big data analysis, business processes planning and optimisation, and autonomous decision-making processes – is a determinant for relocation decisions of production activities (offshoring or backshoring strategies). Additionally, they document a significant positive moderating effect of digital competencies and a negative moderating effect of international ambidexterity only in the relationship between Artificial Intelligence use and backshoring decisions. The results are explained by the fact that exploiting data and automating some decisions can enable firms to enhance control over global network activities, thus facilitating and encouraging offshoring as a suitable production location strategy. An experimental design is instead adopted by Anderson (2019) to compare the predictive power of different decision models, one of which – the modern approach – entails the use of Artificial Intelligence. The decision outcomes in this context concern the selection of cities for Amazon Inc. to locate its second headquarters.

Other studies were conducted by applying and testing algorithms to assess their performance in making specific decisions. For example, Khosrowabadi et al. (2022) conducted a study in the field of judgemental forecasting by applying a random forest machine learning algorithm. Machine learning algorithms (e.g gradient-boosted decision trees algorithm) are also employed in early-stage investment decisions made by business angels, and in such contexts, the hypothetical performance of the algorithms is higher than the performance of business angels' decisions in terms of returns (Blohm et al., 2022). Eventually, as evidenced by Keding and Meissner (2021) in their experiment, the integration of Artificial Intelligence systems strongly influences R&D decisions, and the decision-maker has a strong tendency to trust AI

	Design	Development/implementation of Artificial Intelligence solution	Usage
Artificial Intelligence and input data	**Drivers/Barriers** • data-related issues (data availability, source identification, ethical concerns) (Desouza et al., 2020)		**Drivers/Barriers** • Budding state of AI, reliability of AI in terms of error tolerance, biases and accuracy; data and privacy concerns (Chen et al., 2021; Jiang et al., 2023; Kondapaka et al., 2023); • data leakage, and unpredictable Artificial Intelligence behaviours (Jiang et al., 2023), • lack of reusable algorithms, lack of usable data (Kar et al., 2021). • data transparency (Trunk et al., 2020). • synchronicity for ASI (Metcalf et al., 2019) **Risks** • unpredictable AI behaviours (Jiang et al., 2023); • risk of inaccuracy due to the training of Artificial Intelligence on different datasets, • lack of transparency and exposure to hackers' attacks (Pietronudo et al., 2022).
Artificial Intelligence user as decision-maker		**Drivers/Barriers** • openness towards the integration of Artificial Intelligence (Fares et al., 2022); • lack of awareness of the need of Artificial Intelligence (Chen et al., 2021).	**Drivers/Barriers** • algorithmic aversion (Mahmud et al., 2023) influenced by individual factors, communication, training, explainability, transparency and participation in the process (the idea of "Humans in the loop" (Brink et al., 2023; Volkmar et al., 2022); • trust in AI systems influenced by general and specific personality traits (i.e. propensity to trust) (Riedl, 2022); intention to use AI, depending on framework conditions and on their attitude toward AI, which is influenced by their expectations and personal concerns, and by their perceived threats (Cao et al., 2022); • threat to job security (Chen et al., 2021; Kar et al., 2021); • perceived risk and reliance on AI, as well as perceived control over Artificial Intelligence (Solberg et al., 2022);

	Design	Development/implementation of Artificial Intelligence solution	Usage
			• ethical concerns on the lack of moral responsibility of AI (Trunk et al., 2020). **Risks** • over-reliance on intelligence decision-making (Jiang et al., 2023); • lack of awareness on the accountability and responsibility of their decisions, even when based on Artificial Intelligence suggestions (Volkmar et al., 2022).
Organisation	**Drivers/Barriers** • difficulty in identifying assets and partners, in assessing risks and the quality of the solution (Desouza et al., 2020)	**Drivers/Barriers** • openness towards the integration of AI (Fares et al., 2022); • existence of complex business problems that raise the need for Artificial Intelligence support (Chen et al., 2021); • organisational culture (Eriksson et al., 2020; Fares et al., 2022); • organisational structure, strategy and resource allocation (Trunk et al., 2020); • sustainability, productivity, accuracy, speed, customer satisfaction, well-being, improved predictions and learning capabilities in decision-making tasks, cost reduction (Kar et al., 2021).	**Drivers/Barriers** • lack of AI talent, lack of AI strategy, lack of infrastructure, challenge in problem selection and lack of leadership commitment (Kar et al., 2021); • AI literacy (Trunk et al., 2020); • the lack of trained people may represent a barrier (Desouza et al., 2020); • availability of tools to identify bias (Desouza et al., 2020). **Risks** • spread of a "Blame-AI" culture (Volkmar et al., 2022).
Environment		**Drivers/Barriers** • information processing requirements, boosted by the emergence of Big Data (Chen et al., 2021).	

Table 5: Artificial Intelligence Antecedents and Risks (source: our elaboration)

systems in this setting, also perceiving that it increases the quality of the decision itself. This opens up the discussion on human-machine collaboration from a behavioural perspective, delving deeper into human perceptions. Human decision-makers may not delegate strategic decisions to AI, but they may accept to be supported by it when making evaluations that lead to the final decision (e.g. investing or not). Additionally, specific Artificial Intelligence solutions may generate specific benefits. For example, Artificial Swarm Intelligence, which does not exclusively rely on historical and subject-specific data but on a "human database" of behavioural data, is thought to be more reliable for some kinds of predictions and the consequent decisions (such as sales forecasting context (Metcalf et al., 2019)).

Impact of Artificial Intelligence on capabilities and outcome measures

Some studies in this theme explore the idea that Artificial Intelligence can contribute to the creation or strengthening of specific capabilities. In a large portion of studies, the capabilities analysed are some of those which in turn drive performance improvements and competitive advantage or influence a specific decision. To this end, Mikalef et al. (2023) explore the mechanism through which Artificial Intelligence competencies influence B2B marketing capabilities (Information Management, Planning and Implementation), and in turn firm performance. In the same vein, Chen and Lin (2021) conceptualise and test a model to show how the three capabilities that compose Business Intelligence – namely sensing, transforming and driving capability (all empowered by Artificial Intelligence solutions) – in addition to exerting an influence among each other, eventually affect firm performance. Consistently, drawing on knowledge management theory, Bag et al. (2021), incorporate in their model three variables that operationalise the capability to create knowledge on the customer, user and external market, and a decision-related variable (marketing rational decision-making). Their results confirm that knowledge creation is enhanced by Big Data powered Artificial Intelligence and positively affects decision-making, which eventually impacts performance.

The integration of Artificial Intelligence in the business intelligence infrastructure also leads to improved performance appraisal capabilities, which affects competitive advantage (Wang et al., 2022). Moreover, Polas and Raju (2021) account for the

contribution of Artificial Intelligence in enhancing the entrepreneurial capabilities of a firm concerning opportunity recognition, development and exploitation, thus indirectly influencing its entrepreneurial marketing decisions. Under a similar perspective, Kumar et al. (2023) investigate the effect of AI-enabled CRM capability on innovative performance measured in terms of service innovation. In all these studies, Artificial Intelligence plays a crucial role in transforming information into usable knowledge to inform marketing decisions at all levels, including strategic ones such as product or process innovation. In the innovation field, the role played in reaching a final innovation decision also takes into account its contribution to some intermediate outcomes in terms of innovation capabilities (Recker et al., 2023). Furthermore, in a study focused on product innovation decisions, Jiang et al. (2023) evidence how the improved efficiency in the final decision is greatly due to the enhanced capability of both internal and external stakeholders to collaborate with each other, enabled by Artificial Intelligence.
In their conceptual framework, Chen et al. (2021) highlight the support provided by Artificial Intelligence adoption to learning capabilities and then to some measures of financial, relational (in the B2B marketing context) and innovation outcomes. Other decision-related capabilities that can be reinforced by Artificial Intelligence are rationality, creativity, knowledge creation capability and absorptive capacity, as well as collective intelligence, but also the capability to innovate the decision-making process itself (Pietronudo et al., 2022). In a B2B context, Artificial Intelligence solutions can lead to the development of AI-based partner relationship management (AIPRM) capabilities and therefore improved AIPRM related decision-making, which in turn influences B2B information processing and B2B partner engagement for climate change management, which eventually impact firm performance that drives sustainable competitiveness (Samadhiya et al., 2023).

Impact of Artificial Intelligence on capabilities and/or decision-related constructs
Some contributions explicitly account for the role of a decision-related variable (alone or in addition to a capability-related variable) in influencing performance. These constructs generally express a measure of decision-making performance in terms of accuracy, precision, reliability, time and effort (Speier et al., 2003). For example,

Rahman et al. (2022) test and confirm the hypothesis that marketing analytics capability – the ability to gather, organise, and examine data to obtain valuable insights for marketing decisions – is positively related to competitive marketing performance. This capability is strategic in nature: on the one hand, it allows a more aware product and differentiation based on a deeper understanding of customer needs, on the other hand, it supports learning about and reacting to the competitive environment. A relevant finding of their work is that this relationship is mediated through *holistic marketing decision-making* and strengthened by the *adoption of AI*, which also positively moderates the connection *between marketing analytics capability* and *holistic marketing decision-making*. In this stream, Krakowski et al. (2023) propose a more complex conceptualisation of the relationship between AI, human capabilities and competitive advantage. What they find is that the substitution of human cognitive capabilities, which are considered strategic to gain competitive advantage, with a widely accessible resource such as AI, would eventually erode competitive advantage, and this is consistent with the resource-based view (RBV) theoretical framework. However, their results also show that the combination of human cognitive capabilities referred to previously unrelated domains and machine computational capabilities generates new and enduring advantages. Therefore, according to these findings, the evaluation of the role of Artificial Intelligence in enhancing competitive performance should account for the degree of support provided to human decision-makers. Artificial Intelligence is considered to generate a general improvement in decision-making efficiency and accuracy while also reducing risk and costs of incorrect decisions (Chen et al., 2021).

Artificial Intelligence generally leads to better entrepreneurial decision-making, enhancing the customer knowledge discovery capability as well as the industry benchmarking capability, generating a deeper understanding of customers' preferences and of the competitive environment, and guiding in the identification of market opportunities and in the resolution of operation-related issues (Amoako et al., 2021; Li et al., 2022). However, not only does Artificial Intelligence boost human decision-makers' analytical capabilities, but it also supports their creativity and is becoming increasingly good at performing tasks that require tacit judgment or emotions sensing (Duan et al., 2019). Using the lenses of ambidexterity theory, AI, along with Big Data and an adequate human-Artificial Intelligence interface, is also thought to influence decision quality, decision-makers' rationality and their intuition (Di Vaio et al., 2022). Artificial Intelligence provides a valuable support to decision-making processes aimed at managing complexity and solving uncertainty, increasing the quality of business model- related strategic decisions (Cavazza et al., 2023).

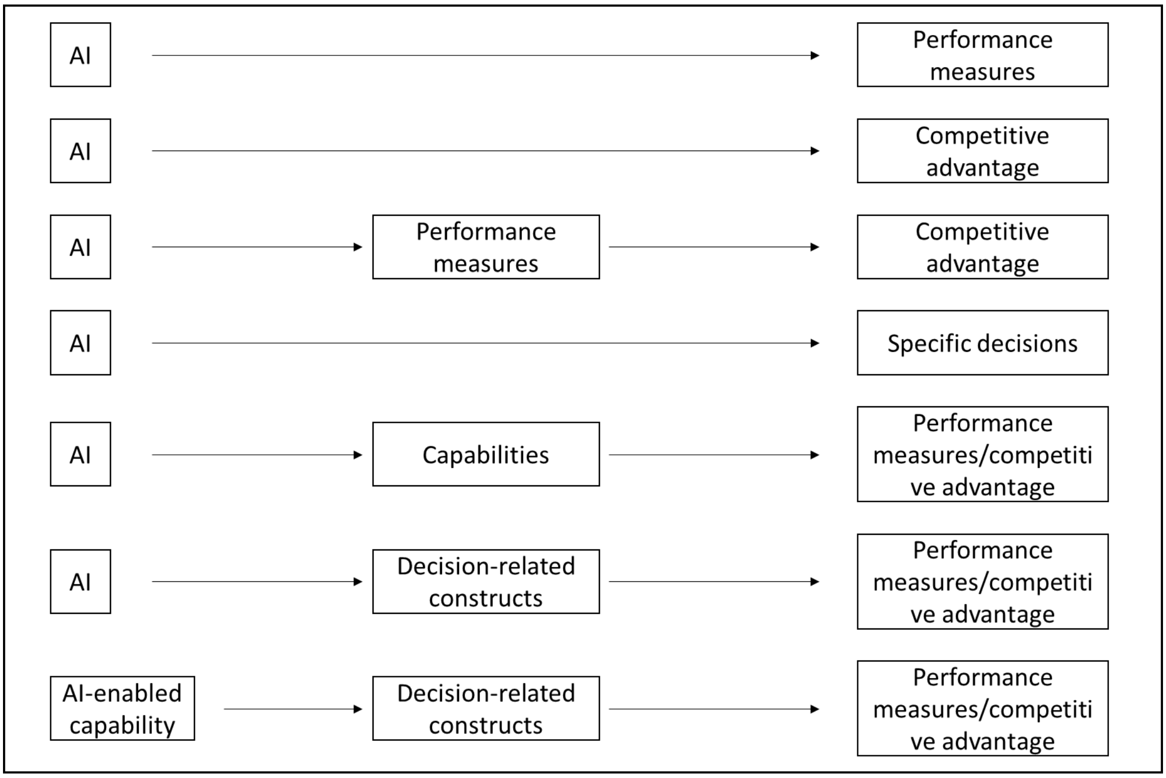

Figure 3: Outcome-oriented constructs and relationships (source: our elaboration)

Artificial Intelligence	**AI-empowered capabilities**	**Decision-related constructs**	**Performance and competitive advantage measures**	**Specific decisions**
• AI/XArtificial Intelligence implementation (Behera et al., 2023; Wang et al., 2022; Chen et al., 2021; Rahman et al.; 2022); • Artificial Intelligence in marketing (AIM) – IoT, Collaborative decision-making systems, VR and personalisation (Abrokwah-Larbi and Awuku-Larbi, 2023); • AI-CRM (Chatterjee et al., 2021 Chatterjee et al., 2022; Saura et al., 2021); • Artificial Intelligence use index (big data analysis, business processes planning and optimisation, and autonomous decision-making processes) (Kinkel et al. 2023); • Big Data powered Artificial Intelligence (Bag et al., 2021); • Specific algorithms or decision models (Anderson, 2019; Khosrowabadi et al., 2022; Blohm et al., 2022)	• B2B marketing capabilities – Information Management, Planning and Implementation (Mikalef et al., 2023); • Business Intelligence capabilities – sensing, transforming and driving (Chen and Lin, 2021); • Knowledge creation (Bag et al., 2021; Pietronudo et al., 2022); • knowledge discovery (Amoako et al., 2021; Li et al., 2022); • Performance appraisal capabilities (Wang et al., 2022); • Industry benchmarking (Amoako et al., 2021; Li et al., 2022) • entrepreneurial capabilities – opportunity recognition, development and exploitation (Polas and Raju, 2021); • AI-enabled CRM capability (Kumar et al., 2023); • Innovation capabilities (Recker et al., 2023); • Marketing analytics capability (Rahman et al.; 2022); • Stakeholder collaboration capability (Jiang et al., 2023); • Learning capabilities (Chen et al., 2021); • Human rationality (Di Vaio et al., 2022; Pietronudo et al., 2022)	• marketing rational decision-making (Bag et al., 2021); • partner relationship management decision-making (Samadhiya et al., 2023); • holistic marketing decision-making (Rahman et al.; 2022); • decision-making efficiency (Chen et al., 2021) ; • Entrepreneurial decision-making (Amoako et al., 2021; Li et al., 2022); • decision quality (Di Vaio et al., 2022; Cavazza et al., 2023).	• Financial performance (Behera et al., 2023; Abrokwah-Larbi and Awuku-Larbi, 2023 Chatterjee et al., 2022; Saura et al., 2021; Mikalef et al., 2023; Chen and Lin, 2021; Bag et al., 2021; Chen et al., 2021; Samadhiya et al., 2023); • Strategic performance, sustainable growth (Behera et al., 2023); • competitive marketing performance (Rahman et al.; 2022); • (sustainable) competitive advantage (Saura et al., 2021; Wang et al., 2022; Samadhiya et al., 2023); • Erosion of competitive advantage (Krakowski et al., 2023); • Internal business performance, learning and growth performance (Abrokwah-Larbi and Awuku-Larbi, 2023); • B2B engagements, employee experience and information processing (Chatterjee et al., 2021); • Customer performance Saura et al., 2021; Abrokwah-Larbi and Awuku-Larbi, 2023); • B2B relational performance (Chatterjee et al., 2022; Chen et al., 2021);); • purchasing function performance (Allal-Chérif et al., 2021); • Innovative performance (Kumar et al., 2023; Chen et al., 2021);	• relocation decisions of production activities – offshoring or backshoring strategies (Kinkel et al. 2023); • Headquarter location decision (Anderson, 2019); • Forecasting (Khosrowabadi et al. 2022; Metcalf et al., 2019); • Business angels' decisions (Blohm et al., 2022); • R&D decisions (Keding and Meissner, 2021); • entrepreneurial marketing decisions (Polas and Raju, 2021); • Product innovation decisions (Jiang et al., 2023);

Artificial Intelligence	AI-empowered capabilities	Decision-related constructs	Performance and competitive advantage measures	Specific decisions
	• absorptive capacity, collective intelligence (Pietronudo et al., 2022); • Human creativity (Duan et al., 2019; Pietronudo et al., 2022); • Human intuition (Di Vaio et al., 2022) • Cognitive capabilitites generated by the appropriate combination of humans and machines (Krakowski et al., 2023); • human decision-makers' analytical capabilities (Duan et al., 2019).			

Table 6: Outcome-oriented findings (source: our elaboration)

1.5.4 Process Orientation

Based on our analysis we identified a theme that focused on AI role in the decision-making process rather than its outcome. Quantitative studies in this theme are mostly characterised by experimental design approaches (natural experiment, behavioural experiment, vignette-based experiment) with some studies adopting a structural equation modelling methodology. Concerning qualitative empirical contributions we found some of them dealing with the topic while also focusing on specific types of decisions, marketing strategic decisions (Eriksson et al., 2020), purchasing decisions (Allal-Chérif et al., 2021), product innovation decisions (Jiang et al., 2023; Recker et al., 2023), others instead adopting a general approach to strategic decision-making. The section is organised in some subsections representing the main sub-themes identified: delegation, complementarity of knowledge and skills, intuition, biases. Table 7 summarises the main findings within each of them.

Delegation

A large and varied body of literature in our SLR explores the facets of human-machine collaboration within the decision-making process. The first aspect to be highlighted in this theme is delegation, the mechanisms through which the collaboration itself takes place. For example, Schneider and Leyer (2019) investigate the willingness of managers to delegate strategic decisions to algorithms depending on the decision complexity and situational awareness of the decision-maker. They find that the degree of complexity does not actually influence the likelihood of delegating, while low levels of situational awareness significantly lead to a higher likelihood of delegating the decision to an algorithm. According to Fügener et al. (2022), delegation may occur in both directions: humans to algorithms and vice versa. Indeed, humans are endowed with hidden knowledge that does not fully manifest itself in human behaviour and, therefore, cannot be “taught” to machines but, conversely, machines have a great potential in discovering solutions that go beyond human processing capacity. Therefore, complementarities exist between the two actors, and this represents the starting point of delegation. The combined performance resulting from the collaboration between the two actors should be higher than the performance of the best-performing actor, but it depends on the ability to properly exploit the delegation mechanism. However, as emerges from their experiments, humans are less likely to delegate effectively due to the lack of sufficient metaknowledge, the knowledge that allows be aware of one's own abilities and of the actual difficulty of the task to be addressed with those abilities. On the contrary, Artificial Intelligence is effective in delegating to humans. The collaboration based on delegation may take different forms: hybrid (human-to-Artificial Intelligence and AI-to-human) sequential decision-making and aggregated human-Artificial Intelligence decision-making (Shrestha et al., 2019).

The delegation issue may become even more complicated in big corporations endowed with analytics centres of specialised data scientists. In such contexts characterised by information asymmetry between data scientist and senior managers responsible for making the decisions based on analytical results, a principal-agent problem arises, which can be mitigated by setting clear shared objectives (Willigers, 2020).

Complementarity of knowledge and skills

Other studies aimed at unveiling how human-machine collaboration occurs in terms of skills and cognitive abilities complementarity. Artificial Intelligence has indeed the potential to elevate the degree of rationality in the management decision-making process, bridging the gap between bounded and full rationality, enlarging the scope of knowledge available to decision-makers (Shick et al., 2023). In the word of decision support systems (DSS), Artificial Intelligence started to become a leading factor with the emergence of knowledge-based decision-support systems. These systems aim at providing decision-makers with clear recommendations or advice on the actions to be taken, based on a more advanced and complete knowledge on the field of interest that Artificial Intelligence allows to reach (Nanda & Kumar, 2022).

Although Arnott et al. (2017) claim that there is limited room for a strong interaction between human intuition and the set of rules and algorithms that can inform decisions in the field of strategic planning decisions, other scholars have attempted to shed light on the relationship between the two actors in a strategic decision-making context. In this stream of literature, a fundamental aspect brought up to the discussion is the different knowledge they can exploit. Explicit knowledge, codified and stored, is the easiest to be transferred to and processed by Artificial Intelligence systems. Tacit knowledge is instead rooted in experience, and this characteristic prevents the possibility to train Artificial Intelligence algorithms with it (Kondapaka et al., 2023). However, the tacit knowledge possessed by individuals is thought to make the difference when it comes to strategic decisions, which Metcalf et al. (2019) refer to as *known unknown*. As emerges from the study by Kondapaka et al. (2023), along with tacit knowledge, in a strategic context there are some human characteristics that are hard to be imitated by Artificial Intelligence and therefore define the role of the human decision-maker: experience, creativity, judgment, wisdom. On the other hand, the role played by Artificial Intelligence is justified by its ability to extract patterns from data and may consist of supporting, assisting, reviewing, consulting, inspiring or helping. According to their findings, the harmonisation of the two roles can be reached by connecting the two actors effectively and by reaching the right balance between explicit and tacit knowledge. Therefore, as pointed out by Eriksson et al. (2020), the role played by Artificial Intelligence in strategic decisions is mainly linked to its rational abilities: it identifies, processes and reviews relevant information that will eventually influence the decision. However, some of the interviewed experts argue that Artificial Intelligence can also make the decision, with the manager acting as a supervisor. The role of humans as supervisors demands them a broad understanding of Artificial Intelligence models and the ability to correctly interpret Artificial Intelligence results and suggestions (Trunk et al., 2020).

This is consistent with the evolution of Artificial Intelligence toward the inclusion of creative analytics tasks, which can also support product innovation. According to Recker et al. (2023) the introduction of machine designers that completely replace human designers is able to disrupt product innovation, by performing two core innovation capabilities that characterise the innovation process: searching and discovering and generating design options. Humans can supervise these machine designers, but a good human-machine designer orchestration is needed in order to guarantee the required coordination in some key aspects, such as configuration, sequencing, problem domain, and innovation goal. In each of the mentioned aspects, human-machine collaboration may take place in different ways, depending on the decision range. Concerning configuration, one-to-one, one-to-many, many-to-one, or many-to-many interactions may occur. The sequencing aspect opens-up to human-first, machine-first, or synchronous interaction possibilities. Concerning the problem domain in which the innovation is sought, machine designers are thought to perform best in well-structured problem domains if directed by humans, but they are instead able to work under delegate autonomy via unsupervised machine learning when it comes to discovering patterns in large datasets humans wouldn't be able to scrutinise. Eventually, even the innovation goal (problem-driven or solution-driven) may influence the level of reliance on machine designers. According to the authors, the optimisation of human-machine ensemble orchestration can be pursued by weighing up three different aspects: type of product design, rate of innovation, and potential bias. As emerged also in some quantitative studies, a key aspect of a successful collaboration between the two players is represented by trust. Still in the product innovation field, Jiang et al. (2023) analyse the iterative product innovation process, pointing out another particular aspect of how Artificial Intelligence can assist humans: the enablement of enhanced interactions between internal and external stakeholders involved in the decision from the origination stage to the marketisation stage, allowing to leverage feedback information to feed the iteration loops.

In line with the idea of reaching a harmonious level of collaboration between the two actors, the achievement of a higher-level intelligence can also occur thanks to the implementation of a particular type of Artificial Intelligence solution, the so-called Artificial Swarm Intelligence (ASI). This is relevant when dealing with strategic decisions since it allows groups of highly competent individuals to work and collaborate as a unique "supermind" (Metcalf et al., 2019). The computational power of Artificial Intelligence in such applications is exploited not just to extract insights from data (e.g. machine learning algorithms), but to realise a powerful collaboration between individuals that can provide a valuable contribution to the decision, thus leveraging both explicit and tacit knowledge.
A different perspective on knowledge and skills interaction is offered by the idea that Artificial Intelligence augments human tacit knowledge by supporting humans' learning processes. Artificial Intelligence has been proven to be an effective artificial learning partner that supports humans in learning strategic interactions, imitating the

behaviour and responses of human opponents, thus compensating for the limited training ability of real opponents. This has been tested by Gaessler and Piezunka (2023) in a difference-in-difference framework based on two computer chess natural experiments. The interactions occurring in such an experiential learning context, despite being far from real-life strategic situations, are thought to be useful examples of complex strategic interactions where the potential of Artificial Intelligence in supporting human learning can be tested. The results of these AI-backed computer simulations show that players who are trained with Artificial Intelligence are more likely to win. However, the study also highlights how, since Artificial Intelligence is not affected by idiosyncratic mistakes (blunders) due to distractions, lack of memory or temporary mood, AI-trained players are less capable of taking advantage of opponents' mistakes to eventually win the game. In this sense, Artificial Intelligence cannot be considered a perfect substitute for humans in the training process. Furthermore, they also show that disadvantaged actors are those who benefit more from AI-based training because it compensates for differences in skills distribution.

A few studies focus on specific decision situations characterised by risk and uncertainty. The analytical model developed by Boyacı et al. (2023) delves deep into the interaction between the two types of intelligence (human and artificial) and to what extent they can complement each other in decisions under uncertainty. On the one hand, humans have the flexibility to draw various sources of information, including the precious domain of human knowledge, on the other hand, machines, which are rigid in this sense, are instead more efficient in processing that information. It turns out that an overall increase in decision accuracy occurs due to the support of machines. Furthermore, machines are expected to reduce humans' cognitive effort because they provide information at no cost. However, according to the authors' findings, contrary to expectations, this is not always the case: machines turn out to increase the cognitive effort when the decision-maker is uncertain about the optimal state and is already under a significant cognitive load, whilst they decrease these efforts when the decision-maker is relatively confident about the optimal state. This study is rooted in the idea that the collaboration between humans and Artificial Intelligence can be beneficial in the decision-making process under uncertainty.

According to Trunk et al. (2020), there is a clear division of tasks between humans and Artificial Intelligence such that the definition of goals can only be performed by humans, Artificial Intelligence can outperform humans in collecting information, but the role of humans remains crucial in identifying the relevant sources and in contributing with the non-codified knowledge they own. Then human may equal or outperform Artificial Intelligence in interpretation tasks. In the definition of alternatives, assignment of utilities and probabilities and weighting and decision tasks, Artificial Intelligence support turns out to be precious in performing the mathematical calculations, which are, however, based on rules predefined by humans and will always have to be evaluated by humans. A crucial factor that influences the successful combination of human and Artificial Intelligence knowledge is model explainability, which may vary from transparency to post-hoc explainability (model-agnostic or model specific) (Weber et al., 2023).

In the attempt to conceptualise how machine learning contributes to entrepreneurial decision, Lupp (2022) delineates how the contribution of ML to the two entrepreneurial decision logics of effectuation and causation: they are respectively preferred in uncertain situations and risky situations, and are influenced by ML, which adds further understanding on how humans collaborate with machines. In the process that leads to the selection of a strategic course of action, the thoughts resulting from human cognitive activity interact with the outputs of computer simulations in the attempt to the actual impact of the decision in terms of actions and final outcomes (Pratt et al., 2023).

In marketing research, the role of Artificial Intelligence in the decision-making process – in terms of its support to human intelligence and the degree of complementarity with it – mainly depends on the type of Artificial Intelligence employed. Three types of Artificial Intelligence are identified: mechanical, thinking and feeling AI. Mechanical Artificial Intelligence is endowed with the lowest level of intelligence and is good at performing repetitive tasks, that can be therefore automated (full delegation); thinking Artificial Intelligence processes big data, with the ability to find patterns in it, being also able to learn from its outputs; feeling Artificial Intelligence represents the highest level of intelligence and should be able to analyse and imitate human emotions (Huang & Rust, 2021, 2022). Artificial Intelligence collaboration with human intelligence (collaborative intelligence) can vary depending on the above-mentioned types of Artificial Intelligence abilities. Different AI-HI configurations emerge, based on the strengths and weaknesses of the two actors. On the one hand, machines outperform humans in computational and repetitive tasks ("narrow AI") but its powerful analytical capabilities, applied to different kinds of data at the three different levels – mechanical, thinking and feeling – are mainly non-contextual. On the other hand, humans' strengths lie in their ability to contextualise at the mechanical level, in their intuition at the thinking level and on their biological capability to perceive emotions at the feeling level (Huang & Rust, 2022).

Intuition

In analysing the human-machine interplay, a key aspect pointed out by various scholars, especially in conceptual papers, is intuition, to which humans generally resort for complex decisions (Simon, 1957). Indeed, Artificial Intelligence can contribute to both rational and intuitive decision-making, which characterise many strategic contexts. The support provided to the former is due to its computational power that allows it to analyse historical data as well as to identify and compare different courses of action. However, surprisingly, it can also support the latter. It is undeniable that the reliance on intuitive decision-making on past experiences and feelings that cannot be taught to Artificial Intelligence as well as the lack of data on similar situations that occurred in the past, thus preventing Artificial Intelligence from providing useful guidelines to make intuitive decisions. However, it is anyway thought that Artificial Intelligence indirectly contributes to the creation of tacit knowledge that feeds the cognitive structures of managers by means of the insights provided in those situations where historical data are available and that eventually feed managers' intuition (Tabesh, 2022). Human-machine collaboration in decision-making can be seen as a partnership built on a strict division of work, based on the advantages of each of the two partners. In decision-making situations characterised by uncertainty, complexity, and equivocality, none of the two actors would be sufficient alone. In facing uncertainty, humans contribute by means of their intuition to face the unknown and Artificial Intelligence provides access to useful real-time information. Confronting complexity, humans identify the necessary data and the sources, Artificial Intelligence is responsible for collecting and processing it and humans, again, will be able to select the best course of action among alternatives equally supported by data. Eventually, in dealing with equivocality, Artificial Intelligence contribution consists of analysing sentiments and providing possible interpretations while the human role mainly implies negotiation and the tentative to build consensus. However, humans are considered to have a superior performance in such situations due to their ability to consider the big picture and evaluate some qualitative contextual aspects such as political and social situations (Jarrahi, 2018). (See Shepherd and Majchrzak (2022) on how it contributes to entrepreneurial activity and decisions). According to Vincent (2021), the key to an effective collaboration between human intuition and Artificial Intelligence lies in two factors: a high level of expertise of the decision-maker and the ill-structured nature of the decision. On the one hand, individual expertise based on domain-relevant knowledge, which is crucial for making intuitive decisions in the specific domain, provides the decision-maker with a sufficient level of confidence to delegate. On the other hand, in the case of structured decisions predominantly derivable from logical analysis, the dominant trend would be to fully delegate to AI, since humans cannot compete with its analytical capability. The author proposes two different approaches that differ in the sequencing of how intuition is combined with AI: the confirmatory method and the exploratory method. The former is preferred when few decision alternatives are available and consists of submitting to the evaluation of Artificial Intelligence the alternatives previously identified by the decision-maker. The latter is instead suitable when many alternatives emerge and involves using Artificial Intelligence to narrow down the set of possible alternatives, which are subsequently evaluated by the decision-maker, who is thus released from the demanding task of processing a large amount of information.

Although human intuition remains an unbeatable human strength, the concept of collaborative intelligence suggests that Artificial Intelligence can complement human intelligence even in intuitive tasks. The idea is that lower-level Artificial Intelligence augments higher-level human intelligence. In this perspective, non-contextual mechanical Artificial Intelligence and analytical thinking Artificial Intelligence are able to augment intuitive thinking human intelligence (Huang & Rust, 2022). A step further is represented by the concept of Intelligence Augmentation (IA), according to which the use of Artificial Intelligence allows humans to shift from an intelligent state to a wise state. This augmented wisdom results from the integration between Artificial Intelligence rationality and human emotional ability and enhances the quality of complex decision-making (Barile et al., 2021).

Biases

An aspect that influences human-machine performance and their interplay in the decision-making process and that deserves even more attention at a strategic level is represented by biases. Not only humans but also machines are affected by biases in their predictions and decisions. To explore this topic, Edwards and Rodriguez (2019) clarify how six relevant types of bias typically associated with humans can indeed affect both machines that perform analytics and humans in relating to it at the different stages of the analytics process (acquisition, information extraction, data integration, analytics and interpretation). They are referred to as biases towards the first information received, keeping the status quo, justifying past choices, supporting instinct, problem-solving methods affecting decisions, and lacking forecast feedback. The authors also propose some strategies to overcome them. Similarly, Van Giffen et al. (2022) highlight some biases affecting machines in the different data mining phases and suggest mitigation strategies: social bias, measurement bias, representation bias, label bias, algorithmic bias, evaluation bias, deployment bias, and feedback bias. Their resolution always requires human intervention. Conversely, some behavioural biases affecting human decision-makers can be circumvented by means of algorithms (Hasan et al., 2022). These biases may lead to suboptimal decisions (Brintrup et al., 2023) and exert several effects on the business, including compromised brand reputation, loss of value proposition and sacrificed market opportunities (Bansal et al., 2023).

Delegation	**Complementarity of knowledge and skills**	**Intuition**	**Bias**
• Human-machine complementarity is the starting point of delegation (Fügener et al., 2022); • delegation occurs in both directions: H-Artificial Intelligence and AI-H (Fügener et al., 2022); • it can be hybrid (H-Artificial Intelligence and AI-H) sequential and aggregated (Shrestha et al., 2019) • Artificial Intelligence is effective in delegating to humans while humans are not due to the lack of metaknowledge (Fügener et al., 2022); • information asymmetry between data scientist and decision-makers results in a principal-agent problem (Willigers, 2020).	• Artificial Intelligence bridges the gap between bounded and full rationality (Shick et al., 2023); • Artificial Intelligence contribution is based on its rational ability to extract patterns from data in order to support, assist, review consult, inspire or help (Kondapaka et al., 2023); • unlike explicit knowledge, tacit knowledge, experience, creativity, judgment, wisdom cannot be transferred to Artificial Intelligence and can only be exploited by humans to make strategic decisions (Kondapaka et al., 2023; Metcalf et al. 2019; Boyacı et al., 2023); • Artificial Intelligence can perform some creative analytics tasks and humans can act as supervisors (Recker et al., 2023); • division of tasks: H identifies source, Artificial Intelligence collect and processes informations, HI uses noncodified knowledge, both perform interpretation tasks (Trunk et al., 2020); • complementarity may take different forms (one-to-one, one-to-many, many-to-one, or many-to-many) and sequences (human-first, machine-first, or synchronous) (Recker et al., 2023); • Artificial Intelligence can augment human tacit knowledge by supporting humans' learning processes (Gaessler and Piezunka, 2023);	• Human intuition allows to face the unknown, Artificial Intelligence provides access to useful real-time information to manage complexity (Jarrahi, 2018); • intuitive decision is based on past experience and feelings that cannot be taught to Artificial Intelligence but Artificial Intelligence can indirectly contribute to feed intuition (Tabesh, 2022); • intuition can be combined with Artificial Intelligence in 2 ways: confirmatory method (submitting to the evaluation of Artificial Intelligence the alternative identified by HI) and exploratory method (Artificial Intelligence narrows down the set of alternatives, subsequently evaluated by HI) (Vincent, 2021); • lower-level Artificial Intelligence augments higher-level HI (Huang & Rust, 2022); • Artificial Intelligence allows humans to shift from an intelligent state to a wise state referred to as Intelligence Augmentation (IA) (Barile et al., 2021).	• Biases may lead to suboptimal decisions and negatively influence performance measures (Brintrup et al., 2023; Bansal et al., 2023); • biases can affect both humans and machines along the analytics process (acquisition, information extraction, data integration, analytics and interpretation) (Edwards and Rodriguez, 2019); • some biases are typical of machines and can be solved by humans: social bias, measurement bias, representation bias, label bias, algorithmic bias, evaluation bias, deployment bias, and feedback bias Van Giffen et al., 2022); • Some behavioural biases are typical of humans and can be solved by machines (Hasan et al., 2022).

Table 7: Process-oriented findings (source: our elaboration)

1.6 Discussion and Future Avenues for Research

The thematic analysis led the identification of three macro areas of research on the topic of Artificial Intelligence support to strategic decisions: Antecedents and Risks, Outcome-oriented and Process-oriented. What is worth noting is that research on antecedents is still scarce. Most attention has indeed been placed on antecedents of Artificial Intelligence in decision-making at more operational or tactical levels, but the strategic level requires further investigation. Additional qualitative research would offer richer insights on specific antecedents linked to strategic decisions peculiarities. In particular, little is known about design-related antecedents and about whether and how all the mapped antecedents are influenced by individual decision-makers perceptions, as well as how they interact between each other to shape the final solution of decision-makers on adopting Artificial Intelligence and on employing it for strategic purposes. Indeed, how strategic decision-makers interpret Artificial Intelligence and its potential in this context as a result of their perceptions and expectations would critically explain their tendency toward Artificial Intelligence adoption as well as their resistance.

The macro theme of Outcome-based findings is characterised by a prevalence of quantitative studies aimed at providing evidence of the relationship between Artificial Intelligence adoption and different types of performance and competitive advantage measures. Some studies adopt a general approach to decision-making, thus providing insights applicable at the different decision levels, others focus on specific decisions such as innovation, R&D, investment decisions, marketing decisions (especially B2B strategies), and location strategies. However, on the one hand, the studies with a narrow focus are limited in number, on the other hand, there is a wide range of strategic decisions that have not been explored yet. Future studies may therefore further investigate the above-mentioned decisions as well as explore whether and how decision-makers could take advantage of Artificial Intelligence support in new market entrance, alliance decisions or internationalisation decisions. The introduction of decision-related variables that account for decision efficiency explicitly is a quite recent trend. Furthermore, Artificial Intelligence adoption, even in contexts concerning decisions with strategic implications, is often considered alongside operational-level efficiency improvements. Further investigations are needed to unveil the mechanisms that lead to the evidenced performance improvements. Additionally, in this theme, the introduction of decision-related variables that account for decision efficiency explicitly is a quite recent trend. Future quantitative studies may identify further decision-related constructs and provide evidence of this relationship.

Scholars in this field evidence the fact that the improvement in decision-making is accompanied by an increased operational efficiency (e.g. automation of lower-level task which frees up managers and allows them to concentrate on more strategically relevant tasks).

Overcoming the logic of measurables outcomes, the effects of Artificial Intelligence may also be shaped by decision-makers interpretative lens and perceptions, which may fuel different attitudes and determine whether Artificial Intelligence is fully embraced as a potential source of advantage or feared as a threat.

Further research may also investigate antecedents and barriers, along with outcomes, under the lens of value creation theory, to reveal how they are perceived as value creation motives and value destruction risks. In this perspective, potential links between antecedents and measured or perceived outcomes may be further investigated by future research.

In addition, drawing on some initial findings on AI-empowered cognitive capabilities, future studies could also explore the impact of Artificial Intelligence on strategic thinking as cognitive processes and managerial skill that feed the individual decision-making process, as well as the impact on already established measures (i.e. decision-related constructs and performance metrics) as dependent on the empowerment of strategic thinking.

The process-oriented theme brings out several insights and inspirations for future research. From the analysis of the contributions in this field and adopting a process perspective, it is evident that AI's role in strategic decision-making may not necessarily be confined to a support/advisory role (giving advice or suggesting a solution). This role may change depending on the activity involved in the decision-making process: Artificial Intelligence can substitute humans in the computational activities involved in even strategic decisions and may complement humans in the final stages of the process where human intuition is empowered by the insights emerging from advanced analytics. However, what existing research still overlooks is that the effectiveness of human-machine collaboration may be strongly influenced by managers' perceptions and ways of interpreting Artificial Intelligence through their cognitive frames. Such perceptions may be also explored as antecedents of the metaknowledge that underpins an effective human-to-machine delegation. Metaknowledge may also be explored as intermediate construct moderating the relationships between Artificial Intelligence and AI-related outcomes.

The key and irreplaceable importance of humans is undeniable when previously domain-unrelated cognitive capabilities (Krakowski et al., 2023) are required, in ill-structured decision contexts (Vincent, 2021). Qualitative investigation may lead to a deeper understanding of human-machine synergies at the different stages of the strategic decision-making process as theorised by Mintzberg et al. (1976) (Identification, Development and Selection) with the purpose of revealing the differences in knowledge and skills complementarity.

Findings	Future research questions
Antecedents	• Which are all the human-related and machine-related antecedents of Artificial Intelligence at a strategic level? • How do they impact the collaboration of Artificial Intelligence at the different stages of strategic decision-making? • How do antecedents at Artificial Intelligence level, decision-maker level, organisational level and environmental level influence each other? • How are antecedents at all levels shaped by individual perceptions and expectations?
Outcome-oriented findings	• What part of the performance improvements is dependent on the operational efficiency and how much is resulting from the advanced ability to exploit strategic knowledge? • Do knowledge management capabilities linked to both tacit and explicit knowledge mediate the relationship between Artificial Intelligence and decision performance? • Are Artificial Intelligence adoption outcomes influenced by strategic decision-makers interpretations and perceptions? • Does Artificial Intelligence influence crucial cognitive processes for strategic decision-making, such as strategic thinking?
Process-oriented findings	• How does human-machine synergy take place at the different stages of the strategic decision-making process?

Findings	**Future research questions**
	• Are there differences in knowledge and skills complementarity at the different stages of decision-making? • Does Artificial Intelligence contribute to tacit knowledge and intuition enhancement? • How do managers' perceptions influence the adoption and effective use of Artificial Intelligence in strategic decision-making? • How do managers' perceptions influence managers' metaknowledge underpinning effective delegation mechanism?

Table 8: Avenues for future research (source: our elaboration)

1.7 Conclusion and Implications

This study presents an overview of the role played by Artificial Intelligence in the strategic decision-making process. Our findings provide valuable insights to both academics and practitioners and aim to stimulate further research in the field, arguing that AI's contribution may be significant not only at an operational or tactical level but also in making high-impact strategic decisions. However, the study has some limitations. Findings are limited to WoS and Scopus databases and are affected by our keywords choice as well as by the manual selection of the final sample of contributions. Second, other AI-related terms may be considered for future developments or to study the role of specific AI systems. Furthermore, since the focus of the study is represented by strategic decisions, which may concern several different topics and entail the involvement of various organisational functions, our findings rely to some extent on context-specific information, whose generalisability needs to be further tested in future research. However, this was a necessary compromise, in the attempt to create a high-level overarching understanding of Artificial Intelligence in strategic decision-making. As for managerial implications, the work provides insights for a deeper understanding of the AI-empowerment of strategic decision-making, which is a crucial process for firms' success and growth. In particular, it can contribute to enhance manager's awareness on the possible short- and long-term effects of integrating AI in this process as well as on the way it can be exploited to create real synergies, unlocking advantages for both explicit and tacit knowledge, for strategic scenarios' creation and enhanced predictions.

2. How do strategic decision-makers make sense of Artificial Intelligence?[2]

Abstract

This study aims to explore how the perception of Artificial Intelligence is constructed by strategic decision-makers, employing a sensemaking lens. We conduct a cross-country qualitative study based on semi-structured interviews to investigate, via reflexive thematic analysis with a comparative approach, which themes shape different ways of perceiving Artificial Intelligence. The findings evidence that the macro-themes of vision, personal adaptability, praxis, reluctance, Artificial Intelligence accessibility, strategic decision-making quality, strategic decision-making approach and knowledge management capabilities are those through which the perception of Artificial Intelligence is constructed. Leveraging the variety of narratives that emerge from our data, we derive a typology of four sensemaking patterns: sceptical observers, tentative explorers, pragmatic experimenters, visionary innovators.

2.1 Introduction

Artificial Intelligence is evolving and spreading at a rapid pace, reshaping both our daily lives and professional activities in unprecedented ways. Within organisations, the impact of Artificial Intelligence is huge for decision-making processes at all levels, spanning from routine, operational decisions (often fully automatised for greater efficiency) to infrequent and complex strategic decisions. However, the application of Artificial Intelligence at a strategic level is still limited and there is therefore wide scope for improved awareness and practical usage. The decision to use Artificial Intelligence in support of strategic decisions and the related outcomes are inevitably

[2] This chapter is based on a research paper that was presented, in an initial short version, at *Sinergie-Sima 2025 Management Conference*, which was subsequently expanded and developed into the present full version.

influenced by the way Artificial Intelligence and the potential collaboration with human intelligence is perceived.
However, despite the numerous studies conducted so far to investigate Artificial Intelligence use antecedents and outcomes, the role played by individual perceptions in shaping them and their mutual influence is still underexplored.
The purpose of this work is to study how Artificial Intelligence is perceived and conceptualised by strategists, adopting a sensemaking lens. The study is guided by the following research question: *how do strategic decision-makers make sense of Artificial Intelligence as a support tool for their decisions?* To answer this question, we investigate their perception of Artificial Intelligence barriers, drivers and outcomes in order to reach a broad understanding the different ways of perceiving it.
Existing management literature has adopted the lens of sensemaking to investigate several phenomena (e.g., IT adoption (Hsieh et al., 2011), IT value (Tallon & Kraemer, 2007), coopetition (Lundgren-Henriksson & Kock, 2016), CSR (Sendlhofer & Tolstoy, 2022)). Building on this body of research, as well as on those contributions that investigate managerial cognition in relation to technology adoption, the present work aims to examine managers' individual perceptions and interpretations of Artificial Intelligence in relation to its current or potential role in strategy, with the aim to derive typologies that explain differences in managers' attitudes and their actual ability to exploit AI.

2.2 Literature background

The background underpinning the present study is threefold. First, we rely on the literature concerning the role of Artificial Intelligence in strategy and strategic decision-making. Second, we integrate the background on managerial cognition and technology adoption, aiming to unveil peculiarities of Artificial Intelligence adoption based on individual perceptions. Third, the design and analysis of the study are grounded in sensemaking theory.

2.2.1 Artificial Intelligence and strategy

The role played by digital technologies in strategic decision-making is a widely explored topic in management literature (Molloy & Schwenk, 1995; Zhou et al., 2025). However, Artificial Intelligence application poses peculiar challenges and opportunities due to its unprecedented cognitive capabilities (Jarrahi, 2018) that are challenging the traditional paradigm of strategic decisions being made exclusively leveraging intuition, expertise, experience and cognition of strategists (Csaszar et al., 2024).

Prior research in management recently started to investigate this transformation by examining factors that can foster Artificial Intelligence adoption in business decisions, such as communication and training, explainability and transparency and participation in the process (Brink et al., 2023a), or drivers like augmentation, task-technology fit, and organizational capabilities to orchestrate Human–Artificial Intelligence collaboration (Raisch & Krakowski, 2021). In Artificial Intelligence and strategy literature, interest has also been placed on the performance gains resulting from its adoption in terms of overall effectiveness (Allal-Chérif et al., 2021; Csaszar et al., 2024), innovation capability (Kumar et al., 2023) and competitive advantage (Wang et al., 2022), as well as on the forms of Human-Artificial Intelligence interactions that can be established (a solution is proposed by Raisch and Krakowski (2021): full human to Artificial Intelligence delegation, hybrid human-to-Artificial Intelligence and AI-to-human, sequential decision-making; and aggregated human–Artificial Intelligence decision-making), and the dimensions that influence such interaction and compatibility (specificity of the decision search space, interpretability of the decision-making process and outcome, size of the alternative set, decision-making speed, and replicability are proposed by Shrestha et al. (2019)). In terms of attitude toward AI, Ruokonen and Ritala (2023) identify three firms' strategic types in relation to Artificial Intelligence adoption: digital tycoons, niche carvers, and asset augmenters, pointing out the specific challenges they face in exploiting Artificial Intelligence potential for strategic purposes. However, the individual perception of managers in this perspective is still underexplored.

2.2.2 Managerial cognition and technology adoption

Managerial cognition is conceptualised as the set of mental schemes, beliefs and knowledge structures through which managers interpret reality and make strategic decisions (Kaplan, 2011). Prior research in technology adoption established the role of managerial cognition in determining managers' interactions with a technological solution (Swan, 1995), along with what are referred to as technological frames (assumptions, expectations and stakeholders' knowledge) (Orlikowski, 2000), while exploring how such cognitive frames may evolve over the technology lifecycle (Kaplan & Tripsas, 2008). Under a broader perspective, Eggers and Kaplan (2009) show how CEOs' decisions to enter a technology-intensive markets is highly influenced by managerial cognition.

Such cognitive frames therefore shape managerial perceptions that subsequently influence their attitude and action. In relation to Artificial Intelligence as a technology with huge transformative power, there is still scope for further investigation. Some quantitative studies revealed key antecedents of managers' attitude and behavioural intentions (Cao et al., 2021); Chaturvedi and Dasgupta (2024) propose an AI-acceptance-avoidance framework based on a qualitative investigation of managerial perceptions of AI, leveraging cognitive absorption theory.

Some contributions recently expanded the understanding of such perceptions by studying them through the lens of sensemaking theory. In this perspective, Sagodi et al. (2023) investigates how organisations manage uncertainties entailed by AI, deducing four sensemaking mechanisms (i.e., cognition, interaction, regulation, and concretization). Engström et al. (2024) conceptualise the initial sensemaking of Artificial Intelligence as founded on two main dimensions: sensemaking triggered by abstract features, and sensemaking triggered by concrete features. Unlike the two mentioned contributions that adopt organisations as unit of analysis, Übellacker (2025) leverages experts' opinions to study individual perceptions of Artificial Intelligence limitations and how they are re-elaborated and discussed in such a way that influences trust, expectations, learning and readiness at an organisational level. While maintaining the individual as the unit of analysis, the present study shifts the focus to managers responsible for strategic decisions and employs the lens of sensemaking to explore which themes shape their sensemaking and how the combination of their perceptions across these themes determines their overall sensemaking approach and related conceptualisation of Artificial Intelligence.

2.2.3 Sensemaking theory as theoretical lens

Sensemaking theory is recognised as a suitable and valuable framework to enhance the understanding of varying interpretations and responses to AI.

The term sensemaking was introduced by the organisational psychologist Karl Weick to define the process performed by leaders to make sense of the surrounding context and of the complex and shifting phenomena characterising it. He literally defines it as the “making of sense”(Weick, 1995, p. 4).

Sensemaking has also been theorised as a key leadership capability included in a broader “4-Cap” model that encompasses: sensemaking, relating, visioning, and inventing (Ancona et al., 2007), as well as a crucial capability for leaders to “explore the wider system, create a map of that system, and act in the system to learn from it” (Ancona, 2012, p. 3), enabling them to effectively face the unknown.

Weick’s model of sensemaking has been developed over the years (Weick, 1979, 1988, 1995; Weick et al., 2005), entailing changes and updates that eventually lead to the following conceptualisation: ecological change, enactment, selection, retention (Cristofaro, 2022). Ecological change refers to all those trigger events arising from a chaotic reality and that represent the input of a sensemaking process. To address the complexity of such events, leaders as decision-makers undergo the enactment phase: they apply existing mental models to maximise the understanding of the world – the so-called noticing activity – and create their own representation of reality (bracketed environments) through what is defined bracketing activity. People therefore go beyond mere observation and interpretation of events, by enacting and creating their own reality. Leaders are then engaged in the selection activity that comprises the application of mental models with the purpose to categorise cues and reduce equivocality and ambiguity, thus creating a reasoning or schema consistent with the past events and preconceptions (i.e. extraction of cues and retrospection activities). Eventually, the selected schema is retained based on plausibility evaluation (selective retention). This schema in turn influences future ways of building meaning.

In summary, sensemaking within organisations enables leaders to make clarity out of complex and uncertain situations by leveraging cues that emerge from the environment to a create plausible understanding of the event that eventually feeds future sensemaking (Maitlis, 2005; Maitlis & Christianson, 2014; Weick, 1995; Weick et al., 2005).

At organisational level, sensemaking is considered a core activity that impacts, innovation processes (Drazin et al., 1999; Hill & Levenhagen, 1995; Möller, 2010; Shin et al., 2017), learning (Christianson et al., 2009; Schwandt, 2005; Thomas et al., 2001), as well as strategy and decision-making (Gioia & Chittipeddi, 1991; Gioia & Thomas, 1996; Kurtz & Snowden, 2003; Rouleau, 2005; Thomas et al., 1993).

2.3 Methodology

We employ an exploratory qualitative approach to investigate the research question, relying on a cross-country sample and on semi-structured interviews as data collection method. Data were analysed through Reflexive Thematic Analysis with the final purpose to construct typologies of patterns based on the key themes emerged. The following subsections describe each methodological step in detail.

2.3.1 Exploratory qualitative study

A qualitative approach is deemed appropriate, given the exploratory nature of the study, which aims to enhance the general understanding of a complex and still understudied topic, as the adoption of Artificial Intelligence to support strategic decision-making. Qualitative research is suitable to accomplish this goal since it enables a direct interaction with people who have hands-on experience, and exploring their in-depth views, perspectives and interpretations of phenomena and, in particular, of processes (Hinings, 1997). The resulting insights may represent a starting point to expand the existing theoretical perspective in the field (Creswell & Poth, 2016).

Among qualitative approaches, the basic qualitative study has been selected (Merriam & Tisdell, 2015). The unit of analysis is represented by managers as individuals responsible for making decisions with strategic implications.

Our study is exploratory in nature since it aims at capturing the different views and perspectives of managers involved in strategic decision-making. This level of decision-making, compared to the tactical and operational one, is still less impacted by the use of Artificial Intelligence tools. This poses the need for a deeper investigation of how Artificial Intelligence is perceived by strategists, to enhance the overall understanding of the mechanisms underlying Artificial Intelligence adoption and use at a strategic level and future avenues of research. Our study is a cross-country qualitative study. Indeed, participants from both Italy and the North East of England have been involved.

2.3.2 Sampling and data collection

We have adopted purposeful sampling to select potential participants (decision-makers at a strategic level) who can provide rich, relevant, and insightful data for the study (Patton, 1990). In particular: we have contacted 100 potential participants, operating both in Italy and in the North of England. We have received 40 replies, and we conducted 33 interviews. There are contrasting guidelines in the literature concerning sample size for interview-based qualitative studies: ≥ 15 (Bertaux, 1981), 12-60 (Baker & Edwards, 2012), 5-25 (Brinkmann & Kvale, 2015). However, we reached data saturation since many participants referred to similar contents during the interviews.

The following table provides details about the interviewees constituting the final sample.

We have relied on semi-structured interviews as data collection method (Kvale, 1994, 2009). The interview protocol was grounded on existing literature. It included questions on the strategic decision-making process, on the current use or non-use of AI, on the perceived barriers, drivers, outcomes and bias of using AI.

ID	Job Title	Male/ Female
1	Founder & Managing Director	Male
2	Sales Account	Male
3	Founder & CEO	Male
4	General Management Consultant	Male
5	Intelligent Automation Expert, Senior Advisor and Managing Director	Male
6	CFO	Male
7	Innovation Manager	Male
8	Director of Organization & Management Systems	Male
9	Accountable Manager & Executive Director Engineering	Male
10	Co-founder and President	Male
11	Founder & Managing Director	Male
12	Chief Operating Officer	Male
13	Chief Administrative Officer	Male
14	Head	Male
15	Chief Executive Officer/Managing Director	Male
16	Chief Executive Officer & Co-founder	Male
17	Founder & Managing Director	Female
18	Head of Supply Engineering	Male
19	Chief Marketing Officer	Male
20	Director	Male
21	Senior Consultant	Male
22	Managing Director	Male
23	Chief Financial Officer	Male
24	Founder & CEO	Male
25	Founder & CEO	Male
26	Co-founder and CEO	Female
27	Board director	Male
28	Expert	Male
29	Marketing Manager	Female
30	Founder	Male
31	Manager and Lecturer	Male
32	Product Transition Manager	Male
33	Senior Knowledge Specialist	Female

Table 9: Sample of participants (source: our elaboration)

All the semi-structured interviews were conducted via an online platform, four of them in English and 29 in Italian, ranging from 30 to 45 minutes in duration. All interviews took place between September and December 2024.

The participants to our study shared reflections based on both their direct experience and their perceptions of other decision-makers' experiences from their network (e.g. those who show to recognise the potential and the value of Artificial Intelligence also provide insights on the behaviour and approach of those who they think are not open to implementing and using it). Therefore, our findings arise from both these direct and indirect perceptions. In addition to the interview's transcripts, notes taken by the researcher conducting the interview were included in the final dataset. Those notes allow to account for impressions of the researcher that capture nuances emerging from participants' tone and attitude. All of this different data contributed to the final theorizations of strategists' sensemaking patterns of AI.

2.3.3 Data analysis: Typology Construction through Reflexive Thematic Analysis

All interviews were analysed in their original language (Italian or English) to preserve the nuances of meaning conveyed by participants in their preferred language.

The transcripts were initially read multiple times in order to familiarise with the data and some notes were taken on some initial impressions (Yin, 2011). The transcripts were subsequently uploaded into NVIVO 14 to conduct the analysis in a structured way (Jackson & Bazeley, 2019).

We conducted reflexive thematic analysis (Braun & Clarke, 2006, 2021; Cooper et al., 2012) to inductively code and interpret the interview data, which allowed us to deeply and iteratively engage with the data, relying on the researcher's reflections to augment the overall understanding of concepts.

The analysis was conducted adopting an inductive approach (Patton, 2014) and encompassed repeated cycles of reading to review and refine the coding structure, as well as an effort in constructing meaningful narratives to explain the derived second and third order codes. The coding structure is presented in Table 2.

First-order codes	Second-order categories	Themes
Artificial Intelligence Embeddedness in Organisational Culture Commitment to Stay Ahead Openness to Artificial Intelligence Adoption Recognising AI's Strategic Potential	Artificial Intelligence Strategic Foresight and Mindset	Vision

First-order codes	Second-order categories	Themes
Developing Internal Capabilities (tools or teams) Externalising Artificial Intelligence Use Stimulating Bottom-Up Adoption	Capability and Resource Development	
Driving and Leveraging Generational Turnover Gradual Adoption Strategy Individual-Level Experimentation	Implementation Path	
Enhanced Environmental Scanning Human Supervision and Refinement Knowledge Synthesis, Systematisation and Mapping Targeted Evidence Retrieval	Diagnosing and Interpreting Reality	Knowledge Management (KM) Capabilities
Comparative Scenario Analysis Enhanced Stakeholder Communication Opportunity and Possibility Exploration Stimulating New Perspectives	Generating and Articulating Future Trajectories	
Consistency and Error Reduction Data-Driven Rationality Decisional Confidence and Reliability Structure and Precision	Enhanced Decision Integrity	
Challenging Human Conformism Encouraging Risk Taking and Experimentation Facilitating Complexity Management Overcoming Experiential Boundaries	Expanded Strategic Horizon	Strategic Decision-Making (SDM) Quality
Increased Efficiency of Business Processes Increased Proactivity Strategic Time Allocation Time and Effort Saving	Process Optimisation	
Data Security Risks Input Data Quality and Completeness	Artificial Intelligence Input Concerns	Reluctance
Lack of Strategic Depth and Nuances Risk of Hallucinations The Black Box Problem	Artificial Intelligence Model and Output Concerns	

First-order codes	Second-order categories	Themes
Degree of Trust Fear of Cognitive Overwhelm and Dependency Inherent Scepticism and Aversion	Human-Centric Tensions	
Cognitive Openness to Dissenting Views Enthusiasm and Curiosity Personal Technological Culture	Mindset	Personal Adaptability
Courage to Innovate and Embrace Change Digital and Artificial Intelligence literacy	Practices and Competences	
Artificial Intelligence Habitual use in Workflows Embeddedness in Personal Life	Routinisation of Artificial Intelligence Use	Praxis
Awareness of Artificial Intelligence Limitations and Fallibility Skilful Interaction and Prompting Training and Validating Artificial Intelligence Output	Critical Confidence	
Regulatory Framework Social Proof Targeted Artificial Intelligence Skills and Competences	Human and Governance Readiness	Artificial Intelligence Accessibility
Artificial Intelligence Infrastructure and Compatibility Availability of Market-Ready Solutions Economic Viability	Technological and Economic Readiness	
Attachment to Long-standing Habits Reliance on Managerial Intuition Strategic Posture (Reactive vs. Proactive)	Decision-Making Culture	Strategic Decision-Making (SDM) Approach
Degree of Process Formalisation Perceived Process Efficiency	Formal Decision-Making Process	

Table 10: Data structure (source: our elaboration)

After consolidating the data structure, narratives and interpretations of participants were compared systematically to find evidence of how the same theme manifests across different managers, with a comparative approach (Eisenhardt, 1989) . This process allows to explore existing variation in the way strategic decision-makers make sense of AI, which eventually led to the identification of distinct sensemaking patterns as different typologies (Doty & Glick, 1994).

To confer greater rigor and transparency to the comparative process, the themes were calibrated constructing a four-level scale for each theme able to summarise participants' orientations toward it, in such a way that preserves narrative richness while enabling a systematic comparison (see Table 11).

For the purpose of assigning a specific level to each participant for each of the eight themes, a framework matrix extracted from NVivo was used. The matrix enabled to draw on relevant quotations from each participant for each theme and assign levels that enabled moving toward a higher level of synthesis. At this stage of the analysis, the role of the researcher as a *sensegiver* was of fundamental importance (Gioia et al., 2013), both in assigning levels on the basis of participants' quotations and in reasonably deriving them in cases where the participant did not state their position explicitly, but the discursive context and tone nevertheless allowed the identification of their orientation toward the theme. Throughout the process, records were kept of cases in which the assignment was made by inference. Some missing values nevertheless remained. However, within a sensemaking perspective, even the absence of engagement with a given theme may help explain a participant's profile and alignment with one pattern rather than another.

The outcome of this stage of the analysis was a cross-case mapping of overall variation, which enabled an initial screening of the levels of the various themes co-occurring across participants, supporting a preliminary intuitive identification of potential sensemaking patterns.

However, the final identification of the sensemaking patterns was conducted through cluster analysis, based on the assumption that four clusters were present in the data as a result of the first round of intuitive analysis) and adopting the condition that participants within the same cluster should share the same level on at least four of the calibrated macro-themes (or three in cases where assignment could not be made according to this initial criterion).

As a final step, the coding and interview narratives within each cluster were re-analysed to identify consistent typologies of sensemaking patterns of how strategic decision-makers interpret and engage with Artificial Intelligence.

2.4 Findings: key interpretative dimensions

The inductive analysis led to the identification of 8 core themes that shape managerial sensemaking of Artificial Intelligence at strategic level. In line with sensemaking theory, we look at Artificial Intelligence as chaotic reality managers are expected to face. In this regard, adopting the sensemaking lens, the emergence of increasingly powerful Artificial Intelligence tools and sophisticated models represents an *ecological change* that triggers managers' sensemaking processes, given the ambiguity and uncertainty associated with it.

The themes that emerged from the study, namely *Vision, Strategic Decision-Making Approach, Personal Adaptability, Praxis, Reluctance, Knowledge Management Capabilities, Strategic Decision-Making Quality, Artificial Intelligence Accessibility,* are interpretative dimensions that characterise the sensemaking process throughout the *enactment* and *selection* phases.

Eventually, *retention* is the phase in which different typologies in terms of sensemaking patterns are placed. These patterns were derived from the comparative analysis of the findings, following the logic of dominance to account for potential overlaps and nuances, thus revealing they are not rigid and mutually exclusive in nature.

Each typology embodies a sensemaking pattern resulting in different meaning being attributed to AI, which will be discussed accordingly.

L	VISION	KM CAPABILITIES	SDMQUALITY	RELUCTANCE	PERSONAL ADAPTABILITY	PRAXIS	Artificial Intelligence ACCESSIBILITY	SDM APPROACH
1	Absent or minimal vision	Marginal capabilities	Minimal or adverse impact	Low reluctance and critical trust	Rigidity	Absent or sporadic use	Distant or uncertain accessibility	Intuitive
2	Emerging vision	Diagnostic capabilities	Process optimisation	Selective prudence	Emerging adaptability	Exploratory use	Fragile accessibility	Hybrid
3	Guiding vision	Potential transformative capabilities	Selective improvement	Cautious stance	Pragmatic adaptability	Frequent use with scope for improvement	Conditional accessibility	Analytical
4	Transformative vision	Experiential transformative capabilities	Integrated enhancement	Strong resistance or aversion	Advanced adaptability	Routine and critical use	Structured accessibility	Proactive

Table 11: Calibration of sensemaking themes (source: our elaboration)

2.4.1 Vision

This first macro theme is shaped by aspects of strategic foresight and mindset, implementation path, and capability and resource development. In this sense, vision in relation to Artificial Intelligence is the result of how favourable decision-makers' mindset is, as well as of the concrete efforts made by them to experiment with it.

Artificial Intelligence Strategic Foresight and Mindset

This sub-theme embraces some of the cognitive and cultural aspects that shape managerial vision with reference to Artificial Intelligence adoption at strategic level. It is articulated in the first level codes of Commitment to Stay Ahead, Recognizing AI's Strategic Potential, Openness to Artificial Intelligence Adoption, Degree of Artificial Intelligence Embeddedness in Culture. In essence, Vision is first reflected in the attitude of striving to remain competitive and being ahead of competitors by leveraging market trends. In this sense, managers with a stronger vision are particularly concerned with not falling behind in the adoption of AI. Thus, even when they acknowledge lacking adequate understanding of the technology, they more or less actively seek to acquire the necessary knowledge to become aware of its potential. In doing so, they can be motivated by the fear of being late, but also, in some specific industries, by the pressure of investors who explicitly value the use of AI.

This idea suggests that visionary leaders perceive Artificial Intelligence in today's environment as a strategic urgency, an imperative that translates either into trying to be "first movers" or, at least, avoiding being the last to act, sometimes deliberately taking the time to leave the technology settle, stabilise, and become more reliable, thus acting as "calculated followers" that harness Artificial Intelligence while mitigating the risks of premature adoption.

A fundamental aspect that determines the degree of vision among leaders lies in whether and how much they recognise Artificial Intelligence not merely as a temporary trend but as a genuine epochal shift. Limited vision is manifested by not acknowledging Artificial Intelligence as a concrete support for decision-making and thus not considering it worthy of investment (P20) or when its value is recognised only in hypothetical or futuristic terms. In this sense, some managers appear to be in a process of gradually developing awareness of Artificial Intelligence and its potential, yet they still lack real and concrete knowledge, hands-on experience, and a clear pathway to adoption. At the same time, varying levels of willingness to invest may coexist with such uncertainty, since ignoring Artificial Intelligence is often perceived as a risk of exclusion. A more developed vision, by contrast, manifests in the perception of Artificial Intelligence as a source of competitive advantage, with full awareness of its transformative potential, not only for decision-making processes but for life in a broad sense (for instance, imagining a world in which routine tasks are handled by AI, leaving humans free to focus solely on enjoyable activities). The extent to which leaders recognise the value and strategic potential of Artificial Intelligence strongly shapes their openness toward its adoption, whether in the presence or projected into the future as a desire or expectation, and their readiness to incorporate it into decision-making activities.

A closed attitude typically characterises those who do not believe Artificial Intelligence could ever know things better than them, or who consider the strategic choices in their sector as being immune from its benefits. Greater openness, instead, is revealed by the willingness to experiment, even by playing with tools such as ChatGPT or Copilot, while noting the improvements these tools continuously show. The most widespread stance, however, even among the most visionary leaders, is pragmatic yet cautious: they remain open to increasingly pervasive uses of Artificial Intelligence but still don't see it as a potential substitute of humans in making strategic decisions.

The degree of vision is also closely related to the extent to which the use of Artificial Intelligence is embedded within the organisational culture. Organisations led by more visionary leaders tend to be characterised by a pronounced Artificial Intelligence culture, in which its use is taken for granted across different levels of the organisation. This happens because Artificial Intelligence is strongly promoted top-down, by those who hold the authority and power to decide whether to invest in it to support a wide range of tasks and decisions. The integration of Artificial Intelligence into organisational culture therefore has a dual role: it represents an expression of strong vision, while at the same time reinforcing and sustaining that vision over time.

Implementation Path

Different methods and speeds of Artificial Intelligence adoption reflect different implementation paths. Among the visionary managers, a recurring theme is the tendency to engage in individual experimentations with AI, sometimes playfully or during spare time, as a way to test the tools and learn how to use them. These experiments, which in some cases evolve into productive applications supporting decision-making once the value of Artificial Intelligence is appreciated, can help overcome the impasse faced by large organizations in promoting a structured and, to some extent, institutionalised use of AI, given the novelty and uncertainty that still surround it. Experimentation often entails testing Artificial Intelligence outcomes (for example, evaluating ex post the validity of its suggestions against actual decisions) or seeking to maximize its potential by combining different tools to create synergies. This already reflects a more conscious and sophisticated use of AI.

At present, a major obstacle to implementation is widely attributed by managers to the limited vision of "old-school" leaders. The coexistence of multiple generations can result in conflicts (this is more frequent in family firms), where older generations seek to hinder innovations promoted by the younger ones. This, however, is not always the case. In some instances, even old-school managers recognise the opportunity carried by Artificial Intelligence and actively foster generational turnover, using younger leaders as catalysts for this transformation, providing them with full autonomy in managing it.

Similarly, there are cases in which senior managers themselves display genuine enthusiasm for engaging with AI, actively promoting it within their organisations while relying on the support of professionals and younger experts. This indicates that mindset, more than age, is the key determinant shaping the vision we are describing.

In organisations with low technological intensity operating in traditional sectors (but not exclusively) some visionary managers who have directly experienced the value of AI, often through these informal experiments, position themselves as pioneers by promoting a gradual implementation of AI. This typically begins with low-risk, less critical applications.

"I would never entrust the restructuring of my house to Artificial Intelligence if I had not first tested its reliability, perhaps on something trivial like choosing the best candy; if it makes a mistake there, it doesn't matter" (P16).

Such incremental adoption allows even less visionary colleagues or superiors to appreciate AI's potential. Testing AI's reliability and introducing it alongside "classical" decision-making methods to validate whether its conclusions prove trustworthy is one way of building confidence and fostering trust over time. The main risk connected with this kind of bottom-up approach is a fragmentation of experiences across managers within the same organisation due to the lack of coordination. Opportunities for synergies, collective learning, and knowledge sharing are therefore missed. Such fragmentation may also prevent organisations from achieving potential economies of scale, for instance through centralised license purchase.

Capability and Resource Development

Closely linked to the theme of the implementation path, is the development of AI-related resources and capabilities, which can be regarded as a specific and particularly significant subgroup of implementation paths. Unlike the step-by-step, incremental approach described above (moving from less critical to more critical applications) that can gradually build trust, another strategy consists in externalizing the use of AI. For instance, firms may rely on external consultants to conduct market analyses by leveraging AI, thereby indirectly benefiting only from the final output, the purchased report, without having engaged directly with the tool. This reflects a visionary yet cautious attitude that corresponds to a "buy" strategy. At the other end of the spectrum, the "make" strategy, symptomatic of a stronger vision, is expressed in the willingness to develop Artificial Intelligence tools tailored to the company's needs and/or to create dedicated teams focused on their development or, more broadly, on data analysis with AI. In organisations where top managers have a pronounced vision, they may also actively encourage the adoption of Artificial Intelligence at operational and tactical decision-making levels, thus initiating a form of re-education across the organisation that eventually shapes and influences organisational culture.

2.4.2 Strategic Decision-Making Approach

This sub-theme describes the established norms and processes that shape the strategic decision-making approach, which represents a starting point of varying sensemaking approaches and the organisation's capacity to embrace AI-driven decision-making changes.

Decision-Making Culture

Concerning decision-making culture, the most pervasive theme is the degree of centrality attributed to managerial intuition and past experience. These elements create a key tension between a culture deeply rooted in intuition and experience, and the transition toward more structured, data-driven approaches. In contexts where the decision-making culture is more traditional, decisions are often taken by gut feeling, mainly relying on personal instinct (P4, P17). This is typical of more traditional sectors and among managers with long careers, where lived experience and market sensitivity are often valued more than data. As one manager put it:

"I would argue that leaders at that level value their own experience, intuition, and, in a sense, their understanding of the world – the intangible grasp of facts – far more than a data-driven dashboard" (P31).

Even when the value of data is acknowledged (albeit without yet approaching the use of AI), intuition is still recognised as the starting point.

"Let's say that the process, the process begins from an intuitive aspect. I am very much guided by what I find appealing; if I have to make a business decision, it is not so much about the business itself, but about something that attracts me that is the initial part. Then, before the decision is actually made, it is of course reviewed through a process of data collection, market information, market research, and studies" (P30).

At the opposite end of the spectrum lies the approach according to which the options that emerge from data analysis or from discussions with collaborators are ultimately assessed through intuition, informed by the organization's prior history (P10).

The role of intuition is less pronounced among younger managers, who appear more aware of the ongoing transition, a shift that is also gradually affecting more traditionalist managers (P32). In this sense, intuition is not necessarily abandoned altogether; rather, data (and, in more advanced cases, AI-driven analyses) are increasingly used to substantiate hypotheses initially generated through intuition, thereby reducing the risk of poor decisions taken solely "by gut." As illustrated by P4, an extreme case occurred when an investment decision was made purely based on a phone call from a supplier, later revealed to be the result of mistaken identity, without any accurate assessment, but relying exclusively on instinct.

This transition, however, struggles to take off when the decision-making process is dominated by managers who display limited vision and remain fully attached to intuition and personal experience. Such an attitude prevents them from even minimally recognising the potential support that Artificial Intelligence could provide, often justified by arguments related to the nature of the industry or of the decisions themselves (P7, P13).

The extent to which intuition is relied upon seems to be largely dependent on the organization's strategic posture (reactive or proactive) and on the degree of attachment to existing habits and routines. In this sense, a stronger vision is expressed by proactive leaders who keep their eyes open to identify opportunities to seise to remain competitive, whereas a weaker vision is associated with a more reactive posture, where strategic decisions are taken primarily out of necessity.

Decision-making culture is also shaped, as noted earlier, by the attachment to long-standing and widely shared habits and practices within the organization. For example, if managers are accustomed to exclusively relying on financial data as the input that triggers strategic decisions, it may turn out to be particularly difficult to break that habit, especially if it has proven to be successful over time (P13). In general, leaders with a more open vision show a willingness to break away from these patterns and to rely on Artificial Intelligence tools, even if this requires setting aside established habits or managerial intuitions. As one manager explained:

"At some point you also need to have the courage to accept simulations, because if you keep rejecting them you are certain to make mistakes. Otherwise, you might as well just stick with intuition and not even bother running so many simulations" (P15).

Closely connected to this is the idea that decisions which proved successful in the past generate a sense of trust and security that makes it more difficult to depart from them, resulting in resistance to change and to the acceptance of alternatives beyond established practices, with the risk of missing relevant opportunities. This reflects what is often described as "success breeds inertia". As another manager noted:

"In an emergence strategy approach, you focus a lot on selecting among the things you have done, those that validate assumptions, what worked and how to enhance it, rather than looking at data to build scenarios. What we examine is what has worked, what has advanced the organization toward its objectives, and what has not" (P19).

"You know, the Artificial Intelligence tools have the potential to disrupt that, so actually the advantages that they get for making strategic decisions with Artificial Intelligence are a lot lower, because it is in their interest to carry on doing what they have been doing, since it has worked out for them. So why would you disrupt it? Success breeds inertia, right? That is exactly what it is like in senior organizations that I have spoken to" (P32).

Formal Decision-Making Process

This sub-theme is related to the formal structures and perceived characteristics of the workflows associated with decision-making. In terms of formalisation, strategic decision-making can be assessed in a range between completely informal brainstorming to highly formalised workflows through committees and business plan elaboration and review. A stronger vision toward Artificial Intelligence can emerge both in contexts with a low level of formalization and in contexts with a high level of formalization. In the first case, a more agile decision-making process and the absence of rigid procedures allow managers to follow their curiosity (where it exists) in conducting individual experiments and in integrating Artificial Intelligence into workflows in an emergent way, testing its benefits. In these cases (P1 and P2 are two examples of young managers hugely experimenting with AI), a low level of process formalization facilitates the integration of Artificial Intelligence in a rapid and bottom-up manner.

However, there may be exceptions represented by contexts such as start-ups with unstructured and agile decision-making processes where, nevertheless, the value of Artificial Intelligence is not recognised and there is no willingness to experiment in this direction. This is more likely to occur where there is an environment open to discussion and encouraging critical thinking. For example, P17 recognises the centrality of her role in defining strategic directives, yet she declares that she greatly values dialogue with collaborators. Therefore, while admitting that she has not experimented yet with the use of AI, she nevertheless shows a certain degree of openness, having begun to reflect on the potential benefits, even during the interview itself.

A high level of formalisation does not necessarily represent an obstacle to the integration of AI. Indeed, a strong vision can also emerge in contexts with highly structured decision-making processes, if top management or ownership encourages top-down implementation (e.g., P14), especially in large corporations. Vision is more likely to be lacking in less formalised and traditional contexts, not because, as in start-ups, the need to decide quickly is prioritized, but because the low level of formalisation results from a strong reliance on the intuition of the decision-maker, especially in more traditional sectors. This scarcely visionary managers that favour informality, deny the need of external tools and are set on preserving the status quo.

The decision-making process is also strongly influenced by a logic of efficiency. In this sense, several participants reflected on the role of speed. Making decisions quickly can be seen as a value if speed is regarded as a requirement for survival in highly dynamic contexts. In some cases, speed is even prioritized over the quality of the decision.

“So being super-fast is better than making the right decision. I do not know how to put it, but it is important to make it quickly and maybe get it wrong, rather than take a long time to make the right one?” (P15).

Speed is therefore a double-edged sword, since it can compromise efficiency, and some leaders experience it as something that deprives them of the opportunity to fully leverage their experience and to reflect adequately in order to make the best possible decision.

"I still suffer from this excessive dynamism and this hyper, how can I say, this hyper movement compared to a somewhat more rigid status that also allows you to be more rational, more reflective, and to make decisions in a more reasoned way, whereas like this everything is always a bit too fast" (P17).

Efficiency is also linked to the degree of formalisation itself. For some, the presence of multiple decision-making levels and a high degree of rigidity in considering analyses and future projections is a symptom of greater efficiency. Consistent with this reasoning, low levels of structure in some contexts may result in inefficiency when intuition takes over in a totalising way.

"But the point is that they bought machinery because it all started from a phone call that came to the company from a supplier [...] In the end, the supplier had met a competitor of the company at a trade fair, who had the same problem, and told him: 'Get in touch once you develop the concept of the machine and I will buy it'. In the end, he practically took this as a divine sign" (P4).

2.4.3 Personal Adaptability

The theme sheds light on some individual characteristics of a strategic decision-maker that can determine a stronger or weaker ability to adapt to and embrace AI-driven changes, making sense of it differently. Adaptability is rooted in two subthemes concerning mindset, and competences and practices.

Mindset

Within the domain of mindset fall the individual background predispositions and attitudes that make a manager more inclined to engage with and adapt to the use of AI.

First of all, an "adaptive" mindset is linked to the level of personal enthusiasm and curiosity toward AI, as well as toward technology in general, which in turn fosters a proactive stance. Enthusiasm and passion for technology, which many managers (mostly younger ones but not exclusively) share, place them in an extremely favourable position. This enthusiasm is expressed both in an extremely optimistic vision of Artificial Intelligence as a tool that can improve human life in general by replacing humans in all boring tasks, and in a genuine sense of wonder at the potential of AI, such as solving complex problems in a matter of seconds.

"When instead one should think that in an ideal world in which Artificial Intelligence does everything – this is my vision –and no one has to work anymore because it has stolen all our jobs, and so on, it will be a wonderful world because we could only paint, play music. No one should ever think again about doing boring things, right? From my point of view, this is my vision" (P1).

"And then look, we, we already use Artificial Intelligence. You are talking with someone who is in love with Artificial Intelligence" (P9).

"Look, I am one of those who, as an extreme lover of technology, supports the idea, as a progressive, that in the future Artificial Intelligence will replace most of the jobs that exist today, mine included, first of all the doctor, the lawyer, but also the more creative jobs, the painter. But this does not mean that the painter will no longer exist, it means that the tool will be different" (P24).

Such enthusiasm and curiosity may also be found in managers who have not yet experienced the potential of Artificial Intelligence firsthand, but are eager to do so, for example by showing curiosity in wanting to understand more about it. It may also be present in old-school managers who, by operating in innovative environments, display a certain degree of openness (e.g., P23). Someone also points out concerns on the risk of over-enthusiastic views. Moreover, personal culture understood as technological background can make a difference in shaping the attitude toward AI. Among younger individuals and digital natives, it is clearly easier to observe a broader and therefore more favourable culture, although, as noted earlier, this type of background and the resulting openness can also transcend age, even if knowledge of Artificial Intelligence is found to be deeper and more conscious among digital natives. The complete lack of technological culture therefore represents a barrier to adaptability, which is often recognised as such precisely by those managers who instead show themselves to be adaptive.

"I think for strategic decisions, I think there's a couple of things. So, the first thing is there's like a cultural barrier in that people who are in those kinds of positions to make decisions in large organisations and have usually got there by playing a particular game and having a certain set of skills and being able to do something" (32).

"Rather, it is a cultural and knowledge barrier" (P8).

Another aspect that intensely shapes managers' adaptability is their degree of cognitive openness to dissenting views, regardless of whether these views come from humans (colleagues, professionals, consultants or experts) or from Artificial Intelligence tools, since AI's point of view and perspective can be regarded as comparable to those of a consultant.

From this perspective, managers who tend to be more open to accepting recommendations and suggestions supported by data and analysis, even when such suggestions are more or less unexpectedly in contrast with their own feelings and with the path their managerial instinct would suggest, may prove to be more adaptive toward Artificial Intelligence and genuinely willing to embrace insights and suggestions coming from it, even at the cost of taking a step back.

"And then I take ten steps back, always. Sometimes my team jokes because they say 'I am playing a joker, I am throwing in a joker, I am asking for a joker' so that in case they raise the alarm, we spend a bit more time, one more minute, two more minutes, reasoning about the issue and then they make me understand it better. Then they give me a bit more explanation. And then we get there, and I say, 'Guys, you are right, I take ten steps back and we go as you say'. I mean, so I am already extremely ready, I

mean, if a simulation came out that was in contrast with what I thought, I would absolutely expect myself to accept the contrasting view" (P15).

Practices and Competences

A key factor shaping managers' adaptability toward Artificial Intelligence and their sensemaking of it is their digital literacy, the overall knowledge of Artificial Intelligence functioning, and the adoption of proactive behaviours and practices that support the embracement of innovative solutions.

Digital and Artificial Intelligence literacy is a prerequisite of any form of adaptation, and its absence may act as a barrier to Artificial Intelligence adoption. In a broad sense, digital literacy is fundamental in order to interact with the tool and to develop practical skills that allow its potential to be exploited. Such literacy helps to overcome the initial resistance that may arise toward any novelty. A key comparison made is with the automatic transmission, after which, once experienced, *"there is no going back" (P1).*

Clearly, more specific knowledge of Artificial Intelligence tools is also desirable, yet according to some managers it is not strictly necessary, given the intuitiveness that characterises many user-friendly tools, which can therefore be approached even with only a basic technological knowledge. Several managers admit their lack of knowledge, which represents an obstacle both to the concrete use of Artificial Intelligence and to the understanding of its potential.

Adaptability, however, also has a more emotional dimension, which is reflected in courageous and innovative behaviours. When this is lacking, it becomes difficult to break away from entrenched habits, as discussed above.

"I am ignorant about the possibilities that Artificial Intelligence can offer, so this is the most limiting thing of all. [...] I am also ignorant about the tactical and operational side" (P30).

"I think that you can argue that the best ones will. You look at organisations that are adapting and evolving alongside. The almost stratospheric rise of tools like Copilot, GPT and all of those very flashy consumer focused examples. The ones that can embrace that and identify opportunities to change, but any opportunity to learn is only

as good as the learner themselves, I think. […] Many senior leaders that I have been interacting with are resistant to change" (P31).

2.4.4 Praxis

This theme explores the practical aspects linked to the hands-on application of Artificial Intelligence to decision-making, from the development of a critical confidence in interacting with it to the emergence of a routinised use of AI, bridging the gap between theory and practice.

Routinisation of Artificial Intelligence Use

Artificial Intelligence use experience may become seamless, natural and fully integrated in managers' tasks and life once they reach a high level of routinisation, based on how much Artificial Intelligence use is habitual in their workflow and on how much it is embedded in their personal lives. The findings therefore show that Artificial Intelligence adoption for strategic decision-makers should be regarded not so much as a formal process, but rather as a process of habituation that often originates in one's personal life and gradually transfers into the professional sphere, eventually becoming an almost instinctive action and thus a genuine routine.

Artificial Intelligence integration in personal life often originates from what we defined as enthusiasm and passion for technological progress that foster some experimental uses of Artificial Intelligence as a recreational tool or as a support to some personal domains, including investment management.

"I am a fan of progress, so Artificial Intelligence is among my hobbies. […] Simply put, it may seem silly, but even in my personal life, for example, I try to allocate part of my salary to market investments of various kinds, ETFs, open positions on gold or similar. I provided an idea of how I would like to invest, and I asked for an opinion based on those evaluations. And in this sense, it also gives you a hand" (P2).

It may precisely be the desire to improve one's performance in these personal activities that can also drive the development of an AI-related culture, especially when individuals recognise their own shortcomings in this area. And experimenting in this way can end up further fuelling enthusiasm toward these tools and the progress they are making, an enthusiasm that is eventually also reflected in the professional domain.

"I happened to do some readings out of my own personal interest alongside stock market investments. And so, I draw a bit on the judgments of others, there are expectations, a kind of power" (P3).

"This morning, I received a ruling on an appeal, I do not remember how many pages it was. I put it into ChatGPT and said, 'Make me a summary in 25 lines'. It made me the summary in 25 lines. I was in the car, I pressed and held, and I told it, 'Read it out loud', and it had a reading quality that Alexa or Siri, in their early days but also in recent times, cannot even come close to. […] In my own small way, I began to appreciate the pleasantness in terms of the validity of the support, from a note written in record time, exactly as I wanted it, to the analysis of databases" (P9).

For managers who are further along in the adoption journey, Artificial Intelligence becomes a true daily habit, and the use of its support becomes natural and spontaneous, *"an obvious thing"* (P1), which is not the case, or can only become so with great difficulty, for those who are strongly attached to old habits as a form of path dependence.

"I mean, it really has to become an obvious thing. And it is not, except for those who do not use it or who are used to doing things in another way. Right? I mean, it makes sense. If you have spent forty years of your career in one way" (P1).

"And so yes, a bit in life, let's say in everyday working life, for example also in research. […] Surely now it is evaluated in a much more natural way, a bit more, how to say, easier to, I mean, to integrate into everyday life, into work" (P14).

Many managers make intensive use of it, but to reach that point it is necessary to overcome the barrier of habit and the willingness to become familiar with the tool, by developing knowledge and skills.

"It is obvious that it is still, in my opinion, a bit lacking, but not because of it, because of us, since we are not yet used to it" (P23).

Critical Confidence

Depending on how often and how deeply managers engage with AI, they develop varying levels of practical confidence, rooted in a clear understanding of Artificial Intelligence limitations and the ability to skilfully interact with it.

The use of the label "critical confidence" is intended to emphasize the importance of developing a certain level of familiarity with Artificial Intelligence that allows one to interact with it in such a way that exploits its potential to the fullest, yet with clarity of mind, which only solid knowledge can provide. Such clarity makes it possible to avoid enthusiasm leading to blind reliance on AI, while keeping the focus on human supervision to recognise and handle the fallibility of AI.

"It is a useful tool that everyone should have. Just like having a fast computer instead of a slow one; it is obviously better if everyone has a fast one. However, having a slow one does not necessarily make you a poor developer" (P1).

The emphasis here is also on the importance of cultivating the skills necessary to interact properly and write the right prompts to obtain the right answers, moving beyond the old logics of interaction with traditional search engines such as Google. In this sense, being shrewd also means asking the right question, reasoning critically and circumventing potential biases of AI, for example its tendency to agree, by not asking about the soundness of a certain idea but rather about the potential risks and problems that could derive from it. This is possible only by drawing on habitual, natural, and therefore expert use of the tool.

"Being a tool, it also needs to be understood and explained, how to use it, to fully exploit its potential. That is, also how to question it, what kind of information it requires, because depending on how – let me simplify it a bit, using more common tools, for example ChatGPT – depending on how you formulate the question… If I, as a layperson, use it, it gives me certain results. Surely, if someone trained in how these tools work uses it, they will be able to exploit its potential much better" (P14).

"At that point, instead, the value may lie in telling ChatGPT when something is not convincing, perhaps reformulating the proposal while taking into account the things it could not have known" (P16).

From this perspective, it is highly significant for managers to acknowledge that Artificial Intelligence requires specific training, which can only be provided if one already possesses a foundational competence in the domain where Artificial Intelligence support is sought. Moreover, the degree of basic expertise of the human decision-maker directly influences the extent to which a critical and informed decision-maker relies on Artificial Intelligence outputs: the greater the expertise, the less likely one is to rely blindly on Artificial Intelligence, and the more capable one becomes of assessing the overall reliability of its responses.
Managers who make a mature and critical use of Artificial Intelligence are those who exhibit increased awareness of its limitations. However, such awareness does not constitute an obstacle to its adoption; rather, it becomes an additional factor to be considered in their regular interaction with the technology.

"But always taking into account the fact that it can make mistakes, so I do not rely blindly on Artificial Intelligence, but rather use it to gain additional information in contexts where I already have expertise […] and I ask the Artificial Intelligence to make an evaluation by providing as much context as possible, thus providing it with as much information as I consider useful" (P16).

"Meaning, if you're going above for research for a project, for an assignment, for anything, you cannot just rely on any research ChatGPT does for you. Because that

model can be biased, and that bias in long term can affect human beings' decisions. That's why I personally believe that in longer term we need to see more trained, specific based on the data where the data sets that are important for every single industry or every single separate reason to give less biased answers" (P32).

2.4.5 Reluctance

This macro-theme explores factors that contribute to the rise of managers' reluctance to adopt or fully utilise Artificial Intelligence for the purpose of strategic decision-making. Such factors are mainly represented by fears and concerns that were categorised as concerns related to Input data, Artificial Intelligence model and output, and human centric tensions.

Human-Centric Tensions

Among human tensions, the first one what we have defined as the fear of cognitive overload and dependency. At the core of this fear lies the concern about a flattening of human cognitive abilities, which have always been fundamental, particularly in strategic decisions. This is seen as a possible consequence of excessive use of AI, which would deprive the human brain of opportunities for effort and reflection, especially in cases where it leads to a genuine form of cognitive dependency, something that strategic decision-makers are careful to avoid.

Another facet of this argument is represented by the fear of confusion, which is especially felt by those who are more conservative and resistant to change. They fear the excess of information and alternative solutions provided by AI, perceiving it as a source of confusion rather than an opportunity for cognitive enrichment, and in some cases even as a danger, when this proliferation of suggestions cannot be properly managed (it is a way of operating that is too new and different from the way it has always been done, like learning a new alphabet) or may prove misleading.

The risk may also be that of being overwhelmed by a range of options that, in practice, decision-makers do not have the capacity or resources to pursue.

This fear materialises in the perceived risk of losing direct contact with raw data: if Artificial Intelligence provides final recommendations but the decision-maker did not engage with the underlying data, he is feared of losing sight of reality.
Another type of tension arises from scepticism and from an intrinsic aversion that may emerge in individuals who are more distrustful by nature or because of adherence to commonplaces. Artificial Intelligence can be seen as something related to science fiction and thus evoking excessive anxieties and fears, first and foremost the fear of substitution.

"There will certainly be, there will be the large army of defeatist flat-earthers opposed to any technological evolution, who will find the weak points, which will certainly exist, in this process and will say that clearly, they cannot replace humans. They did not even carry out the Industrial Revolution in the 1800s if we were to look at these kinds of phenomena" (P6).

Individuals with a basic knowledge of the tool and a broad vision, however, are largely immune to these anxieties, seeing Artificial Intelligence as comparable to many other technological advancements occurred in human history: they are aware that the tool is not dangerous in itself, but that its improper use can be.

"The hammer in itself is neither good nor bad, it is a tool, it is an instrument, just as technology is. It is neither good nor bad, and it is the use you make of that technology that can make it bad" (P24).

The emergence of tensions in the interaction with Artificial Intelligence is also influenced by the issue of trust. There is almost complete agreement on the fact that trust can never be total but is always conditional and must be built through a gradual yet increasing interaction with the tool. The tendency toward distrust may be due to the belief, predominantly rooted in more conservative managers, that Artificial Intelligence can never equal or outperform human intuition and experience.

Artificial Intelligence Input Concerns

Concerns related to input data mainly revolve around their quality and completeness and around their security. With respect to the first theme, concerns emerge primarily about the quality of data in terms of their truthfulness and reliability, which are seen as prerequisites for accurate analyses. P10 recalls a quotation by Oscar Farinetti, stating that *"if you make a mistake in the analysis, then the better you are, the worse it is, because you will be very good at pursuing the wrong objective"*. A recurringly perceived issue is that of missing data and relevant information gaps, due to the impossibility for Artificial Intelligence to access a truly complete information set accounting for relational or geopolitical dynamics, that are extremely hard to encode. This entails the risk of drawing conclusions that may appear sound on paper but are not practicable in reality. Data may also be lacking when operating in highly specialised and niche contexts that are not fully mapped yet.

"Then, on the strategic side, it is very different because you do not have these large amounts of data and, above all, the territory in which we operate is not mapped. So, on this Artificial Intelligence can help me very little, but not because it is not capable. It is because the input data are poor, so it would not allow me to make a difference" (P19).

With regard to input data, another risk that is recurrently raised concerns the biases that may influence input data, potentially leading to misleading conclusions. However, a trade-off may emerge between the use of data that are cleaned of biases but do not reflect reality, and the use of real data that perpetuate human biases. In this respect, however, some participants express confidence in the growing ability of Artificial Intelligence to circumvent the problem of *garbage in - garbage out*.

The second key issue concerns data security and privacy. A strong concern emerges, especially among managers who are more resistant to Artificial Intelligence and have limited familiarity with the tool, regarding the risk of sensitive information leakage, which is perceived as both a regulatory and a strategic risk. This concern is fed by limited experience and awareness.

"Oh my God, we'd like, we're giving away crown jewels if you put something into ChatGPT. So, it's about control now. And I think a lot of organisations are saying we can't use ChatGPT responsibly because we don't, we don't know how yet. So, we're not going to use it at all" (P32).

Specifically with regard to security, a trade-off may emerge between choosing a provider that offers more technologically advanced solutions but is considered less secure and reliable in terms of data protection, and choosing a provider that is more trusted but less technologically advanced. This critical choice can undermine the adoption process. In response to this problem, the use of tools that offer a closed ecosystem, such as Microsoft Copilot, is often mentioned, since it allows managers to attenuate concerns about privacy.

Artificial Intelligence Model and Output Concerns

Concerns about the model that fuel scepticism and, consequently, reluctance toward Artificial Intelligence among managers are mainly related to the black box issue. The lack of transparency about how the model works prevents them from forming a well-grounded judgment on the reliability of its results, which for a decision-maker would mean *"making a decision without understanding why" (P25)*, or imposes the need for a double check, a step that can discourage its use. Moreover, this lack of transparency and intangibility makes it much more difficult for leaders to relate to Artificial Intelligence in the same way they would with other, more tangible issues.

"Artificial Intelligence is a black box, so if I am a company executive, how can I judge whether an evaluation made by Artificial Intelligence is reliable or not, if I do not know how this algorithm is built?" (P7).

"You can't see it, you can't feel it, you can't go to the manufacturing and see how the big machines doing that kind of things...Exactly the same mindset approach could be adopted to Artificial Intelligence but it's just that you can't see it and it makes it really difficult for people to understand" (P31).

On the contrary, according to someone, there is the risk that despite this lack of transparency, humans may be induced to trust the output because of the perception of AI's neutrality, especially when compared to human consultants who may be driven by ulterior motives. In this case, however, it is a matter of false security.
Another risk that gives rise to concerns about the output is represented by hallucinations. It clearly emerges that strategic decisions entail serious consequences in the event of an error, which makes it much more difficult to accept the risk that Artificial Intelligence may experience hallucinations and provide representations of reality that are not entirely truthful and, in extreme cases, completely unfounded. Strategic decision-makers are necessarily very cautious about this, although hallucinations are considered by the most frequent users as easily recognisable.

"Making a mistake in a strategic direction is one of the most serious things for a company. When you hear about hallucinations, you actually become very cautious about this" (P5).

However, what lies at the heart of reluctance and is strongly emphasised (especially by the most expert among managers) is the lack of strategic depth, and the risk that it may lead to overlooking nuances of meaning that are instead crucial in strategic decisions.
A critical issue is represented by the risk of obtaining superficial or trivial responses, generic and laconic even on complex matters. Such responses, although correct, prove useless or at least inadequate to satisfy the thirst for detail that characterises strategic decisions; they may refer to the average rather than focusing on important details that help build the overall picture.

"*You find yourself holding a tool that sometimes gives you the magical illusion of having expressed a thought, but then when you read the answer, even if it is two pages long, it is a bit like hot water, right? […] If at the current stage of Artificial Intelligence development, Artificial Intelligence were a decisive tool in strategic planning, it would mean that you have a trivial company in your hands that will be swept away" (P19).*

This lack of depth and accuracy in strategic nuances is, according to many, attributed to AI's lack of access to contextual information and to that derived from interpersonal relationships. Context here is understood both as the external environment, that is, political, social, and regulatory, and as the market context, which is subject to rapid evolutions that Artificial Intelligence may struggle to learn and internalise quickly enough. Tacit knowledge is often the result of human interactions, for example stemming from organisational dynamics or simply from discussions with individuals who have a certain sensitivity to the issue at hand.

2.4.6 Artificial Intelligence Accessibility

This theme included the factors that are identified as determinant of readiness to access AI: the technological and economic foundations, and the human and governance frameworks required for success.

Human and Governance Readiness

First of all, the need for specific training is emphasised. Although the most enthusiastic and innovative managers do not find it difficult to interact naturally with AI, for many using it at the strategic level would require specific training, beyond the prompt engineering guides currently available, which are not effective for such niche needs. In many cases, learning by doing is identified as an effective solution in the current situation of limited training opportunities for the development of the necessary human capabilities. In addition to this, the need is raised for possible guidelines on the tools available on the market to understand their compatibility with one's own strategic needs.

What would undoubtedly contribute to making managers more ready to access Artificial Intelligence is the availability of success stories and best practices, which would reduce uncertainty through a mechanism of social proof that conveys confidence in the adoption process, while also potentially acting as a competitive stimulus when it becomes clear that Artificial Intelligence has enabled the achievement of concrete results.

"Actually with, clearly, also cases like this one of 'Company X'… One says copy and paste, but why am I stuck at 13 while they are at 60 in the same period? Right?" (P15).

"That's revolutionary. How are we going to manage this new incredible functionality? So, enablers are best practices, story being told from the business perspective first" (P31).

Finally, greater clarity from a regulatory perspective would facilitate access to AI, allowing managers to navigate the adoption process with a clearer understanding of its ethical and legal aspects. The dominant perception is that the regulatory context is not ready yet and that we are in a kind of *"Far West" (P1)*, which can create fear and discouragement. On this topic, however, it should also be noted that there is fear of a potential excess of regulation or over-regulation at the European level, which could block developments and further hinder an already complex adoption process. It is therefore necessary to find the right balance between regulating in order to provide reassurance, without at the same time creating barriers to the potential of the tool and to the willingness to use it.

"Obviously, when we talk about data, we must take into account legal, privacy, and security aspects, and therefore that is a clear factor. A factor that must necessarily be properly regulated, and in this sense, but this is my view" (P12).

"I mean, a world opens up that needs to be regulated. I can also understand this kind of diffidence, but it is the classic diffidence of those who do not know. The rules are not ready yet, so it is a bit like approaching the Far West. It scares you because you have no rules" (P1).

Technological and Economic Readiness

This topic addresses the issue of Artificial Intelligence accessibility for strategic decision-makers from the perspective of concrete factors concerning the readiness and compatibility of the available Artificial Intelligence solutions, as well as their accessibility in terms of the costs to be incurred.

Artificial Intelligence accessibility is complicated by the fact that managers face a technological ecosystem that is still immature and fragmented, characterised by a lack of market-ready solutions specifically targeted to address the needs of strategic decision-making, beyond the general-purpose tools that exist and with which they are already interacting and experimenting. There is widespread awareness that the potential of Artificial Intelligence can increase if it is trained in a customised way in terms of data and field of application, taking into account, for example, the peculiarities of the business. Accessibility further increases in cases of compatibility with existing information systems, for instance Artificial Intelligence integrated into the company's CRM or into the management system that collects production data.

"Those who work with Artificial Intelligence do not deal with ERP. There are other tools called MES (for production), which in turn have a series of satellites, the ones that receive information from IoT and process it. Within the market offer this is something I have struggled to find. In fact, in the end I did not find it" (P4).

The availability of tools perfectly compatible in this sense would make it possible to overcome the logic of silos and would increase the value perceived by managers in using AI, precisely thanks to the high level of specialisation. It would also make the adoption process much simpler, since it could be offered as an "add-on" by vendors to services that are already being used.

"There are vendors who, along with the management or CRM product, also provide you with Artificial Intelligence functionalities integrated. In that case, maybe it is of great value because it is applied to all the clients they have, and therefore it uses the data they already have, and it becomes just an add-on compared to what they already offer you. Whereas when you have to start from scratch, you have to train it yourself and therefore explain the context. The risk of making wrong strategic choices is higher, so maybe you hold back a bit to avoid it" (P16).

The topic of economic viability as key factor influencing Artificial Intelligence accessibility is addressed with contrasting opinions. For those who are still experimenting in a limited way with open tools, it not seen as an issue. Among those further along in the process, who feel the need for and see the potential in premium tools (although general-purpose), there are some who, perceiving Artificial Intelligence as a lever for savings, claim not to have hesitated in purchasing subscriptions for themselves and their collaborators, even considering it an insignificant expense. Others, however, believe that at scale it may become economically demanding, despite the evident advantages already experienced. Another point that deserves particular attention concerns companies (larger and financially solid) that intend to invest in the development of ad-hoc tools, which therefore require greater effort. Economic viability thus depends heavily on the type of company, on expectations, and on managerial perceptions.

2.4.7 Strategic Decision-Making Quality

The theme is a fundamental pillar of the analysis. It shifts the focus to the actual and potential perceived strategic impact of Artificial Intelligence in terms of the value its value added to the decision-making process. It is therefore an examination of both the results already observed and those potentially expected, whether measurable or not. The three areas in which such benefits are located are the general optimization of the process, an expansion of strategic horizons, and an increased integrity of the decisions made.

Process Optimisation

The impact on the process is tangible and explicitly recognized. Overall, Artificial Intelligence helps make the strategic decision-making process faster and more efficient, partially reducing the perceived burden on decision-makers. These benefits are manifested above all in advantages related to the management and use of time as a key resource, both professionally and personally. Strong emphasis is placed on saving time and effort, and therefore on optimizing the resources dedicated to the preparatory activities of the decision-making process. This is a measurable advantage, and the majority of participants identifies it as the main one. Leaders acknowledge substantial time savings in building their knowledge base on a given topic in a very short time frame, or in conducting complex analyses and reaching set goals more quickly. The immediacy with which outputs can be extracted is also strongly emphasised as a benefit, as it removes the need to allocate an entire team to carrying out a full-time analysis activity for a month. The time savings therefore translate into a quantifiable economic saving.

"So blessed be the thirty-five euros that GPT costs! I get it for everyone, I mean, I save an hour a day, and an hour used to cost me more" (P1).

"What would take you two months on your own with a team of five people, instead there with one click you have it a minute later" (P15).

The other side of the coin of time-related advantages is a consequence of what has been described above. The greater efficiency in carrying out tasks that would otherwise be extremely time-consuming allows the time thus saved to be used in a more strategically valuable way. On the one hand, it can simply be reallocated on the professional level to high value-added activities, to which decision-makers can in this way devote themselves with greater clarity of mind (evaluating instead of studying and analysing, reasoning more on strategic trajectories). On the other hand, it remains available to decision-makers to devote to their private lives, something particularly appreciated by individuals in top positions who are often forced into highly unbalanced work–life rhythms due to the great responsibilities they bear.

"So practically this becomes a precondition for you to also have more time to reason in strategic terms and to be less tied up, as in fact always happens, with operations and emergencies" (P10).

"Maybe in removing a lot of the decisions that people take. So, the premise of 'management by exception'. So rather than constantly having to decide things, you only decide things as an individual when there is a decision to be made rather than deciding everything" (P31).

"I think saving time on analysing data and then getting a little bit of better understanding of what can be done instead of digging through the data is the main thing" (P26).

"I always work 11 hours every day, but eh, even my closest colleagues are like me, so they never give up either. And we are helping each other and freeing ourselves a bit and going faster, more quickly. In my opinion, it is about having a bit more time for us" (P15).

Greater speed in the strategic decision-making process enables a proactive approach in terms of ability to anticipate the market, and this is perceived as a driver of competitive advantage over competitors who remain anchored to traditional business models and do not rely on AI. Strategic decision-makers are facilitated in moving beyond the traditional modes of defining and reviewing strategy at predetermined intervals, shifting instead toward a dynamic and predictive approach capable of addressing sudden scenario changes in real time.

"This competitiveness is due to the fact that we anticipate the market thanks to the knowledge that Artificial Intelligence provides us" (P2).

"And one of the one of the things with that is to keep your eye on things when are things moving across because as they move you have to change the way that you act" (P32).

Finally, an important aspect for strategic decision-making process optimisation is the perceived benefit of increased efficiency in operational processes. The time and resource savings occurring at this level indeed indirectly impact the strategic level.

Expanded Strategic Horizon

This theme addresses the support of Artificial Intelligence in the strategic decision-making process in expanding the scope and nature of the strategic options on the table, thereby broadening the horizons of decision-makers. This occurs thanks to its contribution to overcoming certain cognitive limitations, to managing a level of complexity that would otherwise be inaccessible, and to encouraging greater boldness. Starting with complexity management, a key support is represented by the multicriteria analyses AI enables. In strategic decisions, it is indeed crucial to relate simultaneously several variables that exceed human capabilities in order to obtain the most comprehensive possible view of complex realities and, consequently, to be able to balance multiple factors or objectives.

"When you basically have to choose a location where to open a new retail business, typically in addition to going there in person, which is obviously an indispensable value and one that can hardly be delegated to Artificial Intelligence, surely if we analyse a whole series of data and try to correlate them with one another, such as the population density in the area, the isochrones, the wealth in that area, the competitive pressure, the accessibility, and so on" (P10).

Artificial Intelligence can therefore make it possible to manage complex systems, map interdependencies, and facilitate feasibility studies of investments or sets of investments, allowing the gap between theory and practice to be bridged with greater reliability.

"Forecasting of multiple investments leads me to carry out a multi-criteria analysis, where I take into consideration several variables and several actors (I am exaggerating the term) involved in this process, and then the simultaneity of the construction sites: is it possible? Because on paper we can hypothesise any choice and solution, but then in operational terms…" (P6).

A further facilitating aspect is represented by the possibility of integrating data from different sources, thereby enhancing the ability to leverage them and relate them to one another for strategic purposes.
The contribution to overcoming human limitations takes three main forms: challenging human conformism, going beyond the boundaries of limited human experience, and encouraging risk taking and the experimentation with bold solutions.

Artificial Intelligence can in fact act as an external agent that questions the solutions already identified, fostering critical thinking and prompting reflections on the beliefs the decision-maker has built, for example regarding the soundness of a choice, thereby challenging the biases of decision-makers through counterarguments supported by data. It can also push to break established thought routines. Managers may indeed tend to reiterate past choices or to rely on ideas whose reliability is taken for granted. Such behaviours limit the decision scope and fail to consider alternatives that may prove equally or even more valid. In this sense, Artificial Intelligence can help by bringing creative options to the table that break the patterns of this conformism.

"The risk is that, to maintain the standard, you remain very standardised and therefore do not optimize, with the aim of simplifying the process. [...] The machine revealed a creativity that humans did not have because in the end engineering departments have a sort of conformism, that is, if you know that things went well with a certain configuration, you have less drive or you do not want to risk bringing something that might then be poorly received by your boss or by your investor. Conversely, the machine does not have this kind of hesitation and therefore dares more" (P11).

"What emerged was something different, and this allowed us to allocate the budget we had for that marketing campaign in a different way compared to what our initial idea was, and therefore to allocate a portion of the budget to some campaigns aimed at potential targets that, in our view, were not targets at the beginning, and that instead emerged from this Artificial Intelligence analysis, both in terms of the type of target and in terms of the territorial distribution of these targets. [...] We also, for example, internationalised this campaign, something that for us was not initially feasible, but we did it based on what came out of this analysis" (P12).

Another interesting nuance on this theme is offered by the idea that Artificial Intelligence can contribute to overcoming the limitations of human experience, acting like binoculars that broaden perspectives and the range of alternatives, enriching the experiential background of the decision-maker or making them more attentive to details that would otherwise have gone unnoticed, while they continue to look at reality through the limited lenses of past experience.

"There are some blind spots that you might not be seeing because the way that you've been thinking as a manager as a decision-maker for the past 10-15 years is exactly the same that you've you did for years. So that model can give a fresh set of eyes to you" (P26).

"I have some money to spend. Dear technology, help me see phenomena in a different way compared to how I am normally used to seeing them" (P27).

It also emerges, however, that the further a suggestion received from the machine departs from the current way of thinking of the decision-maker, the more difficult it will be for the latter to trust the machine.
Therefore, a crucial aspect stressed by participants is that the support provided by Artificial Intelligence in overcoming the limits of experience and conformism has the effect of stimulating action, even by taking paths that involve the assumption of risks, thanks to the confidence that can be conveyed by a more informed view of the context. This therefore encourages experimentation with bold strategic solutions and helps avoid situations of inaction and immobility.

"We avoided inaction when it was necessary to act, or excessive action when it should not have been taken. On the strategic side, it is about choosing whether to invest or not in a project" (P11).

Enhanced Decision Integrity
Managers perceive that Artificial Intelligence can deeply strengthen their strategic decisions as a result of enhanced rationality, precision, confidence reliability and consistency of the decision-making process.
The use of Artificial Intelligence in supporting decisions indeed pushes the balance from instinct toward data-driven evidence, and this gives decisions a greater degree of objectivity and rationality, making them more aligned with reality because they are

potentially enriched by *"more information" (P1)* and *"better information" (P18)*. In this perspective, Artificial Intelligence contains the risk of relying too heavily on one's own beliefs and instincts or gives greater substance and rigor to one's own considerations. The decision is therefore a conscious one, not impaired by misleading preconceptions but based on a more pragmatic background. Decisions also benefit from increased consistency by providing the basis for a more standardised approach over time that is not affected by the subjectivity of people involved in the decision, especially in terms of criteria and parameters to be considered. Furthermore, Artificial Intelligence helps minimise human errors that may inevitably occur when manually managing data.

"Specifically, today as a company we are able, in the various areas in which we operate, to have more precise information. So, the advantage is having more precise information to support decisions" (P14).

"It is a somewhat long and somewhat costly process, and in which, also in order to maintain it, you are a bit afraid of not maintaining uniformity, that is, that the parameter used in one initiative is not used in another" (P11).

"Here Artificial Intelligence can be somewhat of a facilitator, it really does not solve the problem, but it certainly starts to give you a scenario that is a bit more reliable compared to what it might have been a few years ago" (P27).

Managers also recognise that they reach the decision with greater confidence, solidity, and determination thanks to the support of data and the completeness of the analysis, which makes them feel more aware and leads them to perceive the outcome of the decision as more reliable, since it is based on a more trustworthy background. The decision-making process and the decision itself, as the final output, are overall perceived as more accurate and structured thanks to greater methodological rigor as well as the extension of the knowledge base in support.

"To give you more confidence in the decision and also more quality in the decision" (P15).

"So, having the possibility of something that brings order, that creates correlations, that provides, let's say, a more truthful representation, that helps to have decisions that are well based on better information. [...] A decision can be better, just as creativity can be brought, let's say to higher levels insofar as the assumptions that stimulate it are increasingly reliable, increasingly closer to reality" (P18).

"A more structured and step-by-step organised approach, an approach certainly driven by data" (P2).

"By providing structure and providing consistency and providing a pragmatic basis to the considerations made" (P23).

"Without good data, well managed curated data through Artificial Intelligence pipelines, decisions would not be as accurate in my opinion" (P31).

2.4.8 Knowledge Management Capabilities

Artificial Intelligence is perceived as potentially capable of transforming knowledge management in support of strategic decisions, acting, on the one hand, as a tool that allows the consolidation of knowledge about the present reality and, on the other hand, through more advanced and expert use, as a tool that provides a vision of future perspectives. Strategic decision-makers can therefore benefit from it by being more up to date and informed about the present, as well as more forward-looking and proactive.

Diagnosing and Interpreting Reality

The ability to build and validate a knowledge base about the present reality, in order to develop the most comprehensive and truthful understanding possible, can greatly benefit from Artificial Intelligence support. Our data explain this dynamic as being primarily founded on an enhancement of diagnostic capacity aimed at environmental scanning and/or the extraction of vertical knowledge as forms of research, and more generally, on the capacity to synthesise and systematise vast knowledge bases so as to make them easily accessible and intelligible. The final stage of this process is represented by human verification, which is intended to transform the raw output provided by Artificial Intelligence into reliable knowledge that can then be used to pursue strategic objectives.

In detail, based on the data collected, it emerges that the capacity for environmental scanning is enhanced by using Artificial Intelligence to explore strategic contexts, markets, or trends, especially those about which managers do not have extensive prior knowledge. In this sense, managers are able to conduct accelerated market analyses to build an idea of market dynamics and the size of existing gaps and of the main actors involved, to assess the best geographical positioning, but also to prepare for strategic meetings with a clear understanding of the levers they can exploit to their advantage. It is therefore a way to leverage and capitalise on all the relevant information offered by the context that might otherwise be overlooked and, above all, thanks to generative AI, to have this knowledge already organized and processed for their specific purposes. This is linked to the synthesis, systematisation, and mapping of knowledge, which, however, is understood in general terms and not only as it pertains to the market. From this perspective, the value recognized by managers lies in the ability to systematise enormous amounts of data with great speed, identifying useful correlations and patterns (for example, in customer behaviour), or in creating reports that summarise investigations conducted through surveys or strategic meetings.

"So instead of going to search, do analyses and so on, I ask it for a brief extract of that industry: 'what are the most interesting things? The current events in that

industry? What happened?' This equipes me with talking points during negotiations, because in my view the more one speaks, the better" (P1).

"But where is the demand? That is, what does the market ask for and, above all, where does it ask for it and when does it ask for it? Today it still does not ask for it, but then strategically, is it right to go ahead? Is it right to follow this path? Yes, and why? Because the demand of this market, which will certainly explode after 2030 also thanks to these process analyses conducted by AI, will allow us, having already started a couple of years ago, to begin with a two-year advantage to be, if not market leaders, at least representative of a technology of great importance" (P23).

Beyond exploratory use, another way in which Artificial Intelligence can support diagnostic and interpretive capacity is through a verticalised use aimed at extracting targeted insights to answer specific questions that the decision-maker poses to make their decision. This aspect has been defined as targeted evidence retrieval. In fact, in a strategic decision, *"you do not need to know a lot, you need to know the right things" (P19)*, and AI, while not knowing what those are, can help find them.

In this sense, making use of Artificial Intelligence is also a way to delegate research tasks with extremely specific objectives, which are therefore laborious and time-consuming. An example is asking specific questions such as *"List for me the top 10 companies in the sector with a turnover of less than 10 million euros?" (P24)*, which makes it possible both to save energy in *"the research, which is, let's say, extremely annoying"* and to overcome *"the fear of not having done it properly or completely" (P24)*.

It can also assist in substantiating and validating the hypotheses or intuitions of the decision-maker by providing evidence-based support. This type of use, on the one hand, contributes to overcoming the purely intuition-based decision-making paradigm, but on the other hand, it can fuel confirmation biases. Indeed, in this way Artificial Intelligence is pushed to search only for information that confirms one's own ideas, excluding potential counterevidence. It is therefore important that Artificial Intelligence is used with a degree of awareness that mitigates this bias.

“Artificial Intelligence would perhaps help you validate from a numerical point of view” (P25).

“To have these hypotheses substantiated precisely by an important intertwining of data” (P10).

“And so, it gives me a final validation, but still on something that I already know and where I relied on intuition. It simply reinforced me and gave me additional information by updating me and explaining that there are also various ways of evaluation, for example” (P16).

“It can also be an explicit strategy of mine, that is, I have something in mind, I look for confirmation to understand whether that thing has further fundamentals or evidence, reasons that I consider useful to explore further” (P3).

In making use of this knowledge processed by AI, what emerges clearly and strongly from many voices in our sample is the crucial role that human intelligence continues to play, and this is explicitly acknowledged even by the managers most open to and experienced in the use of AI. From this perspective, the data reveal two nuances that explain the role of the “human in the loop”.
On the one hand, there is the idea that humans must remain in a position of control: “*Proposal from the machine, validation by the human decision-maker” (P11)*. Artificial Intelligence cannot be seen as a substitute at the level of strategic decisions; it remains a tool that humans must know how to exploit, using their capacity for understanding and discernment to recognise, manage, and contain potential errors or distortions. “*It can also be wrong, just as competent people can be wrong” (P16)*. The irreplaceability of humans also lies in their ability to add context and experience that Artificial Intelligence does not possess, in order to control and validate Artificial Intelligence outputs. On the other hand, however, humans are not limited to being supervisors; they must be active participants in the interaction. They should not only passively monitor, judge, and validate, but also conduct the interaction with AI, for example through dialogue, to guide it toward a better result, even making it recognise

its own mistakes in a process of targeted learning and training. This reflects an expert and forward-looking use of Artificial Intelligence itself and represents an advanced way of applying the "human in the loop" principle.

"At that point, instead, the value may be to tell ChatGPT something that does not convince you, perhaps reformulate the proposal taking into account the things it could not know, and so the value of people, in my opinion, in our opinion, is precisely that, the added value they can have compared to Artificial Intelligence" (P16).

"If I give it garbage in and then gradually manage it in terms of interaction, sooner or later it corrects itself, or at least points out that there is something wrong in those assumptions underlying the activation of the generative process, right? And so, the prompt I use starts to indicate that there is something off, and this is fundamental" (P9).

Generating and Articulating Future Trajectories

In addition to the widely recognised benefits in terms of strengthened diagnostic capability, many participants highlight benefits related to the generation and articulation of future trajectories. This type of support provided by Artificial Intelligence is primarily linked to the stimulation of new perspectives, new ideas that transcend the limits of managers' prior experience. Artificial Intelligence therefore acts as a source of inspiration, and interacting with it accelerates a generative process, comparable to reading *"an infinite number of books*", gaining facilitated access to literature that *"opens the mind" (P1)*.

The human role remains predominant in making sense of and harnessing this spark that Artificial Intelligence ignites. In this sense, Artificial Intelligence is the activator of an accelerated learning process, which, if exploited with the right open-mindedness and critical thinking, can lead to questioning pre-existing beliefs and prejudices, to leverage greater creativity based on a renewed way of looking at things, and access new elements of evaluation.

"Well, as I was saying, to broaden horizons. I learned new terms, I saw that there are new classifications I had never noticed before, and so it definitely extended my knowledge base" (P24).

An additional step beyond this is represented by the consequently improved ability to identify a broader range of strategic options, opportunities, and possibilities to explore.

"Surely, using Artificial Intelligence tools to analyse, understand, and evaluate new market needs and demands, that is already an absolutely interesting field of application for us, because by analysing the large volumes of customer data it allows us, on the one hand, to refine and improve what is, let's say, our current service and product offering and, on the other hand, also, eventually, to develop new ones" (P14).

"It gives you a set of possibilities, all among the most logical, to pursue at a given moment and, above all, based on facts rather than assumptions or instinct" (P4).

"There is greater creativity, a greater number of possible options by exploiting Artificial Intelligence" (P11).

"It could give us new elements of evaluation that we might not be able to capture with conventional methods, and this could be of great help" (P20).

The generation of future trajectories also benefits significantly from a strengthened ability to simulate, model, and comparatively analyse future scenarios useful for supporting highly complex decisions. This is made possible rapidly, avoiding the need for entire teams to dedicate extensive time to this activity. This enhances managers' ability to manage uncertain situations and their ability to critically evaluate the pros and cons of various options. These benefits are primarily related to the multi-criteria analyses that Artificial Intelligence can handle, which significantly enrich the decision-making framework.

"Having more scenarios and having ease of [access to] different scenarios truly help, and it is a form of learning, that is certain. Because it quickly allows you to become the little chemist of five-year business case simulations. It is an important open field to explore" (P15).

"If you want to design different scenarios, perhaps very complex ones, with many variables influencing each other, Artificial Intelligence can help you see how to model things" (P19).

Finally, in some specific cases, Artificial Intelligence support also translates into improved communication with external stakeholders, leveraging the ability to persuasively articulate strategic ideas and proposals, making them tangible and giving greater strength to concepts through effective representations. With internal stakeholders in mind, this use primarily involves synthesising and communicating relevant information.

2.5 Findings: typology building of four different sensemaking patterns

Sensemaking theory identifies the retention phase as the moment in which the meaning created is given a stable structure and turns into a cognitive scheme that guides future actions (Weick, 1995). In this study the retention phase is connected to the four sensemaking patterns emerging from the analysis as four different approaches of strategic decision-makers toward Artificial Intelligence that consequently shape their perception of it. The patterns are the result of a cluster analysis of participants, based on their assignment to one of the four levels identified for each of the eight macro themes, as a result of the calibration process (Table 11).
The four clusters have been labelled as follows: Sceptical Observer (S.O.), Tentative Explorer (T.E.), Pragmatic Experimenter (P.E.), Visionary Innovator (V.I.).
Table 4 summarises how levels are distributed across clusters, while Figure 1 is a visual representation of such distribution, allowing to identify distinguishing characteristics of the four sensemaking patterns, which are discussed in further detail in the following sub-sections.

2.5.1 Sceptical observer: Artificial Intelligence as a strategically dismissed resource

Sceptical observers are primarily and clearly distinguished by "absent or minimal vision" (unanimous assignment), as well as by "strong resistance and aversion", "absent or sporadic use", and "intuitive" strategic decision-making.
The prevailing tendency in this cluster is a lack of recognition of AI's potential for strategic decision-making, either because it is excluded a priori, deemed impossible to provide effective support, or because such support is not perceived as necessary (primarily due to a strong attachment to entrenched decision-making habits, thus linking back to the theme of the intuitive approach, another key feature). These cases represent the two extremes of the cluster, yet the absence of vision appears to originate from different sources.
In the first case, it stems from a limited awareness of Artificial Intelligence in general, either because there is no willingness to explore it, because the possibility that it could also be useful at the strategic (and not only tactical-operational) level has never been considered, or because, while vaguely sensing some potential, there has never been the time to investigate it further. In the second case, the denial is instead rooted in a strong awareness and knowledge of the technology, which leads to conceiving it as inadequate to the strategic needs of the company. This perception is often justified by pointing to the extreme dynamism of the sector, which is believed not to grant Artificial Intelligence the necessary time to update its training, thus resulting in an oversimplification of the reference scenario.
In all cases, this lack of strategic foresight translates into an implementation path that is essentially uninitiated (if not for an entirely occasional and disconnected use of free versions of generative Artificial Intelligence tools) and, consequently, into a lack of interest in fostering the internal development or external acquisition of the necessary resources and capabilities. A nuance that lies between these two extremes is represented by a sceptical observer who reports having had the opportunity to observe – albeit indirectly – the efforts of larger and more structured companies in leveraging AI's potential at all levels, admitting that this sparked some curiosity, which, however, remains unexplored. It is often acknowledged that only on the occasion of the

interview did they begin to reflect on the issue in ways they had not done before, which nonetheless represents a glimmer of vision.

As for reluctance, most of the participants in this cluster (5/6) share a strong resistance or aversion toward AI, which is expressed by a sharp focus on their fears and on the limitations that characterize AI, resulting in an overall conservative, at times defensive, attitude. This does not always lead them to a total rejection, but it nevertheless fully restrains adoption, at least at the present time, given the strong emphasis placed on the risks of errors and inadequate responses, which may convey an excessive sense of confidence and thus be misleading for the decision-maker.

This concern is reinforced by the perceived limited amount of useful data that can effectively be provided to the machine for mapping the strategic context, by the difficulty of relying on something essentially incomprehensible (the "black box"), and by the risk of slipping into dependency on its use or worse, the risk for the decision-maker of becoming an Artificial Intelligence tool that ends up shaping his way of thinking. The other defining characteristic for belonging to this cluster is praxis. Most participants are at the lowest level of no or sporadic use, with only two using it exploratorily. These latter are precisely those who have a heightened awareness of the real limitations and aren't just speaking in theoretical terms. For none of them Artificial Intelligence is routine (sometimes because they say they had not enough time to experiment), but those who have explored it, even if only sporadically, are critical and warn against excessive enthusiasm. Another key characteristic is an intuitive approach to strategic decision-making, which is minimally hybrid and therefore characterized by greater openness to data support, even if not in a structured way and without ever abandoning managerial intuition (often justifying this with the characteristics of the sector in which they operate, either because it is too traditional or because it is too emerging).

When it comes to recognising Artificial Intelligence impact on strategic decision-making quality, sceptical observers acknowledge this effect only to a limited extent. Indeed, according to some of them the potential effects are minimal if not adverse (for example, there is the risk for the human decision-maker thought to be shaped by Artificial Intelligence and this is perceived as dangerous, especially for strategic decisions), some of them simply imagine some potential effects they haven't experimented with yet at all, some others scale the effects almost exclusively to optimizations in terms of efficiency, with limited scope for digging deeper. Concerning the underlying knowledge management capabilities, their attitude is consistent: the recognised impact is marginal or confined to diagnostic capabilities. Concerning personal adaptability, managers are equally distributed across the three levels of rigidity (2), emerging adaptability (2), and pragmatic adaptability (2), implying that this theme does not prove to be determining and characterising of the cluster.

The rigidity has been recognised in those participants showing a greater resistance toward implementing the changes entailed by Artificial Intelligence adoption; emerging adaptability is typical of those who have a good digital and Artificial Intelligence literacy and show an even minimal level of curiosity; pragmatic adaptability is recognised in those with courage to innovate and high digital literacy, with a partial cognitive openness toward Artificial Intelligence which is, however, justified with pragmatic awareness. Sceptical observers' accessibility is between distant or uncertain and fragile.

This implies that they focus more on the difficulties in adopting AI, on its low level of maturity and on their limited knowledge while the lack of dedicated regulation is perceived as something blocking.

This sensemaking pattern corresponds to a perception of Artificial Intelligence as a strategically dismissed resource, whose potential hardly applies to strategic decisions necessities.

"It's clear that when you make an investment like this, we're talking about millions of euros. I don't think Artificial Intelligence can help us" (P13).

"I mean, I need a screwdriver, but Artificial Intelligence is a hammer. Does it make sense to use it for what I need? No" (P19).

"How can you support me in the strategic decision-making process; I am fully aware that the question that has remained unanswered is" (P10).

Sensemaking Pattern	N	VISION	KM CAPABILITIES	SDMQUALITY	RELUCTANCE	PERSONAL ADAPTABILITY	PRAXIS	Artificial Intelligence ACCESSIBILITY	SDM APPROACH
Sceptical Observer	6	Absent or minimal vision (6)	Marginal capabilities (2) Diagnostic capabilities (3) *Missing data (1)*	Minimal or adverse impact (4) Process optimisation (2)	Selective prudence (1) Strong resistance or aversion (5)	Rigidity (2) Emerging adaptability (2) Pragmatic adaptability (2)	Absent or sporadic use (4) Exploratory use (2)	Distant or uncertain accessibility (3) Fragile accessibility (3)	Intuitive (4) Hybrid (2)
Tentative Explorer	8	Absent or minimal vision (2) Emerging vision (5) Guiding vision (1)	Marginal capabilities (1) Diagnostic capabilities (3) Potential transformative capabilities (4)	Process optimisation (2) Selective improvement (4) Integrated enhancement (1) *Missing data (1)*	Selective prudence (2) Cautious stance (5) *Missing data (1)*	Emerging adaptability (8)	Absent or sporadic use (4) Exploratory use (4)	Distant or uncertain accessibility (2) Fragile accessibility (2) Conditional accessibility (1) *Missing data (3)*	Intuitive (4) Hybrid (1) Analytical (3)
Pragmatic Experimenter	7	Emerging vision (4) Guiding vision (2) Transformative vision (1)	Diagnostic capabilities (5) Potential transformative capabilities (1) Experiential transformative capabilities (1)	Process optimisation (1) Selective improvement (3) Integrated enhancement (1) *Missing data (2)*	Low reluctance and critical trust (1) Selective prudence (5) Cautious stance (1)	Emerging adaptability (1) Pragmatic adaptability (5) Advanced adaptability (1)	Exploratory use (2) Frequent use with scope for improvement (5)	Fragile accessibility (1) Structured accessibility (3) *Missing data (3)*	Hybrid (4) Analytical (3)
Visionary Innovator	12	Guiding vision (4) Transformative vision (8)	Potential transformative capabilities (2) Experiential transformative capabilities (10)	Selective improvement (5) Integrated enhancement (7)	Low reluctance and critical trust (10) Selective prudence (2)	Pragmatic adaptability (2) Advanced adaptability (9) *Missing data (1)*	Exploratory use (1) Routine and critical use (9) *Missing data (2)*	Conditional accessibility (8) Structured accessibility (4)	Analytical (3) Proactive (9)

Table 12: Overview of theme levels across clusters (source: our elaboration)

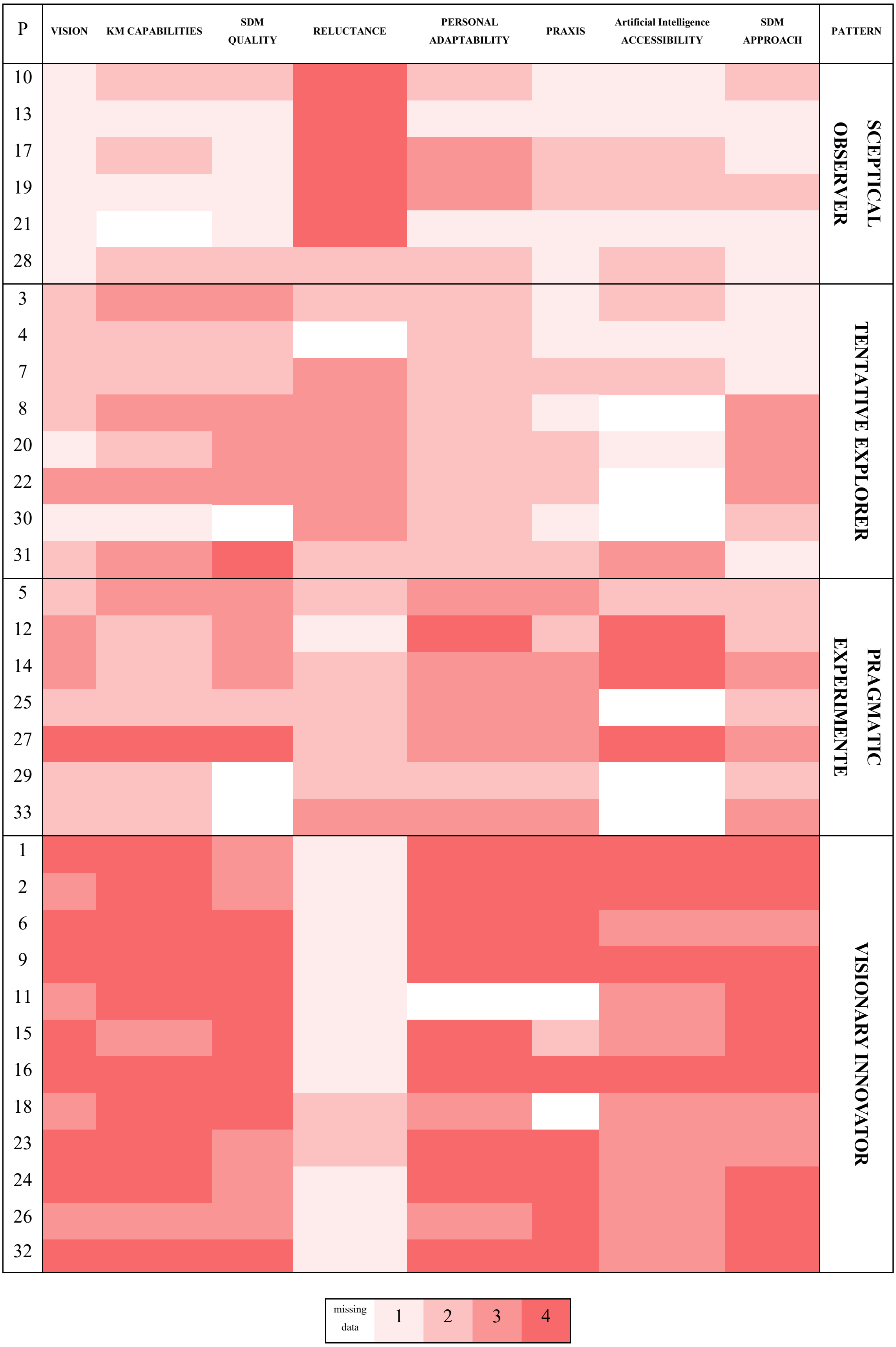

Figure 4: Pattern - theme distribution heatmap (source: our elaboration)

2.5.2 Tentative explorer: Artificial Intelligence as a foggy path

Tentative explorers clearly stand out above all for their emerging adaptability (8/8 participants), followed, consistently, by a prevalence of emerging vision (5/8 participants) and by a cautious stance that reflects the second to last level of reluctance. As for their emerging adaptability, it is rooted in a relatively poor technological culture that is, however, accompanied by a medium-high intellectual openness in admitting one's lack of knowledge and in expressing curiosity to understand more, despite a sort of underlying cautious scepticism toward the idea of a diffused integration of Artificial Intelligence into strategic decision-making processes, which they predominantly describe as intuitive, although some of them being inclined to embracing a hybrid or purely analytical turn. Their cautious stance is justified by the lack of experience and by the (albeit at times vague) awareness of the need to be adequately trained in its use, as well as on the idea (a prejudice with little actual support from experience) that Artificial Intelligence cannot capture nuances related to context. A recurring fear is that Artificial Intelligence is a black box, which is therefore difficult to address given the impossibility of fully understanding how it works. One of the managers indirectly reports the experience of many other leaders he has spoken with, who complain of not knowing how to approach Artificial Intelligence because their prevailing feeling is that they *"don't understand either what to do, how to do it, how to manage it, how do I manage the risk of something incomprehensively complicated and statistical driven making decisions that impacts my business"(P31).*

Their sensemaking is based on an absent or merely exploratory use but disconnected from the scope of strategic decisions and for this very reason they generally have a reflexive attitude aimed at conveying their perception of a potential use of AI. In this sense, the recognition of transformative capabilities prevails only on a potential level and limited improvements in decision-making quality are outlined.

This pattern seems to drive the perception of Artificial Intelligence as a foggy path. Under this lens, Artificial Intelligence is a direction that could prove successful, but currently remains uncertain, obscure, and therefore difficult to face. Managers characterised by this pattern tend to recognise AI's transformative potential but admit their ignorance or inexperience in using it. This degree of perceived uncertainty pushes them to maintain a cautious attitude. Artificial Intelligence thus becomes a future prospect, a possibility to explore but still far from being integrated into strategic processes.

"At the moment, since we are consultants, I cannot imagine that if we have to prepare a presentation on a client we should define not only the strategic but also the political line on how to approach our work, the execution of a project, of a contract, and so on. I do not believe that, at the moment, it could in any way be profitable to consult Artificial Intelligence, because we would have to enter such a large amount of data that it would probably make very little sense. For our clients, certainly yes" (P7).

"The risk is that one loses awareness of the quality of the data that lies at the basis, right? […] I was talking not of imagination, but little more. I have no experience, only based on my perception […] Artificial Intelligence, however intelligent, it may happen that by giving it data and inputs, these do not exactly represent what my intention was… it is not rare the case in which you aim to obtain a piece of information, but in doing so, in processing the information, in chewing it over, you generally realize that you have chosen the wrong field of verification, and so you adjust your aim. But this is a second-level analysis that I believe Artificial Intelligence does not perform" (P8).

2.5.3 Pragmatic experimenter: Artificial Intelligence as a pilot medium

The participants in this cluster primarily distinguish themselves for their pragmatic adaptability, typical of leaders with medium-high digital and Artificial Intelligence literacy and cognitive openness, coupled with a high propensity for innovation, as well as for their selective prudence and their conceptualisation of Artificial Intelligence benefits in terms of knowledge management capabilities as mainly linked to diagnostic capabilities.

This cluster recognises the importance of being willing to question one's own beliefs as a prerequisite for potentially profitable Artificial Intelligence adoption, and this can occur in contexts where the leader is already accustomed to consulting with, for example, external consultants.

Their degree of reluctance stems from a fear that is not a priori and has little basis in experience; rather, it is the result of episodic experiments conducted by the decision-maker (in most cases autonomously and unstructured, and in one case as an experiment outsourcing an analysis conducted via AI). This reluctance takes the form of selective prudence, which relates in an almost evenly distributed manner to input data, to the model and its outputs, and to certain human-related tensions (an interesting point here concerns the risk that AI-generated recommendations may put the decision-maker in a difficult position, clashing with the impossibility of putting them into practice due to organisational, economic, or infrastructural constraints).

Their vision regarding the use of Artificial Intelligence is predominantly *emerging*, with some instances of a *guiding* vision (the two cases where concrete organisational actions have already been undertaken, even though the use has not yet reached full integration). An exception is represented by a *transformative* vision, characterizing the only individual within the cluster who has more extensive direct experience of the advantages generated by Artificial Intelligence in knowledge management and who, consistently, also acknowledges its integrated benefits for the decision-making process more broadly.

What interestingly distinguishes this pattern from that of the visionary innovators is that, for these managers, Artificial Intelligence is not deeply embedded in their personal lives. Their familiarity is therefore more limited, and their use does not reach the level of critical routines but is instead based on episodic tests. Such applications, however, in their view hold the potential to evolve in the near future into more frequent and structured uses, capable of modifying the current decision-making approach, should certain conditions of accessibility be met. In terms of accessibility, two interesting points emerge: first, the emphasis on the need to access customised solutions available on the market, rather than relying on general-purpose tools, which are deemed insufficient for strategic decisions representing a niche; and second, a genuine concern about the absence of regulation, in contrast to how some visionaries frame it (as a problem for others rather than for themselves).

Pragmatic Experimenters view Artificial Intelligence as a pilot tool suitable to conduct pragmatic experiments, testing its potential applications and reliability, which may turn out to be useful for validating decisions through more robust data and alternative scenarios.

“Then I say, in this case it is obvious that the person who had to make that decision is someone who had also initiated the outsourcing of this analysis with Artificial Intelligence through a provider, and therefore already had trust in Artificial Intelligence, and so the two things went hand in hand. […] As for Artificial Intelligence today, we still do not know where it will end up, and not knowing where it will end up, it should gradually be regulated as greater awareness of the phenomenon is gained. Therefore, it is certainly not a static idea, but an absolutely fluid one” (P12).

“While it was done more on the basis of knowledge and relationships in the past, today these tools are also used to conduct a search on the market for a solution, perhaps an innovative one, but what comes out them is not always, so to speak, in line with what we are actually looking for” (P14).

2.5.4 Visionary innovator: Artificial Intelligence as a peer advisor

This cluster is the largest of the 4 identified and the two themes that are revealed to be mainly characterising for this pattern (although there is not an absolute assignment of all participants to the same level, but a majority equal to 10 participants out of 12) are reluctance and knowledge management capabilities, followed by personal adaptability, praxis and strategic decision-making approach where 9 participants out of 12 fall into the same level.

These are the participants with the lowest level of reluctance, since for many of them, Artificial Intelligence adoption is already mature and culturally rooted. In this sense, almost all of them use it routinely and critically, allowing them to recognise its broad-spectrum benefits in terms of improving knowledge management capabilities, including effects on both diagnostic capabilities and the generation of future trajectories. Most of these managers therefore speak from direct experience, except for one who speaks in terms of extremely high expectations. He is, in fact, the only one who recognises the potential transformative capabilities and is still using it only in an exploratory manner but compensates with a strong transformative vision and an enthusiasm that obscures the perception of any critical issues.

Their low reluctance is also manifested in an almost critical tone toward those who fail to recognize the potential of Artificial Intelligence and are almost afraid of it. This seems absurd to them, because they strongly perceive the benefits that managers can experience not only professionally but also in their personal lives and those of their collaborators. For example, the reduction of the intense pressures that often characterize the strategic decision-making process, especially given the need to make certain decisions quickly. This often leads to significant work-life imbalances, which can instead be rebalanced thanks to AI-driven process optimization. A strong connection appears in this pattern between low reluctance and routine use, often reflecting intentionally structured experimentation in private life that leads to a certain familiarity. This familiarity (primarily with generative AI) translates into greater awareness of its use and allows users to view the tool's limitations with a critical but never fearful attitude. Even when it comes to potential outputs, they demonstrate openness, remaining critical in evaluating them (avoiding to blindly trust them), but always perceiving them as opportunities for enrichment. Differently, strong reluctance and limited vision generally lead to perceive them as causing confusion.

A crucial characteristic is a strong technological background (they are mostly digital natives, with a few exceptions, with strong enthusiasm), along with a generalised openness toward accepting contrasting views, which allows them to interact with Artificial Intelligence insights with critical maturity and awareness. A recurring idea is that the ability to assess the accuracy of such insights and to leverage them in the decision-making process is proportional to the manager's baseline knowledge of the topic at hand.

This general openness is based on a common assumption among most of them: a fast, efficient, and proactive strategic decision-making process (with varying degrees of formalisation depending on the company's life cycle).

Furthermore, most visionary innovators firmly believe in the importance of integrating Artificial Intelligence at all levels. Some are or have been involved in the development of Artificial Intelligence tools tailored to the company's needs, thus moving beyond individual use to involve employees at all levels. Their perception of potential impacts on the decision-making process tends to vary, ranging between selective (only some advantages are recognized) and integrated. For many, their perception of the degree of accessibility of Artificial Intelligence is linked to the need (as a condition) for being able to use targeted tools or the need for specific training, which, however, they predominantly cite as a need of others (in this sense, they do not perceive this as a barrier). Some cite problems related to the lack of regulation, but with interesting nuances: on the one hand, the need for more structured regulation to protect user companies is recognised, but this need is either cited as a barrier holding back other managers with limited vision, or there is even a fear that excessive regulation could impede the full exploitation of AI's capabilities. Economic aspects tend to be considered as irrelevant (for someone, they are relevant only as they think to make it usable on a large scale across the entire organisation), or they are considered as crucial adopting the lens of other managers of smaller businesses. Some of them not even consider this aspect as worth noting.

Overall, visionary innovators tend to make sense of Artificial Intelligence as a peer advisor that can support them on a daily basis and continuously simplify their way of making decisions. This pattern is at times marked by the tendency to make sense of it with a somewhat detached attitude: Artificial Intelligence is seen for what it is: it is neither overestimated, neither underestimated. These participants restrain their enthusiasm, likely because they have become fully 'naturalised' to the use of AI. On the other side of the spectrum, there are visionary innovators (mainly more mature managers), who openly display their full enthusiasm for the potential of AI, which they regard as extraordinary and truly unprecedented. Yet, they all agree that it represents a revolution with no way back, one that will transform not only their role as decision-makers but also everyone's life. It is interesting to highlight that all of this enthusiasm and openness do not imply they consider the possibility to fully rely on Artificial Intelligence for strategic matters: it can be of help, up to a certain point. They believe it can augment humans but still strongly put emphasis on the central role of humans and are sceptical on the possibility of Artificial Intelligence to completely replace humans for strategic purposes. As the others, they are aware of Artificial Intelligence limitations and fallacy, but this awareness does not lead them to desist from using it. They see it for what it is and consider it as a peer. They are not worried nor intimidated, simply because they believe they know AI, they are familiar with it, they feel confident in using it, they are able to spot to what degree it can be considered as reliable.

"It is a tool that everyone uses anyway, just as if it were their own right arm, so everyone then with their own role in the company and uses it accordingly for different reasons" (P1).

"I use it absolutely in a friendly manner. I have established a relationship as a work colleague, that is. He is more of a colleague than a machine" (P2).

"Ah it helps me a lot because he is that good co-worker who is always available and does not get impatient and above all follows you" (P6).

"Actually, all the time, because whenever I need, both in my private life and in business, to confront someone, I confront the Artificial Intelligence but always taking into account the fact that it can make mistakes" (P16).

"No one who I think really uses it regrets it. It is the same principle as with the i-phone or the automatic gearbox: that is, if one unlocks, one uses it. You don't unlock those who either don't have that kind of literacy or are not used to it" (P1).

"I went ahead and stated that it is obviously part of any process of human evolution, of technological evolution, or rather of human evolution through technology" (P9).

2.6 Discussion

This work offers a rich overview of the interpretative dimensions that influence strategic decision-makers sensemaking process of AI, as well as of the key patterns that shape their final conceptualisation.
The main contribution our findings is represented by the identification of four distinct sensemaking patterns that determine different managers' conceptualisations of AI:

sceptical observers, tentative explorers, pragmatic experimenters, visionary innovators. Noteworthy points for discussion emerge by examining the study's results from a cross-cutting integrative perspective that combines themes and Artificial Intelligence sensemaking patterns.

First of all, the patterns may be interpreted as sequential, reflecting the gradual shifts across the levels that occurs for most of the themes (from sceptical observers to tentative explores, to pragmatic experimenters, and ultimately to visionary innovators). However, there are some exceptions that deserve consideration about the predominant levels that characterise each pattern. Within the theme of vision, a gradual progression is evident from the first to the final level, yet with a peculiarity: the emerging vision is a distinctive feature of both the *tentative explorer* cluster and the *pragmatic experimenter* cluster, whereas the guiding vision does not represent a distinguishing element in any cluster. Thus, the two aforementioned patterns share the characteristic of an emerging vision, which, however, takes shape as a more theoretical vision for the former and a more pragmatic one for the latter. Concerning knowledge management capabilities, the sequential order is interrupted between the same two intermediate groups: explorers mainly stand out for their attention to potential transformative capabilities, while experimenters for diagnostic capabilities. This again can be understood in light of the more theoretical approach that characterizes the explorers. As for strategic decision-making quality, it is worth noting that the second level of process optimisation is never characterising, and that for pragmatic experimenter none of the levels turns out to be characterising. Regarding personal adaptability, there is no characterising level for sceptical observers, thus suggesting that their adaptability is not extremely rigid, despite their lack of vision, the same is true regarding praxis of tentative explorers, who equally engage with sporadic and exploratory use of AI. What is interesting about Artificial Intelligence accessibility is that only for visionary innovators there is a characterising level, and it is not the highest on the scale (conditional accessibility). This peculiarity suggests that accessibility conditions are of limited relevance in shaping managers' sensemaking. Strategic decision-making approach turns out to be predominantly intuitive for both sceptical observers and tentative explorers. Overall, there are only two cases of unanimous assignment: absent or minimal vision for sceptical observers and emerging adaptability for tentative explorers. The largest cluster is that of the visionary innovators. Within this pattern, a greater coherence in the assigned levels is also evident: for all themes, with the exception of Artificial Intelligence accessibility, the predominant level is the one at the extreme of the scale, which most clearly explains the pattern itself.

The main theoretical contribution of the present work to sensemaking theory is represented by the empirical map of sensemaking pattern that was derived by a cross-theme interpretation of our coded data. These findings show that the interpretative process underlying sensemaking toward an emerging and promising technology like Artificial Intelligence is not unique. The paper also contributes to the literature on managerial cognition and technology adoption (Eggers & Kaplan, 2009; Kaplan & Tripsas, 2008) by proposing how such individual cognition can be consistently aggregated into consistent collective sensemaking patterns. In this perspective, the work further advances the existing understanding of managerial perceptions of Artificial Intelligence (Chaturvedi & Dasgupta, 2024) proposing some comparable typologies that help explain the wide variety of approaches managers may embody. In addition, the theoretical contribution also lies in the fact that the proposed typology of sensemaking patterns does not purely reveal that managers make sense of Artificial Intelligence in different ways, but it also reveals the foundations of such different patterns and the consequent different Artificial Intelligence configurations, linking together vision, mindset, routines, decision practices and outcomes, capabilities. This approach offers a novel interpretative structure of technology (particularly AI) adoption that bridges cognition and sensemaking literature in a robust way.

2.7 Conclusion, implications and limitations

Our study enhances the understanding of the main themes that shape managers' sensemaking of AI, deducing a typology of four sensemaking patterns. The use of sensemaking lens to accomplish this goal allows to unlock new perspectives on key aspects already investigated in prior literature, as well as to shed light on novel nuances and aspects that deserve further investigation.

The study offers managerial implications that address the need for typologies to provide not only descriptive richness but also greater explanatory power (Doty & Glick, 1994). Overall, the findings could help managers broaden their perspective and push them toward experimenting Artificial Intelligence benefits more extensively. Furthermore, some biases or prejudices on Artificial Intelligence may be mitigated thanks to an increased awareness of how Artificial Intelligence is perceived by other managers. More specifically, the proposed typology offers a framework for a series of specific managerial implications. The facilitated recognition of a sceptical observer pattern may allow to accelerate interventions aimed at overcoming existing cognitive barriers, thus helping to avoid the risk of dangerous competitive delays. Tentative explorers usually conduct individual, unstructured and infrequent Artificial Intelligence experimentations; their presence within organisations that are struggling to define an Artificial Intelligence adoption strategy can be valorised by encouraging the exchange of their individual (although still limited) experience that can stimulate further group-level experimentations and ultimately encourage a more structured approach, after cleaning the "fog" as experience of use accumulates. Furthermore, the lesson learned by pragmatic experimenters through their pilot projects or Artificial Intelligence use externalisation for low-risk matters may be of great encouragement for both tentative explorers and sceptical observers. On the other hand, pragmatic experimenters could be inspired by the experience of visionary innovators to embrace a long-term oriented and integrated vision of Artificial Intelligence adoption, while also discovering ways in which Artificial Intelligence can contribute to strategic decisions that they hardly envisioned and that are uncovered thanks to the more extensive and routinised experience of innovators. Eventually, the main implication for those managers that are already embodying a visionary innovator pattern lies in the opportunity to strengthen their awareness of both the benefits and the risks, thanks to the structured and systematic view provided by the typology. Such benefits and risks might otherwise be underestimated or overlooked until they are externalised and shared. In particular, this may make them more cautious in facing the risk of overconfidence or overestimation, pushing to maintain a balance between enthusiasm and critical assessment. Despite our sample being fairly large and varied, there still remain potential concerns in terms of scope and generalisability of our findings.

Future research may contribute to operationalise the macro-themes underlying sensemaking typologies through the development of measurement scales, to enable quantitative tests on their contribution to the emergence of the different patterns. In addition, the impact different patterns on performance measures can be tested (e.g. decision performance, innovation performance), while considering some contextual factors as potential moderators. The patterns can also be reinforced through a longitudinal approach, following the shift of managers' sensemaking from one pattern to the others, while also considering the effect of the rapid technological evolution that continuously occurs. Eventually, there is scope for investigating them in relation to team dynamics in group decision-making.

3. Perceptions of the Artificial Intelligence Among PIs in Supporting Value Creation: The case of KM3NeT4RR Research Infrastructure[3]

Abstract

Principal Investigators (PIs) are recognised as central value creators who drive cutting-edge scientific discovery and contribute to research commercialisation and value creation for society at large.

Despite the growing interest on Artificial Intelligence across all industries, limited attention has been placed on how it may reshape value creation dynamics and therefore impact scientific discovery and research commercialisation. This work aims to uncover the role Artificial Intelligence may play in the value creation dynamics handled by Principal Investigators, leveraging their micro-level perceptions of Artificial Intelligence adoption in their role.

We employ a single case study design to uncover how Artificial Intelligence can contribute differently to enhance or hinder value creation of scientists in the PI role, selecting KM3NeT4RR large-scale research infrastructure as suitable context for our investigation.

Our findings reveal that PIs perceive Artificial Intelligence as a significant support to their value creation across a wide range of their responsibilities, including scientific ideation, strategic alignment, team coordination, stakeholders' engagement, project orchestration and research exploitation, since it acts as an enabler of enhanced knowledge acquisition, improved decision-making and faster and more efficient problem solving. However, the findings also outline some potential value destruction risks, including misalignment and reduced robustness, relational and autonomy concerns and the unrealised potential of Artificial Intelligence itself due to individual,

[3] This chapter is based on a research paper that was presented, in a short version with preliminary findings, at the *Technology Transfer Society (T2S) 2025 Annual Conference* and at the *Workshop "Il Knowledge Management niello sviluppo di una comunità scientifica globale (3rd edition).* The initial version was subsequently expanded and developed into the present full version.

technical and attitudinal factors. These findings offer an integrative view on Artificial Intelligence value creation and value destruction mechanisms across the broad spectrum of PIs responsibilities.

3.1 Introduction

Artificial Intelligence (AI) role in supporting several tasks and processes has been and is still being widely investigated in academic literature. Artificial Intelligence can provide relevant support to project management, driving overall efficiency through resource allocation optimisation and enhanced decision-making (Salimimoghadam et al., 2025). Recent streams of research started to explore AI's impact on scientific research, highlighting its implications for data analysis, methodology, research management (Erduran & Levrini, 2024; Van Noorden & Perkel, 2023), improving the overall efficiency of research processes.

Concerning management functions in scientific research, Artificial Intelligence has been recognised as able to support task division/allocation, direction, coordination, motivation, supporting learning (Koehler & Sauermann, 2024).

Artificial Intelligence transformative power can bring significant changes even in the research environment, by supporting Principal Investigators (PI) driving high-dimensional research projects.

PIs play a crucial role in the research ecosystem by acting as value creators that, within the quadruple helix framework, connect university, industry, government and society by contributing to scientific discovery, as well as to dissemination and commercialisation of the produced knowledge (Cunningham et al., 2018), while also being engaged in capturing value from publicly funded research by extending the research impact to a wide range of stakeholders within the ecosystem (O'Kane, Zhang, et al., 2020).

PIs are first of all scientists and therefore, their core responsibility is mainly linked to scientific discovery. However, their role has become more complex by incorporating a wider scope of responsibilities and expectations from stakeholders.

Such complexity deserves further investigation into the peculiarities of their interaction with AI. We have identified a gap at the intersection of two distinct streams. On one hand, the AI-adoption literature has extensively explored how Artificial Intelligence tools augment a broad set of managerial and entrepreneurial tasks at various organisational levels. On the other hand, research on PIs has shed light on the complexity of their roles. Despite considerable scholarly attention on the mentioned fields, the underlying motivations that drive PIs to adopt Artificial Intelligence as well as the specific risks they perceive as linked to its use in relation to their role remains scarcely explored.

The study is therefore guided by the following research question: *when it comes to Artificial Intelligence adoption, how do principal investigators perceive the value creation motives and value destruction risks in relation to the complexity of their multifaceted role and responsibilities?*

The gap this study seeks to address concerns not only the ways in which Principal Investigators adopt Artificial Intelligence, but more critically how they perceive its current and potential value in relation to the diverse set of responsibilities they are expected to fulfil.

To address this gap, we adopt the theoretical lens of value creation with particular attention to value creation motives and risks of value destruction. This framework is deemed suitable to capture the complex and multidimensional nature of PIs' perception.

We design a microlevel single case study that investigates the use of Artificial Intelligence by Principal Investigators as peculiar strategic decision-makers, in the specific context of a public funded research infrastructure. The selected infrastructure is KM3NeT4RR (Kilometer Cube Neutrino Telescope For Recovery and Resilience), as a suitable environment to study the phenomenon under investigation, using PI, co-PIs and Scientific Project leaders as our unit of analysis.

The remaining of the paper is organised as follows. Section 2 presents literature considerations on PI roles and responsibilities, section 3 introduces the theory of value as theoretical lens of the study, section 4 outlines the research design, including details on data collection and coding procedure. Section 3 is a structured overview of our findings, which are presented through thematic categories and supporting quotations.

The findings are then discussed in Section 6 to highlight the theoretical contribution of the paper. Eventually, we draw some concluding thoughts and outline the main implications and limitations of the paper, as well as some potential future research directions.

3.2 Literature review: Principal Investigators role and responsibilities

The role of Principal Investigators is multifaceted and complex as it comprises responsibilities around the advancement of scientific knowledge as research leaders (Kidwell, 2014) as well as the overall management of a research project. On the one hand, PI's are responsible for the development of a research agenda, for securing funding and for the scientific direction of a project, on the other hand, they ensure the successful accomplishment of the identified goals (Cunningham et al., 2015; Del Giudice et al., 2017). The PI therefore oversees the project from its genesis, through its development up until its completion.

From a practical point of view, this entails several tasks, from research design to securing funding, and from project management to knowledge valorisation.

Their overarching responsibility starts with setting boundary spanning research objectives that can actually contribute to the creation of relevant knowledge (Sekine et al., 2023).

In a highly competitive funding landscape, they navigate funding opportunities and identify those for which to compete, then develop a research proposal in the attempt to secure fundings (Cunningham et al., 2019), sometimes facing disparities in the allocation of fundings (Gillen et al., 2023). In addition to being engaged in grant writing, they eventually oversee all aspects of grant management in compliance with the requirements of the funding agency financing the project (O'Kane et al., 2022), articulating research goals and selecting members of their research team and network (Cunningham et al., 2019). If necessary, they are responsible for the establishment of the physical infrastructure required to conduct the research and they ensure that the allocated funding is spent appropriately and in compliance with the timeline, rules and regulations set by the agency. Overall, they operate as intermediaries between the funding body and the institution and respond to both of them for their activity, making sure to align their research endeavours with funding agency directions (Cunningham et al., 2015; O'Kane, Mangematin, et al., 2020).

From a behavioural and attitudinal point of view**,** PIs are expected to possess a broad array of capabilities essential to successfully manage complex research initiatives. As highlighted by Boehm and Hogan (2014), a PI should act as a "jack of all trades" interact with a wide array of stakeholders, filling the gap between industry and research. Furthermore, they need to show entrepreneurial capabilities in strategically competing for funding and navigating the political and institutional framework (Casati & Genet, 2014), which is named among the inhibitors of PIs' activity in the specific context of publicly funded research (Cunningham et al., 2014).
They also play a pivotal role in managing, motivating, mentoring, and supporting research team members to foster a collaborative and harmonious team working environment aimed at achieving shared research objectives (Antes et al., 2019). This is accomplished by promoting team functionality and effectiveness through the strategic exercise of leadership capabilities (Stedman & Adams-Pope, 2019). Their leadership and entrepreneurial capabilities are critical for them to manage complex collaborations and relationships with a wide and diverse range of stakeholder to bridge academia and society, acting act as key agents of change within the entrepreneurial ecosystem, facilitating the shift from technological to social innovation (Carl, 2020; Cunningham, O'Reilly, et al., 2016).
Indeed, PIs' effort flows into the realisation of impact from academic research. Such impact can be measured in terms of new knowledge creation as they are scientist in the first place. The exploitation of this knowledge as a way to expand the generated impact takes place through knowledge management practices (Cunningham et al., 2022) and the commercialization of knowledge that leads to economic results leveraging technology transfer process (Menter, 2016), but also in a broader sense as the utilisation of the developed knowledge by all helix actors (Cunningham et al., 2017). In this regard, PIs are considered as boundary spanners between academia and industry since they in shape the research agenda aligning it not only to scientific

inquiry needs but also to broader market needs (Mangematin et al., 2014) to ensure a broader dissemination and application of research beyond academia (Kidwell, 2014). The inherent complexity of the PI role led to the emergence of different definitions and categorisations in the literature. Such definitions and categorisations aim to incorporate strategic and intangible dimensions of the role. Kidwell (2013) primary describes the PI as a knowledge broker, whose core responsibilities centre on the activities of extrapolating, seeking, aligning and anticipating. Extrapolating refers to extending research findings outside of academia so as to find potential applications within industry and society. Seeking entails searching for knowledge and opportunities that can improve the research outcomes and their impact. The activity of aligning involves mediating between differences characterising academia and industry in terms of goals, languages and expectations. Anticipating refers to the strategic effort to foresee future challenges as well as needs and opportunities to ensure innovativeness and relevance of the ongoing research activity. Casati and Genet (2014) emphasize the idea of the Principal Investigator as a scientific entrepreneur. Their definition focuses on the entrepreneurial dimension of their scientific leadership, that enables them to lead research teams and conduct research aimed at developing knowledge and shaping future research trajectories, consequently influencing the broader scientific community, but also to drive innovation and address challenges that are relevant to markets and industries. O'Kane et al. (2015) propose a classification of PIs into research adapters, research pursuers, research designers and research supporters, based on their reactive or proactive posture toward funding opportunities. Cunningham, O’Reilly, et al. (2016) reach a comprehensive and insightful synthesis of the main responsibilities the PI role encompasses for the orchestration of a research project: scientist, research strategist, project manager, team leader, administrator, stakeholder manager, project promoter, resource manager, supervisor & mentor, knowledge broker engaged in technology transfer activities to bridge science and industry. These big picture on PIs’ responsibilities enhances the clarity on their complex role. O'Kane, Mangematin, et al. (2020) identify four main PI roles that synthesise the main tasks and attitudes PIs are expected to embody, Science Networker (organizer), Research Contractor (visionary), Project Manager and Entrepreneurs, stressing the hybrid nature of this role and the importance of learning mechanisms in shaping it. Foncubierta-

Rodríguez et al. (2023) identify three PI profiles based on human capital attributes: research-oriented PIs, accomplished PIs, management-focused PIs, while stressing the idea that there is no optimal human capital equipment for a PI that can fit any project and any situation.

In conclusion, scholars proposed various categorizations of PI responsibilities to reach a clearer and more comprehensive understanding of such a complex and hybrid role. This complexity stems from the variety of skills required to engage effectively with the wide set of stakeholders and to reconcile scientific goals with institutions, industry and society expectations: advanced scientific skills, relational and managerial skills, leadership skills, problem-solving skills.

3.3 Theoretical background: value theory, value creation motives and value destruction risks

“Value creation is a central concept in the management and organization literature for both microlevel (individual, group) and macrolevel (organization theory, strategic management) research. Yet there is little consensus on what value creation is or on how it can be achieved” (Lepak et al., 2007, p. 180).

The literature on value creation in management is indeed multi-faceted: as a cross-cutting topic, it has been investigated by various theories offering different perspectives to explain the mechanisms of value creation itself and the actors involved in it.

Looking at the key building blocks of value creation within the firm, key explanations arise from Resource-Based View (RBV) (Barney, 1991; Wernerfelt, 1984), according to which superior value is created by those firms possessing assets that are difficult to replicate by competitors. As crucial extension of RBV, the Knowledge-Based View (KBV) highlights the centrality of knowledge, its acquisition, generation, integration, sharing and application, as the core strategic resource, mainly responsible for value creation (Grant, 1996).

According to Teece et al. (1997), what enables firms to create value and sustain their competitive advantage over time is their dynamic capabilities. Dynamic Capability

Theory (DCT) argues that the ability of firms to reconfigure resources or get new ones enables them to adapt to the evolving competitive landscape. In the theoretical framework proposed by Porter (1985b), the value created by firms lies in performing those activities composing the value chain more effectively than competitors do.

The focus has then shifted on the dynamic interaction among different actors, including individual firms and their stakeholders, in a value co-creation logic (Nenonen & Storbacka, 2010; Payne et al., 2008).

In marketing literature, this focus on interactions is stressed with the shift toward a service dominant logic (Vargo, 2009; Vargo & Lusch, 2004, 2008), according to which value is created as a result of synergistic interactions among actors that exchange service as "process of using one's competences (knowledge and skills) for the benefit of another party" (Vargo, 2009, p. 374). As opposed to good-dominant logic, service-dominant logic argues that the firm alone cannot actually create value, which is instead created collaboratively by consumers based on the input (the value proposition offered by the firm).

Under a stakeholder theory perspective (Freeman, 2010), value is created for a broad set of stakeholders, that involves customers, shareholders, employees and the whole society.

The creation of value at an ecosystem level is predominantly linked to entrepreneurial activity as driver of innovation and economic impact (Cavallo et al., 2019; Cunningham et al., 2024). This value creation conceptualisation shift reflects a perspective evolution, from firm centric to network centric.

A crucial perspective is the one that emphasises the interlinkages between value creation and value capture mechanisms, proposing the idea that value creation for the firm does not terminate with creating and delivering benefits to consumers and all the stakeholders' groups, but culminates in the process of getting back advantages (profits and other types of benefits) that partially reflect the value created (Boardman & Ponomariov, 2014; Bowman & Ambrosini, 2000; Lepak et al., 2007), thus feeding a sustainable business model (Biloshapka & Osiyevskyy, 2018), in line with the idea of a collaborative co-creation effort driven by various actors.

To clarify the distinction between value creation and value capture, Bowman and Ambrosini (2010) distinguish between the Use Value (UV), defined as the usefulness subjectively perceived by the end user of the value proposition (be it a product or service) that results from the value creation effort, and the Exchange Value (EV), represented by the monetary price the firm receives back as expression of value capture. As counterpart of value creation and capture, they also raise the issue of value destruction, regarded as a reduction in value capture resulting from inefficient activities that actively erode and undermine the value created, or unproductive activities that do not actively enhance it. Such activities should be identified and managed to limit their negative effects.

The different conceptualisations of PI role align with different ways in which PIs create value in interaction with their team members and with other stakeholders.

They are responsible for new and relevant knowledge generation, which expresses the value created on the scientific side, by setting the conditions and guiding the processes that lead to it (Cunningham et al., 2022; O'Kane, Mangematin, et al., 2020). In this sense, they are key actors that feed academic discourse and foster scientific excellence, positioning their research at the frontier of scientific inquiry in their field of specialisation (Cunningham, Mangematin, et al., 2016; O'Kane et al., 2015).

They also build collaborative environments through their leadership and mentoring capabilities, thus contributing to value creation in terms of human capital development (Antes et al., 2019).

All the challenges and stressors they face throughout this process at a micro-level are obstacles to value creation, and their ability to successfully address them reinforces the sustainability of the value-creation process (Cunningham et al., 2014).

Furthermore, by engaging in knowledge transfer processes, the scientific value is converted into broader economic value, since they facilitate knowledge commercialisation (Cunningham et al., 2020; Menter, 2016), and act as engaged innovators (Kidwell, 2013).

They also contribute to a broader societal impact, leveraging the knowledge they create and valorise (Cunningham et al., 2017). Their action as scientific entrepreneurs that aims to funding acquisition and strategical usage of the secured funds also supports territorial development (Del Giudice et al., 2017; Romano et al., 2025).

The categorisation proposed by Cunningham, O'Reilly, et al. (2016) broadly captures the complexity of the PI role in its strategic and practical dimensions. Drawing on this categorisation and leveraging the concepts of value creation and value capture as unfolding across the different PIs' responsibilities, as showed in Table 13, we have mapped value-creation goals and value-capture dimensions associated to each of the identified areas of responsibility.

Across the spectrum of management theories that provide different perspectives on value creation, two overarching concepts emerge: *value creation motives* and *value destruction risks*.

The former refers to those underlying drivers that motivate organisations and/or individuals to actively engage and put effort into activities that contribute to value creation. The latter refers to the possibility that inefficient activities or decisions may reduce the value created, hinder its capture or fail to contribute to the potential value otherwise generated.

A strategic management perspective suggests to look at value creation motives and value destruction risks as linked to efficiency and profit maximisation as well as to a push toward generating innovation (Chesbrough, 2006), gaining competitive advantage through different strategic trajectories, developing and leveraging key resources and capabilities (Barney, 1991; Peteraf, 1993; Sirmon et al., 2007), creating, managing and exploiting strategic knowledge (Grant, 1996).

Stakeholder theory (Freeman, 2010) broadens this perspective, by emphasising the willingness to meet expectations and needs of multiple stakeholders groups, generating benefits for them, even beyond an economic profit-maximisation logic, in light of a normative engagement perspective that values stakeholders for their own sake (Donaldson & Preston, 1995). This view if furtherly integrated by a service-dominant logic that identifies value co-creation with stakeholder, value-in-use, and resources integration and orchestration as key motives that drive actors value creation activities (Vargo & Lusch, 2004, 2008).

PI responsibilities	Value creation objective	Value-capture dimensions
Scientist	Produce scientific knowledge; contribute to innovation.	Publications; scientific reputation (Cunningham et al., 2019; Romano et al., 2025).

PI responsibilities	Value creation objective	Value-capture dimensions
Research Strategist	Be proactive and visionary in developing research agendas; be competitive in funding calls.	Anticipation of challenges to be addressed; funding acquisition (Cunningham et al., 2017; Laudel, 2006)
Project Manager	Drive and oversee project implementation.	Adherence to time/budget constraints (Cunningham et al., 2019).
Team Leader	Foster team commitment to a shared scientific mission; promote cohesion.	Human capital development, team harmony (Boardman & Ponomariov, 2014; Foncubierta-Rodríguez et al., 2022).
Administrator	Conduct financial and activity reporting; ensure compliance with agency and institutional requirements.	Administrative productivity through timely and adequate reporting (Cunningham et al., 2019; Romano et al., 2025).
Stakeholder manager	Engage external stakeholders.	Simmelian ties with helix actors; networking, partnerships; generation of multidimensional territorial impact (Cunningham et al., 2018; Cunningham et al., 2019; Kidwell, 2013; Romano et al., 2025).
Project Promoter	Effectively position the project.	Public science programs delivery (Cunningham et al., 2019).
Resource manager	Select and acquire human and technical resources; allocate them appropriately.	Strategic and effective utilisation of all available resources to accomplish the scientific mission (Boardman & Ponomariov, 2014; Cunningham et al., 2019; Del Giudice et al., 2017).
Supervisor and Mentor	Guide junior researchers and inspire team members.	Human resource development (PhD completion, career advancements) (Antes et al., 2019)
Knowledge broker	Bridge science, industry and policy.	Knowledge/technology transfer; innovation outputs; new technologies; patents, spin-offs (Baglieri & Lorenzoni, 2014; Cunningham et al., 2019; Del Giudice et al., 2017; Kidwell, 2013; Romano et al., 2025).

Table 13: PI roles and related value dimensions (source: our elaboration)

For the purpose of this study, we employ a micro-level perspective on value creation with a focus on scientists in the PI role, specifically leveraging the concepts of value creation motives and value destruction risks. In particular, we investigate how Artificial Intelligence can enhance or hinder a Principal Investigator's ability to achieve his goals, above conceptualised as different forms of PIs driven value creation. Despite the firm-centric nature of the mentioned views, they can serve as a suitable lens to understand PIs' motives in being supported by Artificial Intelligence as a resource and additional actor in the value creation activities entailed by their role.

3.4 Research design

We adopt an exploratory qualitative approach based on a single case study design. The following subsections present a justification for this research design choice, as well as the methodological steps undertaken, from case selection to data collection and data analysis.

3.4.1 Exploratory qualitative research design: a single case study

Our study is a qualitative study, exploratory in nature, given the novelty of the phenomenon under investigation that requires further in-depth contextual understanding (Creswell & Poth, 2016).

The phenomenon of embracing Artificial Intelligence for value creation is indeed investigated in the specific context of research infrastructures, knowledge intensive environments where scientists in the PI role and their collaborators engage in broad value creation processes through their scientific initiatives. Given the peculiarities of such a knowledge intensive environment, it deserves further investigation with an open and exploratory approach.

Indeed, Artificial Intelligence use in knowledge-intensive environments, such as research infrastructures and agencies, is still at an embryonic stage: it is still unusual for them to rely on general purpose Artificial Intelligence and/or implement targeted Artificial Intelligence solutions in support of their activities.

We therefore privilege a deep understanding of one pioneering infrastructure that, leveraging a fruitful collaboration with the local university, sensed the potential value of embracing such a disruptive innovation to push the boundaries of PIs' strategic and operational activities.

3.4.2 Single case selection: KM3NeT4RR

We employ an exploratory single case study design, which is deemed suitable for the emerging and underexplored nature of the phenomenon (Eisenhardt, 1989) of Artificial Intelligence use within knowledge intensive research infrastructures, by Principal Investigators as key strategic decision-makers, whose decisions and actions shape their value creation and capture.

In this perspective, our goal is to privilege depth over breadth by seeking for a richer contextual understanding of the phenomenon (Dyer Jr & Wilkins, 1991), unveiling peculiar complexities and implications (Flyvbjerg, 2006; Stake, 1995).

In addition, the selected case is worth a dedicated single case analysis due to some characteristics that make it unique or revelatory for the purpose of our study (Yin, 2009).

The reasons behind the choice of KM3NeT4RR (Kilometer Cube Neutrino Telescope For Recovery and Resilience) are mainly linked to the nature and relevance of the research activities it enables, to its dimensionality, as well as to the initiative recently undertaken to develop a targeted Artificial Intelligence tool. KM3NeT4RR uniqueness is first linked to the undersea neutrino telescope infrastructure that enables real-time data collection and transmission, at the core of highly relevant research activities. It is part of a consortium of universities and research entities in a broad cross-regional and cross-university project within international networks with huge implications.

Furthermore, the nature of the research conducted in it, engaging scientists with physics and astronomy background, typically entails the use of technological instruments as well as specific software applications. As also highlighted by some of the participants, particle physicists were among the first to use Artificial Intelligence for data mining to deal with the enormous amount of data in their experiments.

In addition, a peculiar initiative has been carried out in KM3NeT4RR aimed to develop a specific Artificial Intelligence tool by means of a dedicated call. This tool has been designed to support activities of the various actors operating it, including the PI, the co-PIs and their team. These characteristics make KM3NeT4RR infrastructure suitable to investigate the changes brought about by Artificial Intelligence in the role and activities of PIs, supported by their Co-PIs and Scientific Project leaders. These individuals are indeed our unit of analysis. Some of the Co-PIs and Scientific Project leaders, although they do not take the role of PIs in this specific research project, have long experience in the PI role in previous projects (so-called serial PIs). They therefore embrace the PI approach and mentality properly, thus having a more comprehensive view of the potential impact of AI.

The KM3NeT4RR project envisages an upgrade of the KM3NeT submarine infrastructure and of the various integration sites used for its construction. KM3NeT (Kilometer Cube Neutrino Telescope) is a deep-sea research infrastructure and it is part of broader European programme that involves other large infrastructures (ESFRI, ASPERA, APPEC and AstroNet) and is a founding member of the Global Neutrino Network (GNN), which aims to orchestrate the various neutrino projects undertaken worldwide under a common strategy (KM3Net.org).
KM3NeT4RR (Kilometer Cube Neutrino Telescope for Recovery and Resilience) is a further improvement and development of the KM3NeT neutrino observatory, especially the ARCA (Astroparticle Research with Cosmics in the Abyss) detector off the Sicilian coast. Such infrastructure indeed comprises a network of ARCA neutrino detectors in the Mediterranean Sea, one of which is located in Portopalo di Capo Passero, in the south of Sicily (Italy), and the other off the coast of Toulon (France), to do neutrino detections and thus fundamental physics research (KM3Net.org).
This project involves approximately 360 professionals, including researchers, technologists, engineers, and computer scientists and it is a large-scale scientific collaboration characterised by the simultaneous progression of multiple parallel activities, reflected by the various working packages (WPs). It has a strong multidisciplinary nature, involving physicists, astronomers and marine scientists and has a strong connection with regional and national context (km3net4rr.infn.it)
The scientific, infrastructural and operational complexity of the initiative poses the need for a structured and systematic approach to project management. In this context, the role of a Principal Investigator is essential for defining operational plans, coordinating activities, and acting as the primary point of contact with funding bodies (the European Union, the Italian Ministry of University and Research (MIUR), and, in

the specific case of this experiment, the Sicilian Regional Government, given the project's location within the Sicilian territory).
The entire submarine infrastructure, which did not exist prior to the project's inception, is a tailor-made infrastructure developed by the collaboration, in partnership with selected industrial suppliers. It consists of both onshore and offshore components. Focusing on the Italian side of the infrastructure, the onshore facilities include a laboratory located in Portopalo di Capo Passero, which houses computing systems, power supplies, and other critical equipment. From this station, two submarine cables, each approximately 100 kilometers in length, extend to the underwater site. These cables end in specialised subsea cable terminations that provide underwater connection ports for additional secondary cables. From the cable terminations, connections are made to structures referred to as junction boxes, which are titanium units of approximately two meters height, equipped with pressure-resistant chambers designed to operate at depths exceeding 3,000 meters. These junction boxes serve as distribution hubs, each capable of connecting up to 14 detection units of the telescope.
A particularly interesting aspect, highly relevant for the present research, is that the management has recently launched a collaboration with an external technology partner aimed at developing a knowledge management platform that uses Artificial Intelligence algorithms to facilitate the navigation of the numerous and complex knowledge flows of the infrastructure. This clearly reflects a strong inclination toward the adoption of Artificial Intelligence in even novel ways, previously unexplored in knowledge intensive contexts of this type.

3.4.3 Data collection and analysis

Data collection primarily took place through semi-structured interviews. We contacted the PI and all the Co-PIs of the selected research infrastructure involved in the research activities taking place on the Italian side of the project (scientific coordinators and leaders). We contacted 24 potential participants, and the final sample was composed of 12 participants, that were interviewed between March 2025 and June 2025. In addition, some documentary data concerning the customised Artificial Intelligence development initiative were collected. We conducted thematic analysis (Braun &

Clarke, 2006, 2021; Cooper et al., 2012) on NVivo software to support the coding process (Jackson & Bazeley, 2019).

Interviews were transcribed and a preliminary phase of familiarisation with the data was undertaken, before starting a two-step coding procedure. Figure 5 illustrates the main steps of our data collection and analysis. Initially, first-order codes tied to the participants' language and perspectives were identified. Subsequently, such codes were organised into second-order constructs, reflecting more abstract, theoretically informed themes inductively emerging from the data. The data analysis process was guided by an abductive approach aimed at developing theoretical concepts from the data while iteratively revising and refining them in relation to existing literature background (both PI responsibilities literature and value theory) used as interpretive framework. Abduction was introduced by Peirce (1934) as a form of creative and intuitive reasoning, that leads to the best possible explanation of observed phenomena and supports the generation of novel ideas. In business and management research, the adoption of an abductive logic is regarded as a suitable approach to conducting qualitative research (Timmermans & Tavory, 2012). In particular, in case study research, abduction lies at the core of what is known as "systematic combining" case study research (Dubois & Gadde, 2002). It is described as method to investigate phenomena by iteratively integrating empirical insights into a suitable theoretical framework, in a dialogical process that ultimately leads to more refined and conceptually robust analytical categories.

Consistently with the described approach, the present study did not aim to deductively test hypotheses. After identifying emerging codes and categories, we have used theoretical foundations of value theory and the concepts of value creation motives and value destruction risks, along with the theoretical background on the roles and responsibilities of PIs as interpretative lenses. This abductive process allowed us to refine the coding and eventually categorise our themes as value creation motives and value destruction risks and link them to specific PI responsibilities.

Table 14 provides an overview of participants and Table 15 summarises the data structure with the related supporting evidence from the data in terms of participants' quotations. The findings are presented by reporting the themes resulting from the coding activity as value creation motives and value destruction risks.

P	Role	Motivation	Exp. years	Training in Artificial Intelligence usage	Current Artificial Intelligence usage	Expectations
P1	Principal Investigator	Overcome bureaucracy	20	No	"Speculative use": scientific data analysis; ex-ante development of the project	General openness toward a broader use
P2	Previous deputy spoke person; Scientific coordinator, WP leader	Research team coordination and harmonisation	5	No	Writing, comparing with existing scientific production	Market analysis for technological solutions
P3	Scientific coordinator, WP leader (Local PI)	Interpersonal relationships management	10	No. Self-learning supported by personal curiosity	Keep up with scientific production	Real support in decision-making; improved knowledge sharing and monitoring.
P4	Scientific coordinator	Resource allocation	20	No	No	Project management, administrative support, coordination, scientific data analysis
P5	Scientific coordinator, WP leader	Alignment to changing normative environment	20	No	No	Strategic and administrative documentation production, project management and coordination
P6	Scientific coordinator, WP leader	Stay innovative	5	No. Self-learning supported by personal curiosity	"Explorative use" for problem-solving	General openness toward a broader use
P7	Scientific coordinator	Human resource management, optimised and correct use of resources (human, economic, technological)	3	No. General purpose Artificial Intelligence training	Project writing	Problem-solving, coordination
P8	WP leader	Seeking for funding (project writing and team building), facing organisational and bureaucratic issues, balancing delegation and authority	6	No. Marginal references included in other training programmes	Studying and summarising scientific production; communication	Project development and writing, general-purpose facilitator

P	Role	Motivation	Exp. years	Training in Artificial Intelligence usage	Current Artificial Intelligence usage	Expectations
P9	Infrastructure manager	Research team coordination and harmonisation	25	No	Communication	Project planning and management
P10	Scientific coordinator, WP leader	Coordination, act as a mediator between different stakeholders, monitor scientific progress, overcome bureaucracy	25	No (not available yet)	Scientific data analysis; learning	Delegation of mechanical tasks
P11	Scientific coordinator		8	No	Scientific data analysis	Issues prevention
P12	Scientific coordinator	Stimulating commitment of various actors	15	No	Scientific data analysis	More advanced scientific support, strategic planning

Table 14: Overview of participants (source: our elaboration)

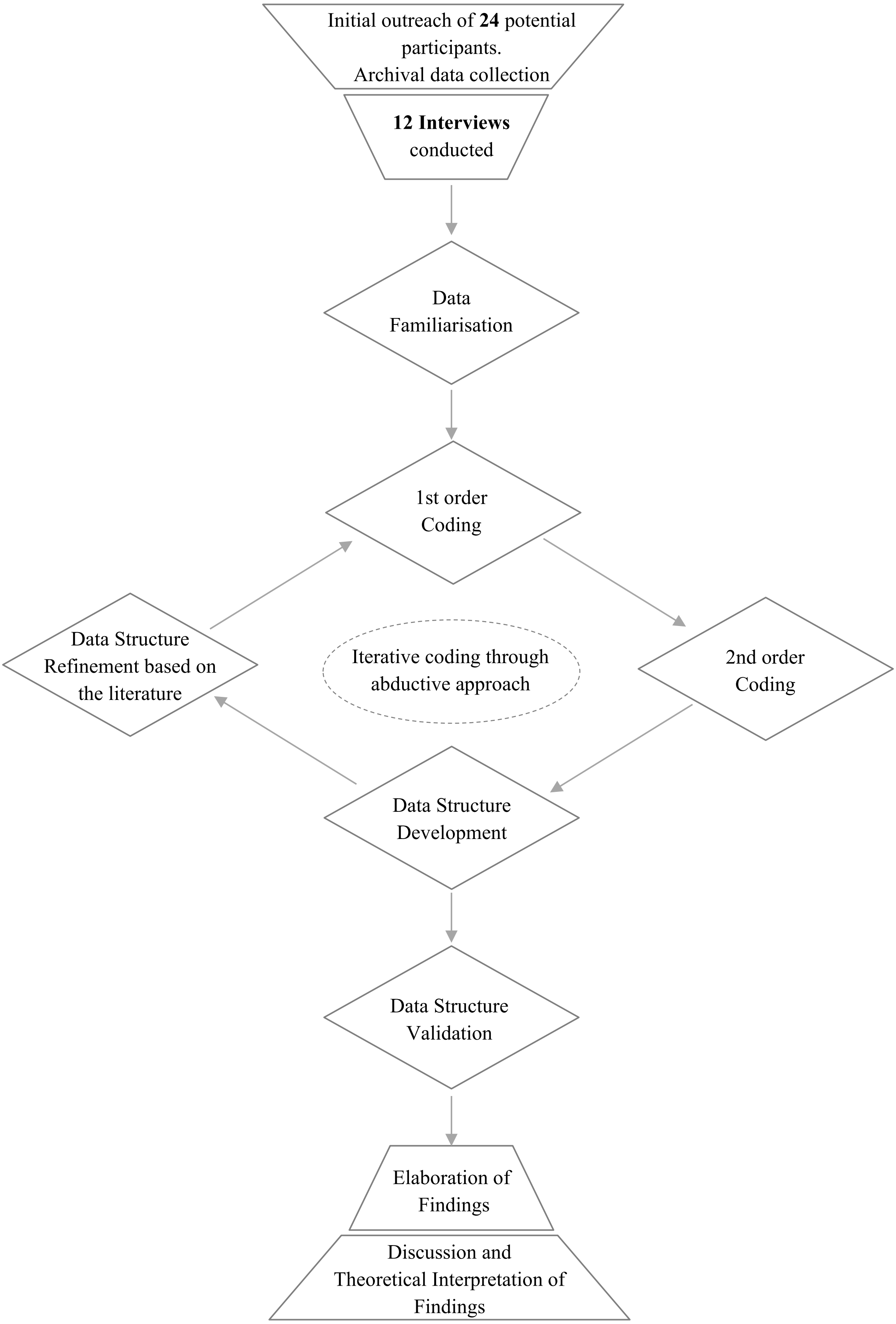

Figure 5: Data collection and analysis strategy (source: our elaboration)

3.5 Findings

The findings are presented by distinguishing between AI-related value creation motives and AI-related value destruction risks that emerge from our participants' perceptions, both in terms of their actual direct experiences of Artificial Intelligence use and in terms of expectations about its potential. AI-related value creation motives refer to those activities and responsibilities within which PIs and Co-PIs perceive a real or potential positive contribution by Artificial Intelligence to their value creation processes, thus representing motives for them to embrace it in their role. AI-related value destruction risks instead pertain to those conditions under which Artificial Intelligence is seen as potentially failing to contribute to value creation or, in worse scenarios, as an obstacle to PIs' value creation activities. The following sub-sections discuss AI-related value creation motives and risks in detail.

3.5.1 AI-related value creation motives

The analysis of our data led to identify the following AI-related value creation motives: Scientific Ideation, Strategic Alignment and Fit, Collaborative Leadership, Project Orchestration, Business Intelligence, Research process and output quality, Research Exploitation. All of them are further discussed below.

Scientific Ideation

The first key area where PIs and co-PIs show to see great potential in terms of Artificial Intelligence support is represented by the identification of truly innovative research ideas, as a crucial task that influences the overall scientific relevance of the entire project, as well as its competitiveness in the process of funding allocation. According to participants, Artificial Intelligence can support this value creation activity by allowing for enhanced bibliographic search that accelerates the study process of the state of the art in the literature, which facilitates the identification of potential gaps to be filled by the research.

This process, enabled by Artificial Intelligence, goes beyond traditional literature searches typically conducted through keyword queries. It turns into a contextualised search that provides users with more relevant content thanks to the possibility to ask fully articulated and meaningful questions. In this way, Artificial Intelligence can suggest the reading of articles that would not have been retrieved through the traditional keyword search, thereby guiding the research process towards a more exploratory approach. Although human validation is still thought to be necessary, this kind of semantic-driven and context-aware literature search is more intelligent and structured. In this sense, what Artificial Intelligence enables is a significant acceleration in the acquisition of crucial knowledge, shifting towards a more contextualised, and therefore more useful and conscious, form of knowledge acquisition.

By supporting a more targeted and streamlined acquisition of relevant knowledge, this approach strengthens both the study and learning processes. It helps the PI keep up with a rapidly growing knowledge base. In addition, it facilitates him in remaining updated and aligned with methodological and/or technical advancements (e.g. learning how to use a new software).

"I managed to learn on of the programming languages that are now used by almost everyone in astrophysics. I had fallen a bit behind for personal reasons, but I was able to catch up thanks to this" (P10).

More broadly, the ability to acquire knowledge in a highly focused way, consistently aligned with specific research needs, enables researchers to not only enhance the value of knowledge itself, but also facilitate a conscious internalisation and usage of what is truly useful for the researcher's aim. This is particularly useful in the current environment where the huge amount of knowledge available may be overwhelming and the identification of truly relevant knowledge may turn out to be extremely complex and time-consuming.

"If I have zero information, I have zero information. But if I have too much information, I still have zero information, because in fact I haven't read it. So actually, the use of ChatGPT or another of these 'speaking intelligences' as a tool for study

support and bibliographic research can be seen as a means to access information faster" (P8).

In case the project is situated at the intersection of different research fields and the expertise of the scientist in the PI role is limited to part of them, using Artificial Intelligence can make him acquire knowledge outside of his primary area of specialisation thus overcoming barriers associated with inevitably limited and often highly specialised nature of researchers' backgrounds.
Artificial Intelligence therefore enables a multidisciplinary perspective that would otherwise require way longer time to be acquired and that can strengthen the overall process of designing a project in two ways. Using Artificial Intelligence accelerates the construction of a multidisciplinary background that can be exploited to design project with a broader focus that reconciles different fields and has a greater potential in terms of impact; this allows to face the tension between the high degree of compartmentalisation in research and the complexity and cross-domain interconnectedness of real-world phenomena.
This empowered faster contextualised and multidisciplinary search ability enables the PI to gain a stronger awareness of the state of the art that leads to a more comprehensive and robust understanding of existing knowledge gaps. What truly matters in research and especially in large-scale, externally funded projects, is ensuring the genuine innovativeness and originality of the core idea driving the entire research process. To achieve this, it is essential to *"stand on the shoulders of giants, by building upon existing knowledge, rather than reinventing what is already established" (P3).*

In this sense, Artificial Intelligence support can be twofold. On the one hand, it helps avoid orienting the research toward already investigated topics (this evaluation of the real innovativeness of the research idea the PI is envisioning becomes even harder when the PI steps even slightly outside of his main area of expertise, as anticipated above).

"Unfortunately for many years in my life, I had to reinvent the wheel. That's how it was in the 1980s and 1990s when there was limited circulation of information. So, we

often found ourselves doing things that had already being done elsewhere. And that's a problem, because it slows down all functional processes, it slows down development, and the PI's activity ends up being channelled into this dynamic. […] And so Artificial Intelligence is a facilitator of not reinventing the wheel" (P3).

On the other hand, it may re-orient PI attention, offering the opportunity to critically re-evaluate previously neglected, underestimated or simply overlooked aspects that may instead hold significant potential in shaping the priorities of the research agenda that will guide the project as it unfolds.

In line with all the above-described aspects, Artificial Intelligence is overall perceived as a powerful tool that can potentially orient the research focus, guide the identification of promising research opportunities and, consequently, contribute to amplifying the PI's visionary capacity.

Strategic alignment and fit

Another key area of value creation strengthening is represented by the effort PIs make in ensuring the strategic alignment and fit of the research proposal with open calls of funding agencies. This theme is closely related to the previous one, as the identification of research ideas to be developed within funded projects must simultaneously meet the criteria of innovation and originality, while also ensuring coherence and alignment with the context of reference and the specific call. Both conditions are indeed essential for the project to be competitive and for the PI to secure funding in the competitive mechanisms characterising selective calls.

In this sense, given the highly competitive nature of this process, they can benefit from the support of Artificial Intelligence in scanning the research domain with the aim to identify potential gaps that could be leveraged to shape an original research idea that could also be in line with open calls or to re-orient an already existing research idea to make it better fit.

"Based on a call, for example, that comes out, it conducts a search to identify items covered and uncovered at a national and international level" (P12).

"To orient my project, my research, and my areas of focus, starting from my own research needs, which I already have, but with the aim of shaping and adapting them more effectively to the calls, to what we might call the opportunities coming from this market" (P1).

Another essential support of Artificial Intelligence in creating value is represented by the possibility of testing the validity, reliability and feasibility of one's project idea. This may be crucial to provide reassurance about the strength and robustness of an early-stage preliminary research idea that is still vague or uncertain in the mind of the researcher. Receiving positive feedback may, in such cases, reinforce the idea itself, making it more legitimate and providing additional suggestions to build on it and define a more articulated research direction.

"It was mostly curiosity, and sometimes that positive feedback you get when you have a rough idea in your head, you write it down thinking it's probably nonsense, and then you put it into a language model and what comes out is a text that makes you say: 'Wow, that's actually great!'" (P7).

In addition, Artificial Intelligence potential is also recognised in performing fast and automated assessments of the project's alignment with the specific requirements of the funding call, as well as with relevant regulatory frameworks. When preparing a proposal, Artificial Intelligence can be helpful by verifying and ensuring consistency with core concepts and themes of the call, as well as by assisting with the completion of specific sections of the proposal scheme that can be difficult to conceptualise and fill in based on the researcher's background and/or on the project specificity, while meeting strict word count constraints (for example, sections about the economic and social impact of the project).
In terms of alignment with the call, it can be of help by automatically scanning both content and format requirements and suggesting how the idea developed by the team can be best presented to be highly competitive, while also taking into account the funding agency characteristics.

"So, it's really about asking: 'Ok, we are writing the proposal, and it needs to be submitted to the Sicilian Region: how should it be structured?' That's one aspect, and maybe we are beginning to move in that direction, aren't we?" (P8).

In this perspective, Artificial Intelligence can assist them in a strategic writing process aimed at ensuring such alignment, by suggesting linguistic nuances that strengthen consistency with the call or, in some cases, by stimulating reflections on how to fill specific sections while meeting the word count constraints, or which aspects to leverage more to valorise the project potential. Artificial Intelligence can be also a valid support for non-native English speaker to significantly improve the quality of writing, which contributes to the overall quality of the research proposal. In terms of content, as referred to in the previous paragraph, this strategic writing is also supported and oriented by the broader knowledge base to which PIs have facilitated access thanks to AI.
Another matter of strategic alignment concerns the normative base to which PIs need to adhere. Some insights emerge from the data about the usefulness of Artificial Intelligence in checking for incontinences or misalignment in the documentation based on an automatic scanning of the whole set of valid rules and regulations. In this way, potential oversights or human errors can be identified and corrected in time, thereby preventing any disruption to the regular progress of the related procedures.

Collaborative Leadership
The complex and multifaceted nature of PI roles and responsibilities also entails them to act as collaborative leaders who mediate between different actors (members of the research team, stakeholders) for the achievement of the scientific goal. In navigating this interdisciplinary and multi-stakeholder environment, they combine scientific and administrative knowledge to interpersonal leadership soft skills. This PI capability is strictly linked to the idea of PI as a knowledge broker and scientific leader. PI leadership in complex research environments can benefit from Artificial Intelligence usage through improved knowledge sharing mechanisms, facilitated interaction among involved actors. This can be realised by means of a dedicated platform where various actors involved in the project can easily exchange information between each other

while also interacting with AI, leveraging its capability to build on the common knowledge base and provide targeted solutions and responses to all participants. This streamlines the problem-solving process which would normally require multi-actors' meetings to share information and reach a common solution. Having access to such a shared knowledge base would enable individuals that are facing similar issues, even from a technical point of view, to easily retrieve previously identified solutions, fostering more time-efficient and organic collaborations.

Given that PIs leadership is also shaped by the breadth of vision and by the problem-solving capability, Artificial Intelligence can contribute to strengthening it by enabling a more inclusive and multi-perspective approach to problem-solving, mainly grounded on the facilitated and fast access to a broad knowledge base that ensures a more comprehensive understanding of the emerging issues. In this regard, they become increasingly open-minded by easily incorporating a wide range of viewpoints and therefore able to provide more effective responses and solutions. This accelerated and simplified way to address strategically relevant issues, helps prevent the PI from being overly absorbed in problem-solving tasks, enabling him to more actively participate in team dynamics, thus reinforcing his presence as a leader and guide within the team. This overall improvement in problem solving still remains grounded on PI rich set of accumulated experiences, that enable him to properly evaluate AI-suggestions and strategically select and leverage the best one to solve group problems.

"You might say: what you are doing - solving the problem using Artificial Intelligence - could also be done by them (other members of the research team), since the tool is available to everyone. But it's not that simple, because there's experience behind it. Such experience translates into a more effective use of the too, both in formulating better queries and in interpreting the solutions it produces, ultimately making a meaningful difference" (P6).

Project Orchestration

PIs responsibilities extend to a comprehensive planning and coordinating of strategic, organisational and relational nature. This theme emerges from the coherent aggregation of codes that, although analytically distinct, are strongly interconnected.

Some of them are linked to the coordination responsibilities that are deeply strategic for the overall success of the project, while taking shape through operational activities. These include the selection and allocation of key human resources, stakeholder relationship management, identification of enabling technological solutions, and the set-up of high-level project plans that, however, should be flexible and adaptable to evolving needs or emerging challenges. Other tasks, identified as process and work optimisation, administrative work, continuous checking and monitoring, and problem-solving, although operational in nature, play a pivotal role in ensuring overall strategic alignment.

We first examine how strategic coordination can benefit from Artificial Intelligence support starting from resource orchestration. In the selection of human resources and their allocation, Artificial Intelligence job market scanning capability can be of help in identifying profiles that could suit the highly specialised needs of the project.

"In my view, Artificial Intelligence could significantly support a Principal Investigator in evaluating the profiles of candidates to be recruited. For instance, based on the specific needs of the project, it could provide useful insights regarding the types of profiles to be targeted both ex ante and ex post. This might include CV screening, skills assessment, or even job market analysis to identify suitable talents, since finding highly qualified individuals is often a major challenge" (P12).

Secondly, it can assist in the efficient allocation of these resources to the relative processes. This is also considered achievable through the implementation of automatic task assignment mechanisms that could add further value by helping mitigate potential human biases, such as emotional biases rooted in personal preferences. Moreover, by making the assignment process less arbitrary, such mechanisms could act as an incentive for greater efficiency, as the assigned task may be perceived as less negotiable or flexible.
The overall coordination capability is also shaped by how the PI manages the complex network of relationships with different stakeholders and partners. In this sense, Artificial Intelligence can assist by helping him understand the different languages

used by the various actors of a heterogeneous group. In addition, Artificial Intelligence can support the PI in flexibly adapting their communication style in a way that remains unaffected by personal feelings, which might otherwise compromise strategic relationships, for example when addressing delays or non-compliance by a project partner.

In selecting technological solutions that are instrumental to the execution of the research activities, the PI may benefit from market analyses conducted by Artificial Intelligence systems. This type of support may prove particularly valuable in cases where the solutions under consideration are technically or engineering-wise complex, thus falling outside of the PI's primary area of expertise (here again the support to multidisciplinary approaches comes into play). By providing structured and up-to-date market analyses, Artificial Intelligence can fill technical knowledge gaps and feed a better-informed decision-making process.

Another area where PIs expect help from Artificial Intelligence – and which could significantly create value for them – is primarily expressed in terms of roadmap definition and dynamic planning of the complex and interdependent flows of activities that they are strategically required to manage to ensure the timely achievement of the project's ultimate objective.

This kind of planning activity is often carried out by means of Gantt charts, which however are not necessarily linear or fixed: they frequently need to be updated to evolving conditions that are not always under full control, but which the PI must acknowledge to timely assess their ripple effect on the original plan.

In this sense, the automation of planning process through Artificial Intelligence systems that simultaneously account for all ongoing developments as well as issues or bottlenecks (scientific, technical or administrative ones) and dynamically adjust the rest of the planning, accordingly, may prove crucial in simplifying and optimising a task that would otherwise be extremely complex to manage through human capabilities alone.

"In my view, at this stage, it can serve as a valuable tool for analysing processes and offering suggestions aimed at their optimisation" (P4).

"It could be very useful to have an AI-based tool capable of automatically generating project Gantt charts based on specific inputs he could retrieve, for example, from databases. That is, if I had a tool that checks purchases, the status of procurement procedures, the progress of administrative processes, the state of construction advancement, and that produces a Gantt based on all that, keeps it updates, gives me warnings and so on, that would be a very, very interesting tool" (P12).

Furthermore, a similar perspective is also offered by PIs with regard to the operational level at which the higher-level strategic planning is translated into concrete tasks, which are then allocated to specific teams according to the resources at hand. In this perspective, a twofold support of Artificial Intelligence is expected. On the one hand, it helps optimising and streamlining the processes in terms of automated coordination of activities undertaken by the different subgroups, by enabling a more efficient use of time, which is no longer absorbed by mechanical and labour-intensive operations.
These overall improvement in planning and process optimisation is also strictly linked to enhanced problem-solving capability that enhances the PI response time to emerging issues that would otherwise slow down project activities, indirectly allowing for a more effective time management and for a stronger presence of the PI alongside the team throughout the project lifecycle.

"The ability to quickly support members of the group who often reach out either for information, advice on how to proceed, or more frequently because they are facing some blocking issues, is essential. Providing timely support ensures that their work is not delayed or interrupted" (P6).

Delving deeper into how this augmented problem-solving process takes place, first and foremost, what emerges more clearly is the perceived benefit of increased speed in scanning the range of possible solutions to a given problem, alongside the advantage of receiving highly targeted suggestions. This significantly reduces the overall time required for studying and researching and accelerates the evaluation phase, being the proposed options already tailored to the specific needs of the PI. This is closely related to the concept of knowledge access: AI-supported problem solving is made possible by the enhanced access to knowledge, in terms of speed, breadth, and contextual relevance, guiding researchers through the creative processes that lead to identify or even develop solutions.

"It would help by reducing the time needed to address a problem. Artificial Intelligence can provide suggestions and proposals, so the PI would only need to devote time to reviewing and selecting the best one among them, rather than formulating the proposal from scratch, that is typically much more time consuming" (P4).

""It didn't actually solve the problem for me, but in some cases, it helped me reach the solution more quickly. [...] It pointed me toward solutions I hadn't considered, and in that sense, the problem was resolved because it gave me access to the information I needed. That was a very positive experience. In those cases, I would say I even made friends with it" (P3).

The final decision, however, always remains in the hands of humans, who must review the proposal and assess their reliability, while also drawing on their valuable experience to determine which solution is best suited to the problem under consideration.

"I've always believed that, in the end, it must be the human who takes the lead and decides how to act" (P4).

"One must always carefully review the responses it provides. For instance, I've noticed that sometimes it gives an incorrect answer, and then immediately corrects itself by saying something like, 'You're right, that's not accurate.' So, just like with any other tool, it's essential to use it with great caution" (P6).

In principle, problem-solving – whether oriented toward strategic or operational issues – is grounded on a structured effort in monitoring and analysing ongoing processes and project dynamics, which is essential to promptly detect any critical issues that require PI's intervention. Solving problems effectively indeed depends not only on the ability to identify suitable solutions, but also on the ability to timely recognise emerging issues that deserve attention. In this regard, both PIs and Co-PIs recognise the significant potential of leveraging Artificial Intelligence algorithms to carry out monitoring activities. A particularly promising aspect lies in the ability of such systems to anticipate in a predictive logic potentially critical issues before they actually emerge, thus preventing disruptions to the research process.

"Like everyone else, I closely monitor my infrastructure, and I have, perhaps somewhat utopically, the vision of having a predictive mechanism that could tell me: 'Look, that critical switch is about to fail, take action.' However, I am fully aware that this is far from being simple" (P11).

Another perspective offered by PIs concerns the idea that Artificial Intelligence would enhance the analyses that they already perform by offering a complementary perspective that would mitigate potential biases affecting their judgment. Furthermore, the value of Artificial Intelligence support would also lie in its ability to accelerate ex-post verification processes of already implemented procedures (an activity that typically requires considerable amounts of time and attention). Most importantly, such systems are envisioned as enablers of comprehensive project monitoring that simultaneously consider different levels of analysis (scientific, technical, administrative and reporting-related aspects), while offering an integrated, holistic and interactive visual representation of the project's overall progress. These contributions streamline the orchestration of a complex research project.

Business Intelligence

The theme of Business Intelligence as a value creation activity encompasses all the tasks related to collecting, generating and using information of varying nature, both from internal and external sources, with the purpose of supporting the overall project planning, the scientific activity itself and the reporting process. Such support is intended to ensure that all actions are aligned with the requirement of the funding call and the broader contextual framework where the project takes place.

The support provided by Artificial Intelligence in this type of activities is primarily realised by facilitating the PI in navigating strategic documentation, which is often extensive and therefore time-consuming to be reviewed and/or interpreted. In this respect, Artificial Intelligence contribution can be twofold, involving two complementary dimensions: summary and depth. On the one hand, it enables summarisation of highly detailed documents for specific purposes, allowing the PI to gain a clear and concise understanding in significantly reduced time. In performing this task, Artificial Intelligence can also incorporate elements that customise the result to respond to specific informational needs.

On the other hand, Artificial Intelligence can play a critical role in enabling in-depth retrieval of specific pieces of information contained in the vast and complex documentation available to the PI. Relevant examples include the funding call itself (part of which might need to be reviewed and referenced even throughout the project execution), the scientific outputs produced over time by the research team (e.g. journal articles, conference proceedings), financial and administrative reporting documents, as well as varied materials concerning project partners and relevant stakeholders. Key information is also contained in descriptive and technical documents on the infrastructure itself. In enabling summarisation and in-depth exploration, Artificial Intelligence may also identify both communalities and/or inconsistencies (such as the coexistence of multiple contrasting versions of the same matter) which can drive to look for clarifications and improve coherence and accuracy. There is in this sense a more active interaction with strategic documentation. This enhanced capacity to retrieve targeted information quickly and accurately contributes to streamlining the PI's decision-making process.

"In project drafting, the usual practice is to provide extensive detailed content accompanied by summary sections that help frame the overall context. This task can be effectively replaced by Artificial Intelligence. With the additional advantage that, when decision-makers require further insights, they can request them and receive them on demand, something that is not possible with a passively generated document, which simply exists in its final form. One can either read the summary or delve into the full

text, but there is no possibility of requesting real-time in-depth analysis. From a usability perspective, this represents a clear benefit" (P3).

"Artificial Intelligence also plays the role of an archivist, as it can retrieve information that you may have lost track of or no longer know where to find" (P8).

Furthermore, PIs express a strong interest in leveraging Artificial Intelligence tools to support administrative and reporting activities consisting in generating documentation. First, Artificial Intelligence can automatically generate reports on strategic meetings that can serve as inputs of the monitoring processes. In addition, it can assist in drafting official documentation such as reports on activities undertaken and on expenses justification.

In international projects, such documents are required to be submitted in English and therefore Artificial Intelligence can improve the overall quality of writing. However, nowadays reporting obligations are becoming increasingly demanding, asking for highly detailed and technically complex descriptions that may represent a significant burden to the PI. Therefore, apart from the linguistic improvement, Artificial Intelligence can provide critical support in terms of content, by enabling fast and efficient retrieval, synthesis and re-organisation of information extracted from multiple sources (e.g. action plans, deliverables).

Research process and output quality

Although managerial and administrative demands and constraints may often prevail, the PI remains primarily a scientist, and as such, his core mission continues to be the achievement of scientific goals that can make a meaningful contribution to advancing knowledge in his field.

In the scientific domain Artificial Intelligence can turn out to be crucial in improving the overall quality of the research process and output. This improvement is enabled by facilitated access to the progressively generated knowledge base, and by the ability to uncover hidden insights that often remain unnoticed in data-intensive contexts, such as those involving large-scale experimental research, such as Physics and Astronomy. In these scientific domains, data often reach huge volumes that make human analysis extremely demanding and, for this reason, the use of Artificial Intelligence in data analysis has a longstanding tradition. Although currently available tools are not yet fully tailored to the specific needs of researchers, their application remains widespread and growing. Among the most relevant benefits highlighted by PIs and Co-PIs there is the possibility of querying Artificial Intelligence systems by using targeted prompts to automatically obtain the desired analytical outcome. More importantly, the speed with which these systems deliver results is repeatedly emphasised. While time efficiency is an overarching advantage recurring horizontally in the data, in this context it assumes an even more critical role. Not only Artificial Intelligence merely accelerate the data processing, but more importantly, it reduces the overall time required to reach meaningful scientific outcomes, thus potentially enabling relevant discoveries to be made significantly faster than would otherwise be possible. This acceleration in the path to scientific knowledge advancement is recognised as a major form of value creation acceleration. In this perspective, Artificial Intelligence proves to be particularly valuable where the scientific insight under investigation lies at the intersection of multiple domains, thus requiring the integration of heterogeneous datasets extracted from diverse sources. In such interdisciplinary contexts, AI's ability to manage and cross-analyse vast and complex databases becomes decisive.

"It is a tool that enables the discovery of (scientific) knowledge that would otherwise be extremely difficult to retrieve. […] I have observed among younger colleagues a growing use of AI, particularly in Life Sciences applications. In this domain, Artificial Intelligence has shown remarkable capabilities in uncovering correlations across distinct environments or between heterogeneous variables, such as genomic data, pharmacological profiles, and disease expression patterns, which I would have never expected to detect so quickly" (P1).

Closely related to this is the sub-theme of coding, an activity commonly undertaken by scientists as an instrumental phase of software-based data analysis. In this regard, the conversational use of Artificial Intelligence appears to be particularly valuable in supporting code development or in resolving issues that hinder its functioning. These challenges have traditionally been highly time-consuming, as they often require extensive searches for solutions that may already exist. Identifying and resolving errors and technical issues that may arise in coding activity is therefore a specific form of problem-solving support that is strictly connected to scientific research rather than to managerial tasks.

"When I query it to optimize a piece of code, it sometimes returns a syntax or something I wasn't previously aware of" (P6).

Finally, it can support the drafting of scientific manuscripts by generating language in an academic style, a particularly time-consuming task for researchers who are not native English speakers, especially when they need to express in the best way possible very complex ideas and concepts.

"When writing scientific article, especially for those of us who are not native English speakers, it is often very helpful to let Artificial Intelligence rework what we have written, so as to put it into a much more elegant and, at times, more comprehensible form. This is particularly useful when the ideas being conveyed are complex and not easy to articulate clearly" (P10).

Research Exploitation

Another crucial activity PIs and co-PIs are responsible for is linked to what we defined in our coding structure as research exploitation, the process that leads to translating and transforming the findings into tangible outcomes for various groups of stakeholders (scientific community, industry, society at large).

The way in which Artificial Intelligence can support this crucial activity of creating value in a broader sense, based on the scientific knowledge produced by the project, are primarily conceptualised in terms of enhancing awareness of the potential impact of results. This represents a novel and still underexplored application of Artificial Intelligence in this domain, which the PIs involved in this specific project are currently experimenting with, thanks to the customised Artificial Intelligence tool externally developed and that is still in its pilot phase. Artificial Intelligence can process the extensive body of documents generated within the project domain and generate narratives that offer original perspectives on the impact of the research that may not have been previously considered.

"I was able to identify correlations that, so to speak, led me to understand, to realise, and to become aware that the KM3NeT4RR, the neutrino telescope, had generated impact in terms of broader societal benefits, which I would not have been able to perceive on my own. I was aware that such an impact might exist, but through Artificial Intelligence I was able to gain a clearer understanding of it" (P1).

This enhanced awareness may also be indirectly driven by AI. Achieving scientific results faster thanks to Artificial Intelligence frees up a lot of time for the PI that he can instead devote to reason on them, engaging in deeper reflections that can ultimately lead to a deeper understanding of their real potential.
In addition, it can assist in better positioning and disseminating such results across diverse audiences, being able to easily adapt language and style accordingly, thus facilitating effective communication, despite the high degree of complexity of the topics. For instance, AI-generated explanations can be tailored for industrial stakeholders to support potential pathways for commercialisation, or for other non-specialistic audiences like school students visiting the research infrastructure. In this latter case, this facilitated stakeholder engagement may inspire future educational and career choices.

3.5.2 Value destruction risks

The second domain of our findings pertain to AI-related value destruction risks: Misalignment and robustness risk, Relational and autonomy risk, and the overarching risk of Unrealised potential. All of them are discussed below.

Misalignment and robustness risk
The overarching theme concerning the risk of misalignment and reduced robustness in the PI's activity emerges from our data as primarily linked to three concerns: the

possibility that the PI's focus on the core objectives of the project may be somehow negatively affected by the use of AI, the risk of relying on unreliable input data, and the diminished control over critical matters.

First and foremost, concerns have been raised about the need for the PI to always maintain a clear, strong and deep awareness of the ultimate objectives of the project. Artificial Intelligence should not support in their definition since, without a solid framework of reference, any AI-generated recommendations may prove ineffective or even misleading, carrying the risk of diverting attention from core objectives.

In this regard, it is crucial that PIs apply a strong critical approach toward any Artificial Intelligence recommendations, along with a clear awareness that underlying input data may produce misleading and potentially detrimental outputs.

"Because if you're not certain – this, in my opinion, is always the key issue – about the underlying data you're working with, then you might find yourself going down paths that are somewhat far from the intended direction. In other words, it can lead you off track" (P1).

Moreover, it is important to acknowledge that Artificial Intelligence itself may lose focus and coherence over time, and users should interact with it keeping this in mind. One of the participants articulates this concept in a particularly insightful way, drawing on some notions coming from his background in physics: unlike humans, Artificial Intelligence has a limited ability to remain focused and to produce reliable outputs when subjected to numerous and repeated prompts.

"There is a concept in physics called 'coherence length', which is, let's say, the distance over which a wave signal remains stable. Beyond that, it gets lost in the noise. Now, the coherence length of generative Artificial Intelligence is increasing. However, as of today, it is still much shorter than that of a human, who can in fact remain focused on a task for years, despite his many limitations. After 50 questions on the same topic, Artificial Intelligence either starts repeating itself or loses track. […] It kind of proceeds by word association" (P3).

Relational and autonomy risk

Some value destruction risks are perceived in relation to human relationships management and to the delegation of work planning and organisation to Artificial Intelligence system, thus undermining the autonomy of individuals involved in the project. In terms of relationship management, there is a broad agreement that this remains a domain deeply rooted in human skills and capabilities, one that Artificial Intelligence is still far from being able to fully understand or manage. As a leader, the PI leverages the degree of familiarity he has with the individuals he interacts with, be they team members or external stakeholders, and he must rely on personal sensitivity and soft skills to interact effectively and strategically maintaining a balanced approach that integrates assertiveness and flexibility, to maximise both results and engagement. Artificial Intelligence systems are currently unable to grasp the individual intangible characteristics of interlocutors and still struggle to handle cultural differences, a crucial aspect in the coordination of large-scale international projects.

"When it comes relationships, particularly the communication aspects, I personally have a concern: that an algorithmic component, especially one based on optimization logic, may risk oversimplifying the complexity of international projects involving diverse people, cultures, and relational dynamics. At this stage, I fear that relying on a single validation algorithm might be inadequate or even counterproductive in capturing such nuanced diversity" (P12).

Regarding the possibility that Artificial Intelligence might support the PI in the assignment of tasks and the related monitoring of progress, concerns have been raised on potential risk of disclosure and threats to individual freedom and autonomy.

There is also some reluctance about the use of Artificial Intelligence in problem-solving activities as well, since such processes may require the detailed disclosure of information pertaining to critical or potentially blocking issues within the project. This, in turn, raises concerns about data protection and privacy.

Unrealised potential: an overarching risk of value destruction

A latent risk of value destruction is associate to the unrealised potential of AI, resulting from barriers to an effective adoption and usage of Artificial Intelligence that may lead to underuse or sub-optimal use of Artificial Intelligence systems, thus hindering to fully exploit their potential. This risk therefore does not necessarily stem from intentional and active misuse, but rather from individual characteristics (such as age and the digital generation gap), behavioural factors (habitual use and attitude), barriers linked to misalignments between Artificial Intelligence and the specific needs of research projects.

Age is acknowledged as an influential factor, especially by senior participants who recognise that they are, in this sense, at a disadvantage compared to younger colleagues. The latter, as digital natives, are generally more comfortable and proficient in using Artificial Intelligence tools. This generational gap is seen as one of the main reasons why some scientists in PI roles tend to make less frequent and less exploratory use of AI, especially when it comes to support their decision-making. As closely related to age, PIs also tend to refer to habitual use as a relevant factor, suggesting that younger researchers tend to more frequently engage with it even in personal life. This greater exposure to Artificial Intelligence enhances their familiarity with it, which typically translates into a greater readiness to rely on AI, even with appropriate caution and critical thinking. As a result, they are in a better position to exploit Artificial Intelligence potential within their processes.

"Artificial Intelligence is not a tool I use on a daily basis. [...] My barrier lies in the fact that I am now 65 years old and there is undeniably a cultural issue at play. The generational gap is significant and it is clear that such tools will never be used with the same depth, ease and natural inclination by those who are, let's say, 'differently young', as by individuals currently undergoing their education and training" (P1).

"I observe that the more easily one interacts with these tools, the more this transfer of tasks occurs, leaving the PI with a higher-level reasoning role. This is certainly a very interesting development" (P10).

"I have now become a regular user, and I employ Artificial Intelligence not only in my role as Principal Investigator but also across various other activities" (P3).

The risk of value destruction under this theme is also associated with a limited knowledge of its underlying mechanisms and its concrete potential or with misconceptions on what Artificial Intelligence can and should be used for. The latter case includes situations of overreliance and/or generalised reliance, which could trigger a tendency to perceive it as a one-size-fits all solution and to overestimate it instead of looking at it as a source of potentially useful inputs and insights to then critically assess and integrate thanks to the personal and professional background. When misjudgements of this type are in place, potential risks of methodological weaknesses in the decisions made may arise.

"First of all, I must admit that I still have some doubts about how Artificial Intelligence actually works. In particular, I refer to my own ability to use it and to learn how to use it effectively. In my case, there has been no specific training, so I openly acknowledge that I would not know how to make the most of it" (P4).

An additional issue concerns a misalignment between Artificial Intelligence tools and their desired use, which manifests in two primary ways. On the one hand, participants acknowledge the lack of Artificial Intelligence tools specifically tailored to the peculiar needs of scientific research environments (especially in highly complex projects or infrastructures), thus limiting a full exploitation of its power. On the other hand, especially in terms of managerial and administrative tasks, there emerges a trade-off between the time required to train a general-purpose Artificial Intelligence system to meet the highly specific needs of a research project and the quality and actual usability of the outputs.

"For the execution of this project, feeding an Artificial Intelligence system with these data would be too time-consuming, especially given that the results are highly unique and customised for the specific activities that make up my project. From this perspective, I do not consider it efficient at this stage" (P9).

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
Contextualised search Knowledge acquisition Study State-of-the-art awareness Facilitated multi/interdisciplinarity Scientific focus and research agenda definition Vision	Scientific ideation	*"My use of Artificial Intelligence is always aimed at reducing the time needed to acquire knowledge […] 95% of it is about information gathering, specifically, contextualised information" (P3).* *"It has much more knowledge than I do. On any topic. Because clearly, since the machine can access all databases on earth quickly and then select the information that is relevant to a specific research need, it provides information rapidly and allows me to acquire knowledge in a short time, including information processed by others and stored in databases" (P4).* *"In this regard, Artificial Intelligence can truly give me an extra edge as it drastically reduces the time I need for learning" (P4).* *"Another aspect could be suggestions on research directions based on existing knowledge. Because again, it can access a vast database much more quickly and efficiently that a human can, and therefore it can provide suggestions" (P4).* *"I would avoid – how can I say – pursuing or imagining activities that are actually already available and that I simply wasn't aware of" (P1)* *"So it helps you to redirect your attention to projects or aspects you may have previously overlooked" (P12)* *"It can then say: there is also this other article that talks about this, and this can actually serve as a stimulus for new ideas at this level" (P10).* *"It seems to give me an extra edge, in the sense that it becomes much easier for me to acquire information that allows me to enter a context that is not originally my own."*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		"I am not sure whether AI, at this point, is able to propose anything beyond what it already known, whether it can truly extrapolate knowledge and generate something truly new, as human intuition does. However, the knowledge it can provide may enable me as a human to make better use of my intuition and thus move forward more effectively in my work" (P4). *"Fundamentally, I see its use ex ante, in the ability to better direct my project, my research, and my focus" (P1).* *"The opportunity is related to the role of the PI, in the sense of his visual and visionary ability, using the Artificial Intelligence tool to create further opportunities for themselves in research" (P1).*
Scanning research opportunities Assess feasibility and competitiveness Align the project with the call and with normative constraints Project writing	Strategic Alignment and Fit	*"Based on a call, for example, that comes out, it conducts a search to identify items covered and uncovered at a national and international level" (P12).* *"In developing and testing ideas, texting project hypothesis" (P10).* *"Once we have a clear idea, then yes, it certainly helps – as I mentioned earlier – to perform specific types of analysis. However, there is always an initial analytical design phase which, at least in my case, is carried out either by myself or by my colleagues" (P10).* *"The idea, in itself, is something very simple, something that can be said in just a few words. What matters then is assessing whether it's feasible, determining the feasibility and the level of innovation of a project idea. In this, I believe, (AI) could be helpful" (P5).* *"As director, we had to prepare a regulatory document - a national regulation - that involved the application of laws and regulations. It was written by a working group and then checked by AI, which found inconsistencies with the legislation and allowed us to align the regulation" (P4).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		"Sometimes it happened to me, while writing a project proposal, that they ask for rather specific fields (like, I don't know, the economic impact of a project, which, in the case of a physics project, is not always easy to define immediately). And in those cases, I sometimes asked ChatGPT: 'Do you have any ideas?' Maybe it comes up with ten silly ones, but maybe one of them isn't bad, and from that, you get a starting point to write something meaningful, let's say" (P7). *"At the moment, we're drafting the proposal, and one possible use of the tool is simply to ask: 'Can you check the Italian or the English in this section?' But what we could ask is also: 'What would you suggest? Which aspects should I focus on, based on the content of the call?' For example: I take the call: 'how should the project be written?' In my view, that's an interesting way of using it" (P8).*
Facilitated relationships Knowledge sharing Plurality of viewpoints	Collaborative leadership	*"The use of AI- enabled shared chats would allow people to participate in the interaction with Artificial Intelligence and share responses, so they don't have to report them during meetings, but can instead collaborate directly in this process" (P3).* *"If, for example, an Artificial Intelligence system could advise me on how to manage a situation of interpersonal conflict or indecision..." (P2).* *"I'm convinced that it can have a positive impact on project dynamics, as it clearly offers different perspectives from mine. This helps me look at problems from other points of view. As a result, it gives me the opportunity to analyse multiple solutions and choose the one that, in my opinion, is the best" (P3).* *"Now, speeding up these activities, gives me more time to follow and support the work carried out by the team. In the past, I often found myself stuck on solving particularly complex problems, which led me to overlook other aspects that I then had to catch up on. Today, instead, I'm able to devote more time to the overall management of the group" (P6).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
Resources selection and allocation Relationships management Technology development Dynamic planning Process and work optimisation Problem-solving Analysing and Monitoring project performance	Project orchestration	*"It could, for example, help identify potential candidates or suggest, based on specific project needs, whether it is more appropriate to look for one type of engineer rather than another. It could also conduct a skills-based mapping of research institutions and assist in drafting accurate job descriptions for the personnel needed in the project—both those already available and those still to be recruited" (P12).* *"It would reduce the margin of real or perceived arbitrariness. That is, if there's an AI-based system assigning tasks, using an algorithm that people assume follows objective criteria, and setting deadlines accordingly, individuals are likely to perceive the assignment as more legitimate. By contrast, when a task is assigned by a person who simply says, 'I need this done by the day after tomorrow,' it might be perceived as too sudden or arbitrary" (P5).* *"A large part of the projects are highly technical – we're really getting close to engineering-level matters. They are very technical and at the cutting edge. In these cases, Artificial Intelligence could potentially be helpful, for instance by supporting market research for specific products" (P2).* *"Having a support tool for the PI that generates the Gantt chart and identifies scientific, technical, and administrative bottlenecks, clearly highlighting them, would be extremely valuable" (P12).* *"The thing that immediately comes to mind is how it can speed up processes" (P8).* *"In this regard, an open Artificial Intelligence system like the one I use proves to be highly powerful, particularly due to its advanced programming capabilities. This contributes significantly to optimising not only individual tasks but also collaborative group work" (P5).* *"It might also prove helpful in addressing the issue I mentioned earlier regarding the different 'languages' spoken by the various actors within the same project. When working with highly*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		heterogeneous partners, Artificial Intelligence could offer valuable support in bridging communication gaps and facilitating mutual understanding" (P7). *"From this perspective, Artificial Intelligence can support the rapid identification of solutions to potential organisational and optimisation-related problems" (P4).* *"In these activities, I have always relied on committees that address technical issues and formulate proposals. This is the standard approach in large-scale projects. What I envision is that Artificial Intelligence should become a member of these committees" (P4).* *"Let's say that in limited or highly specific domains, it can be useful by facilitating the recognition of certain issues and helping to address them" (P11).* *"So, with regard to the more immediate management of the project—namely the administrative part, the local and perhaps national aspects, the scientific component, and the technical dimension—it does help you keep the process under control, that's for sure" (P12).* *"In other words, an evaluation of the process based on criteria that are distinct from those applied by the PI, whose judgment may be influenced by cognitive bias. […] Artificial Intelligence should represent an additional tool, a form of analytical or semi-analytical comparison to support and complement the PI's own assessment" (P12).* *"I am confident that, if it doesn't already exist, someone is certainly working on developing an Artificial Intelligence tool to support project management tasks holistically. Just as we have tools like the Canva whiteboard or the Scrum manager, we will likely see AI-based support systems that can monitor and follow the progress of a project. If such tool does not yet exist, it is only a matter of time before we will have it" (P3).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		"It can support the verification of the accuracy and appropriateness of implemented procedures" (P4).
Summary In-depth exploration Reports preparation assistance Administrative tasks	Business Intelligence	*"For example, I may want to check how much has been reported under the 'personnel costs' budget line as opposed to 'scientific equipment'. Or I may wish to examine what a single partner has reported over all two-month periods. Current reporting platforms do not allow for the analysis of the same data from multiple perspectives. Without adequate analytical tools, the same work must often be repeated several times to meet different reporting or managerial needs" (P9).* *"Let's say that the decision-making of the PI, with this Artificial Intelligence, certainly receives support related to document access. In this case, it's a specific kind of document access, because you know that because you know that any question you pose will be answered based on the material you have previously provided to the system" (P8).* *"Artificial Intelligence also plays the role of an archivist, as it can retrieve information that you may have lost track of or no longer know where to find" (P8).* *"Based on the composition of the uploaded document base, the Artificial Intelligence system is able to identify and classify the different themes it contains, generating a hierarchical tree structure composed of main topics, subtopics, and paragraphs through which the user can easily navigate" (Archival data).* *"As commitments increase, and as adherence to increasingly high levels and standards of work quality is demanded - let's say, twenty years ago a short report was enough, today detailed reporting is required, accounting for daily activities, objectives must be clear, as well as how the funding contributes to achieving those objectives, and so on - what is particularly problematic is that there is less and less time available. [...] And from this point of view, Artificial Intelligence truly represented sometimes a source of hope for carving out a bit of time" (P3).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		"It proves useful both in the context of publications and in the preparation of proposals, for example, when drafting project proposals or submitting observations, as well as in the writing of reports" (P10). *"In simple terms, I would see it as a support to the activity of the PI, which is very complex and involves administrative tasks, secretarial work (such as text drafting), and technological developments" (P4).*
Scientific knowledge discovery Coding Academic writing	Research process and output quality	*"Artificial Intelligence can support data analysis by enabling targeted queries aimed at identifying aspects of specific interest. In this sense, it represents a valuable analytical tool capable of assisting researchers in exploring data more effectively and efficiently" (P4).* *"Especially as we increasingly deal with large volumes of data, from which mining can only be carried out using Artificial Intelligence methods. […] Data analysis would take such a long time that it distances us from being able to uncover the hidden knowledge or the hidden data within the large amount of data we collect" (P1).* *"It is a tool that enables the discovery of (scientific) knowledge that would otherwise be extremely difficult to retrieve. […] I have observed among younger colleagues a growing use of AI, particularly in Life Sciences applications. In this domain, Artificial Intelligence has shown remarkable capabilities in uncovering correlations across distinct environments or between heterogeneous variables, such as genomic data, pharmacological profiles, and disease expression patterns, which I would have never expected to detect so quickly" (P1).* *"There is, first of all, an aspect related to data analysis: all the research projects I am involved in deal with the processing of astronomical data. These may include results from simulations or observational data, and in both cases, Artificial Intelligence provides a significant and undoubtedly positive contribution from this perspective" (P10).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		“We are beginning to adopt Artificial Intelligence tools, particularly in the scientific domain of data analysis. However, we are still in the early stages, because, as you know, Artificial Intelligence tools currently have somewhat limited scopes when it comes to scientific applications. They are mostly designed for tasks such as image recognition or tracking, and these algorithms were primarily developed for commercial use or for broader consumer applications, rather than for specialized scientific purposes. […] In the scientific domain, we are beginning to experiment with using them for data analysis, specifically for noise reduction and signal classification” (P12). *“To perform data analysis, essentially in place of the human operator, or at least to support the human in a more efficient and time-effective manner.” (P12).* *“I also know that it is an excellent tool for writing calculation codes” (P4).* *“We’ve occasionally used it to solve some problems, since we do a lot of programming. For instance, when a piece of code doesn’t work properly” (P7).* *“When writing an article, especially for those of us who are not native English speakers, it is often very helpful to let Artificial Intelligence rework what we have written” (P10).*
Commercialisation Results awareness, positioning and dissemination Stakeholders’ engagement	Research exploitation	*“(It can help) better position my research and the results we are able to achieve throughout the project, particularly from the perspective of their potential impact on the world at large, where by ‘the world’ I mean both society and the industrial sector” (P1).* *“So, let’s say, it allows for more time to contemplate the results, so to speak, and also to focus on their scientific implications and any potential further directions. In this sense, it represents a shift, and from this point of view, it is a positive one” (P10).* *“To facilitate the exploitation of its results, in particular by local enterprises, and the achievement of the desired impact” (Archival data).*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		"However, it can also be interesting from a generative perspective. For instance, one of the tests we conducted involved asking Artificial Intelligence to generate a text for middle school students visiting the infrastructure, specifically, a piece of text tailored to that level of understanding" (P8).
Misfocus Loss of control Data reliability	Misalignment and robustness risk	*"Those who don't use it are definitely disadvantaged. It's like a car: if you have one, you can quickly get where you want to go, but if you don't know where you're going, you'll just end up going around the block" (P3).* *"I have experienced firsthand that it is an extremely powerful tool, but ultimately it is something programmed by humans and, therefore, it can fail. Moreover, it may be trained on incomplete or even incorrect sources" (P6).* *"The abuse or, more importantly, the lack of certification of the data sources on which Artificial Intelligence operates can pose a significant problem, potentially becoming a critical vulnerability for the development of a project" (P1).* *"I am somewhat concerned about the possibility of giving too much control. Not being fully familiar with how Artificial Intelligence works, I am unsure whether it is even possible to retain oversight over its operations" (P5).*
Relationship management Disclosure and productivity concerns	Relational and autonomy risk	*"The only thing I think is difficult to find is precisely dealing with people — that is, knowing how to interact with them and finding the right balance, never being too assertive or categorical. […] It is difficult for an Artificial Intelligence to understand your interlocutor, what role they have, what they would like to do, what kind of person they are. Let's say, all those things that you, as a person, start to understand when you've known them for a while, when you've spent time with them, when you know how they act, and so on" (P2).*

First order descriptive codes	**Second order interpretative themes**	**Relevant evidence by quotations**
		"With an automated system, stakeholder engagement cannot be effectively managed. Stakeholder involvement relies on soft elements that, at least for now appear extremely difficult to identify in analytical form and thus to provide as input to an Artificial Intelligence system" (P9). *"It bothers me, precisely as a matter of individual freedom" (P5).* *"Everything is now compressed, and it has become overwhelming, almost unbearable. What makes me sceptical about Artificial Intelligence is that I see it as aligned with this broader technological development which, at least in part, has ended up limiting individual freedom. I am not saying that this was the intention from the beginning, but the way it has unfolded has, to some extent, restricted people's freedom. And by freedom, I mean even freedom to do nothing at all, everyone should be free to choose how to behave" (P5).* *"At this stage, Chat GPT clearly knows what my technical issues are, as well as all of my weaknesses" (P11).*
Age and habit Clarity and attitude Knowledge of the tool and (mis) understanding of usage Customisation	Unrealised potential	*"The main difficulty for me lies in not being a native of this technology" (P1).* *"Because I am an older woman, or almost, so I am not used to these new tools. […] On this aspect, I think Artificial Intelligence is still somewhat behind, although it is also possible that I am mistaken. As I said, I'm not used to it" (P2).* *"I have to admit that I may hold a cognitive bias on this matter" (P12).* *"Mental resistance is certainly a factor, but it is likely to diminish over time, as exposure to the tool increases. Its use will gradually become more natural. […] I see it as similar to the evolution of mobile phone usage: today even elderly people use smartphones, whereas twenty years ago they might have used one to crack nuts and dismissed it as some kind of sorcery. The reality is that the more we*

First order descriptive codes	Second order interpretative themes	Relevant evidence by quotations
		are exposed to new technologies, the more we grow accustomed to them" (P3). *"I believe that, at least in my case, one of the main barriers lies in not being used to working with such a tool. Consequently, it takes time to explore and understand the wide range of tasks that can actually be performed with it. Personally, I started with something quite basic, such as editing and improving English language texts" (P6).* *"Another major barrier, however, can be a misunderstanding of how the tool is meant to be used. I see this happening at various levels, not only in the role of PI. Many people assume that it will solve the problem for them, but it does not. At least, it has never done so for me. That said, in some cases, it has helped me arrive at a solution more quickly" (P3).* *"The only caveat I have is that what is produced by Artificial Intelligence should not be taken tout court but should be carefully considered. I see it as a tool to be used as a source of inspiration, but certainly not as a managerial substitute" (P4).* *"And perhaps the real barrier lies precisely in not fully knowing its potential—there may be many tasks that, while 'delegating' might not be the right word, could actually benefit from the support of Artificial Intelligence. And yet, one might not even consider that possibility" (P6).*

Table 15: Data structure with supporting evidence (source: our elaboration)

3.6 Discussion and future research avenues

This study is among the first attempts to address how Artificial Intelligence usage, in the peculiar knowledge-intensive environment of a large-scale research infrastructure, can accelerate or hinder value creation activities that characterise the multifaceted PI role, under the form of value creation motives and value destruction risks.

Our study primarily contributes to the literature on value creation in relation technology integration in the context of knowledge intensive environments such as broad and complex research infrastructure, and more strongly to the literature on PIs roles and responsibilities. Specifically, we aim to contribute to a deeper understanding of how PIs value creation can be empowered by the adoption of Artificial Intelligence tools and which changes this brings to their complex role.

We identified seven value creation motives, and three value destruction risks associated with Artificial Intelligence use in the PI role. Each of them can be traced back to one or more conceptualisations of the complex hybrid PI role as proposed by Cunningham, O'Reilly, et al. (2016) and situated within one or more of the key phases that characterise the research project lifecycle (ex-ante, during, ex-post), thus highlighting the primary contribution of the work to the literature on Principal Investigators role. Therefore, from a theoretical point of view, we contribute to explain how the different responsibilities of the PI as strategic actor in charge for creating value can be reshaped by the adoption of Artificial Intelligence (Cunningham et al., 2014; 2016; Kidwell, 2013; Casati e Genet, 2014; Romano et al., 2016; Del Giudice et al., 2016). We also contribute by showing how Artificial Intelligence can strengthen value capture mechanisms (O'Kane, Zhang, et al., 2020) by potentially enhancing strategic alignment and proposal competitiveness, research exploitation through improved stakeholder communication and research dissemination, as well as some potential risks to hinder value capture due to inaccuracy or undermined relationships within the research team. Table 16 provides an overview of this theoretical contribution.

Regarding the scientific responsibilities of the PI, the findings highlight the potential contribution to value creation by supporting and stimulating scientific ideation, pushing the boundaries of specialisation, and enhancing and accelerating the PI's evaluation capability.

Artificial Intelligence VC motives/ VD risks	**PI responsibilities**	**Project phase**	**Value-capture dimensions**
Scientific ideation	Scientist	Ex-ante	Enhanced gap spotting ability, enhanced robustness and originality of scientific ideas, amplified vision and facilitated exploration of promising interdisciplinary ideas.
Strategic alignment and fit	Research Strategist	Ex-ante	Improved idea-call alignment, increased competitiveness, improved project-institutional framework alignment
Collaborative leadership	Team leader, Supervisor and Mentor	Ex-ante, during	Faster coordination, shared problem-solving, multi-perspective integration.
Project orchestration	Project Manager, Resource Manager	During	Optimised project workflow, disruption prediction and minimisation, bias mitigation, increased time and resource management efficiency, increased PI responsiveness.
Business Intelligence	Administrator	During	Improved reporting, enhanced agility through data-driven decision-making.
Research process and output	Scientist	During	Acceleration of discovery, Increased output quality.
Research exploitation	Project Promoter, Knowledge Broker	During, ex-post	Improved results communication and dissemination, improved awareness of research impact potential, enhanced valorisation of scientific results.
Misalignment and robustness risk	Scientist, Research Strategist	Ex-ante, during	Risk of reduced accuracy and potential misinterpretation, risk of misalignment with real needs of stakeholders
Relational and autonomy risk	Resource Manager, Team leader, Supervisor and Mentor	During	Risk of undermining relational and soft skill-based leadership

Table 16: AI Value creation motives and value destruction risks across PI responsibilities (source: our elaboration)

This shift allows a transition from a micro-level scientific focus to a meta-analytical one, with the potential to revolutionise the way innovative research trajectories, otherwise potentially unnoticed, are identified. In this sense, Artificial Intelligence may multiply the vertical and specialised knowledge owned by the PI, empowering its ability to design and drive the project on the scientific side, as traditionally conceptualised (Cunningham et al., 2015) by more fully leveraging a deeper knowledge discovery (Cunningham et al., 2022) and opportunity recognition capacity (Casati & Genet, 2014). Closely related to this is the notion that the PI can also enhance effectiveness as a research strategist. In this domain, the value of Artificial Intelligence lies in enabling broad-spectrum analyses, facilitating the assessment of the feasibility and competitiveness of ideas with reference to the requirements of funding calls. In this way, additional rigor is introduced into the process, thereby overcoming the limitations of the PI's individual knowledge, while enabling a dynamic and data-informed approach to ensure a strategic positioning of the project and secure the relative fundings.

Within the PI's role as Resource and Project Manager, there is a contribution in terms of process optimization, consistent with the notion of advanced project management and project orchestration (Taboada et al., 2023). This explains the mechanisms through which value is added by AI, for example by means of dynamic Gantt generation and predictive monitoring of bottlenecks. The delegation of operative and time and effort-consuming tasks enables the PI to make a better use of its capabilities and time on strategic and value-added tasks. However, the findings also highlight a relevant value creation risk linked to the loss of misalignment and robustness, in terms of coherence with the project objectives and with the scientific goals. This risk goes beyond the well-known risk of Artificial Intelligence hallucinations and represents a significant contribution to the literature on PIs' roles, opening up the pace to future research on a novel category of managerial challenges affecting PIs' activity with reference to Artificial Intelligence adoption (Cunningham et al., 2015). Indeed, for the PI, relying on inaccurate or unreliable data and analyses represents a major challenge with broad implications for the overall robustness of the project from both a managerial and a scientific perspective. Beyond issues of reliability, however, the identified risk also lies in the possibility of deviating from the intended objective and losing effective control over the activities required to achieve it, due to an excessive reliance on AI. It is emphasised that clarity about "where one wants to go" must always be maintained; otherwise, the tool's support and its potential for value creation are nullified. An additional concept emerges that is particularly relevant for a better understanding of this risk of value destruction: unlike humans, Artificial Intelligence lacks coherence over time, which may lead to conceptual drifts if not adequately managed.

With respect to the role of Artificial Intelligence in relation to the PI's responsibilities as team leader and project manager, an interesting paradox emerges. On the one hand, Artificial Intelligence contributes to value creation by facilitating team collaboration, through shared problem-solving and the integration of multiple perspectives. In this sense, it strengthens the PI's leadership, since time and energy are not absorbed by time-consuming activities. Moreover, overall project management can benefit from tasks and resources allocation optimisation, and by the mitigation of potential subjective biases, which in turn may contribute to better conflict management (Foncubierta-Rodríguez et al., 2022). On the other hand, a risk of value destruction emerges, and it is linked to human relations: automated task assignment and activity monitoring may be perceived as a threat to autonomy and individual freedom, connected to issues of organisational well-being and the psychological safety of the team. This insight therefore reveals a new nuance that deserves attention in future research: while the emerging literature highlights many positive effects of Artificial Intelligence use on employee well-being, particularly through the reduction of workload and the delegation of time-consuming tasks, the potential negative consequences arising from leaders' use of Artificial Intelligence need to be further investigated (Hougaard et al., 2024; Reitz & Higgins, 2024).
The overarching risk of unrealised potential can be read under the lens of absorptive capacity (Cohen & Levinthal, 1989), as a lever to deeply and fully integrate an innovative solution so that its potential in terms of value creation can be fully realised and exploited.

In terms of future research, the macro-themes can be enriched and strengthened by complementing the single case study design with the study of PIs from other research infrastructures or large-scale projects. Specifically, we are planning to extend the scope toward a multiple case study design, including participants from *Growing Resilient, Inclusive and Sustainable (GRINS) Project*, and from SiciliAn Micro and NanO TecHnology Research and InnovAtion Center (SAMOTHRACE) Project.
In addition, the proposed value creation motives and value destruction risks can be operationalised and tested as predictors of research performance outcomes, as well as

in consideration of fixed conditions (project size, funding levels) and contextual condition.

3.7 Conclusion

The study reveals that Artificial Intelligence is predominantly seen as an opportunity to enhance value creation, while more limited attention is currently placed on the risks for value destruction. Artificial Intelligence is mainly perceived as enhancer of value creation in terms of scientific ideation and discovery, improved project-call fit, process optimisation benefits, knowledge dissemination, human collaboration benefits and social and economic impact. The main perceived risks to hinder value creation or cause value destruction are related to the inability to exploit its potential for value creation, weakened strategic coherence, and compromised human collaboration.

In addition to the theoretical contribution, the study also has practical and policy implications.

From a practical point of view, it may potentially lead to the development of protocols for an institutionalized and structured use of Artificial Intelligence in the research environment. Such protocols could allow to maximise AI's potential for value creation while mitigating risks associated with value destruction. Indeed, Principal Investigators' perspectives on Artificial Intelligence value creation for research purposes is essential to reach an effective integration of Artificial Intelligence tools in the research environment, as they are key gatekeepers and key decision-makers within academia.

The main limitations of this study are associated to its single case study nature. The findings are therefore influenced by context-specific characteristics of participants. Furthermore, the object of our analysis is linked to the use of AI, with which PIs and scientific leaders are still just experimenting, since it's use is not institutionalised yet. This implies that the findings capture their current perceptions which should be further investigated in the future for potential generalisability of our theoretical implications.

Concluding remarks

The dissertation aims to contribute to the growing literature on Artificial Intelligence in management with the investigation of Artificial Intelligence integration within strategic decision-making processes. Indeed, apart from Artificial Intelligence inherent technological value and objective potential, its effective integration is dependent upon how its potential, and its limitations are perceived with respect to its use in the decision-making context. The research sheds light on new aspects that underpin the interplay between human and Artificial Intelligence in contexts where it is intended to affect strategic decision-making, also revealing novel nuances on those aspects already mapped in previous literature.

The systematic literature review in Chapter 1 aimed to lay the foundations for a broader understanding of the support provided by Artificial Intelligence to decision-makers called to deal with strategic choices. The review process was designed and conducted with the aim to isolate and include in the sample scientific works with a strong management perspective (Artificial Intelligence is indeed a multidisciplinary and cross-cutting topic), as well as with a clearly stated or inferable focus on strategic decisions. The findings were organised and presented into three main thematic areas: (1) Antecedents and Risks of Artificial Intelligence Use in strategic decision-making, (2) Outcome orientation, (3) Process orientation.

Key findings in each area were mapped to provide a clear overview of main constructs and results characterising existing research in the field. In particular, antecedents and risks emerging from the sample were grouped, on the one hand, according to the main phases of design and implementation that ultimately lead to the concrete use of Artificial Intelligence tools, and, on the other hand, according to the factor or actor to which they relate (Artificial Intelligence and input data, decision-maker, organisation, environment). Outcome-oriented findings include an overview of what have been found to be the main outcomes of Artificial Intelligence adoption for strategic decision-making, in terms of performance measures, competitive advantage measures, specific decisions, decision-related constructs, and Artificial Intelligence empowered capabilities. Process-oriented finding eventually clarifies what are the key mechanisms and factors that influence human-machine relationship occurring within the scope of strategic decision-making: delegation, complementarity of knowledge and skills, intuition, bias.

Overall, the literature review findings led to the identification of some avenues for future research. There is a need for investigating design-related antecedents and the interrelationships and interdependence among antecedents occurring at different levels (Artificial Intelligence as a technology, managers as decision-makers, the organisation within which they operate and the external environment). In this regard, the review also highlighted that a deeper understanding of such antecedents and risks could be reached by exploring individual decision-makers perception of them. This consideration was a guiding insight for the design of the empirical paper presented in Chapter 2.

In addition, in terms of AI-driven outcomes, a promising direction to be explored concerns the potential impact on underexplored cognitive capabilities that are crucial for decision-making (e.g. strategic thinking). Strictly related to this idea, also emerges as a challenging area of inquiry the underlying dynamics of human-machine complementarity in knowledge and skills. Future studies may unveil whether and how Artificial Intelligence can indirectly feed human tacit knowledge and human intuition as fundamental and inimitable aspects that guide leaders in making complex decisions. The finding and the research agenda derived from them in Chapter 1 inspired the subsequent empirical works in chapter 2 and chapter 3, in terms of research design and in practical terms, by representing the guiding framework for the interview protocols employed to conduct semi-structured interviews as data collection method.

Chapter 2 is grounded in the core idea that managerial perceptions are crucial for gaining a deeper understanding of the mechanisms underlying the adoption and use of Artificial Intelligence by strategic decision-makers. These perceptions are examined through an exploratory approach within a qualitative study based on semi-structured interviews conducted with a heterogeneous sample of managers, including both those who have already used Artificial Intelligence and those who have not adopted it yet. This design allows for the identification of perceptions stemming from direct experience as well as those rooted in expectations, aiming to uncover how managers make sense of Artificial Intelligence at the highest level of the decision hierarchy.

The adoption of the sensemaking theoretical lens in this second study leads to the construction of a typology of sensemaking patterns: sceptical observers, tentative explorers, pragmatic experimenters and visionary innovators. The contribution of this study lies in explaining the heterogeneity of managerial postures toward AI, going beyond the generalised antecedents and outcomes mapped in the literature. Instead of looking at these factors in isolation, the study shows how they are interpreted and processed by managers in an integrated way, consequently shaping different "enacted realities" and potentially different adoption trajectories. Therefore, the findings not only categorise different managerial sensemaking patterns but also reveal the underlying mechanism through which they are activated.

Anchoring the discussion in the findings of the literature review from Chapter 1, this empirical work on managers' sensemaking of Artificial Intelligence provides a key theoretical contribution by helping better explain the mapped antecedents and risks, process and outcome constructs, providing novel insights on some of them, proposing some new concepts that enrich the overall picture, unveiling potential interdependencies between the different levels at which antecedents and risks manifest themselves (AI, individual, organisation, environment), and proposing a novel perspective under which both antecedents, outcomes and interaction mechanisms can be perceived differently and can jointly contribute to shaping patterns of Artificial Intelligence sensemaking.

As for the theme of *Vision*, the work shows the importance of individual and unstructured experimentations that are triggered by existing vision, but at the same time end up feeding it, while also contributing to explain that the subjective aspects of some barriers and drivers, such as openness and awareness of Artificial Intelligence need and potential, can be more deeply understood when analysed as part of a broader picture, as sensemaking patterns are. The same applies to algorithmic aversion and trust, whose manifestations are far from uniform; rather, they may exhibit varying degrees of intensity, which can be understood in light of the patterns themselves. Concerning the commonly recognised barrier of threat to job security, the research reveal that this barrier is scarcely perceived by strategic decision-makers, who frequently refer to it as characterising attitudes they do not identify with. In this regard, the findings also show in more detail the underlying mechanisms that can shape a reluctant posture, in addition to uncovering those that shape favourable personal adaptability, which are not limited to a pre-existing digital literacy but also find their origin in a general enthusiasm, curiosity and courage to innovate. Another contribution of this chapter lies in introducing the role that pre-existing strategic decision-making approach may play in shaping managers sensemaking and their consequent attitude. Furthermore, some evidence of interrelationships between individual and organisational barriers and drivers which may be further investigated by future research is provided, such as the interrelationship between the emergence of Artificial Intelligence strategic foresight and the recognition of Artificial Intelligence strategic potential with Artificial Intelligence oriented culture. Another aspect emerging from the research that extends the findings from existing literature is the importance of Artificial Intelligence embeddedness in personal lives of managers, which shapes their familiarity and confidence, eventually influencing their perception of it as a potential support for decisions. Familiarity and routinisation of Artificial Intelligence use also drive what was labelled as critical confidence, which seems to neutralise to some extent the fear of being overwhelmed, of being unable to deal with Artificial Intelligence biases and of being influenced by human biases in interacting with AI.

The findings also raise relevant considerations that can inspire future research on Artificial Intelligence outcomes in relation to human-machine complementarity in knowledge and skills. The paper indeed uncovers the perceived support of Artificial Intelligence to those knowledge management-related capabilities that mainly influence strategic decision-making: the ability to diagnose and interpret present reality and the ability to articulate reliable future trajectories. In this regard, the findings point a subset of activities that can benefit from using AI, enabling managers to make some strategic decision with a confidence that would otherwise be hardly reached. Overall, the main implication of this work lies in broadening the perspective of strategic decision-makers on Artificial Intelligence use for strategic decisions. The findings may indeed encourage managers to adopt a critical lens in self- assessing their current state toward AI, having an overview of other existing approaches, and letting themselves being inspired by potential benefits they would not even imagine otherwise.

The third study in Chapter 3 shifts the focus to the research environment to explore how the potential value of Artificial Intelligence is perceived by Principal Investigators in relation to their complex and hybrid role as value creators and to all the strategic decisions it entails, adopting the theoretical lens of value creation and destruction. The findings reveal that Artificial Intelligence is seen as a powerful driver for value creation, by means of its potential contribution to ideation and to the acceleration of scientific discovery, while empowering project management PI's capabilities. As fort value destruction risks, they are mainly perceived in relation to the loss of focus and the emergence of negative consequences in team dynamics.
The theoretical contribution of this chapter is mainly anchored to the explanation of how the different responsibilities of the PI as strategic actor in charge for creating value can be reshaped by the adoption of AI, as well as on how Artificial Intelligence can strengthen value capture mechanisms by potentially enhancing strategic alignment and proposal competitiveness, as well as research exploitation through improved stakeholder communication and research dissemination, as well as some potential risks to hinder value capture due to inaccuracy or undermined relationships within the research team.

In conclusion, the work contributes to explain how the value of a technology as complex and high-potential as Artificial Intelligence in strategic and knowledge-intensive decision-making contexts does not exclusively reside in the technology itself but is instead constructed through the dynamic interaction between the technology and the interpretative frameworks of the strategic decision-makers who are expected to use it.

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Appendix

Interview Protocol – Chapter 2

General/introductory questions

1. Tell me about how strategic decisions are made in your firm.
2. What kind of strategic decisions can benefit from the use of AI?
3. What kind of AI tools do you use in support of your strategic decisions?

Drivers and barriers

4. What are the barriers linked to AI in strategic decision making?
5. What are the enablers linked to AI in strategic decision making?

Outcomes

6. What are the consequences/outcomes of using AI in strategic decision making?
7. How has AI enhanced SDM

Decision making Process

8. How has your strategic decision making changed through AI technology adoption?
9. Tell me about how AI supports human decision makers in managing knowledge for strategic decision making.
10. What have you learned using AI? Have you increased your knowledge base? Can you provide some examples?
11. What are the main biases that can affect strategic decision making on both AI and HI sides?

Interview Protocol – Chapter 3

Introductory Questions

1. How would you describe your role and main responsibilities as a PI or project scientific manager?
2. How many years of experience do you have as a PI, and what was your main motivation for becoming a PI?
3. What are the main challenges you face as a PI?
4. Have you received specific training in the use of artificial intelligence?
5. Do you currently use artificial intelligence to support your PI activities?

If yes:

How do you use artificial intelligence to support your role as a PI?

Describe how you use AI in your decision-making process as a PI?

What activities of the PI role does AI support?

What motivated you to use AI?

What were the main barriers to adoption?

How does AI help overcome the main challenges faced by PIs?

How does AI influence project dynamics in terms of project development and the relative commitment of various stakeholders?

relative commitment of various stakeholders?

What are the main benefits of AI in your business in terms of management and leadership?

What have you learned from using AI in your IP role?

If not:

What would motivate you to use AI in your IP role?

What are the main barriers to adopting AI in your IP role?

How would you use it?

How could it help overcome the main pitfalls faced by private investigators?

How would AI be useful for your current IP activities and responsibilities?

How would AI influence project dynamics?

What are the main changes you expect from AI in your IP practice?

Do you expect to learn anything from using AI?

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