Master's Thesis

From Intelligences Apart to Industry 5.0 – How Will Artificial Intelligence Impact the Role of Leadership in the New Normal?

MSc in Economics and Business Administration – Strategy, Organisation and Leadership

Authors:
Hanna Kleinings (93766)
Delfina Aleksandra Szorc (93054)

Supervisor:
Thomas Michael Brinch-Pedersen

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Copenhagen Business School

Abstract

Artificial Intelligence (AI) – an intelligent system that is able to encompass cognitive abilities – brings promise to the future of businesses and workplace, and has been the core driver for Industry 4.0. As a result of exponential developments in this techno-economic environment, businesses and society alike are experiencing a shift from putting technology in the forefront of the businesses, yet, working with "Intelligences apart" – towards the seamless integration of the human touch of business and intelligent systems – Industry 5.0. This new normal will create opportunities and challenges for the leadership of businesses, as well as academia.

A review on existing literature outlined significant gaps in the academic body of knowledge that take AI for what it is – a technological agency that does not operationalize statically and one that interacts within an organization and its actors. As such, following a mixed-method research design and grounding our conceptualizations in primary data collected through interviews with companies who are in the forefront of AI development and implementation, two assisting themes have been identified: processes, including decision-making and collaboration, and transparency, pertaining to among others, knowledge and trust.

Therefore, this thesis aims to advance the current research on the temporal changes in the role of leadership in the context of AI by investigating the role of AI in the organization; the effects this role has on organizational transparency; and what importance future workforce places on these. This interplay thus contributes to the field of leadership studies and provides guidelines for organizations in this new technological realm. The research suggest that in this shift towards Industry 5.0, it is more important than ever for leadership to know and understand the internal and external processes of the organization, embrace change and AI agency, develop soft skills concurrently with technical literacy and develop a mindset that allows leadership to frame problems in a multitude of settings – both cognitively and in stakeholder relations.

Keywords: Artificial Intelligence, Leadership, Industry 5.0, Intelligent Systems, Management, Organization, New Normal, Process Management, Change

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1. Introduction

1.1 Setting the Stage

Over the past decades, the notion of leadership has gained significant traction both in academic as well as managerial literature. However, there is much ambiguity in defining leadership in academia and practice. Leadership is often bound to decision-making, designing processes and management practices, and carries the notion of entity, meaning a leader defines and determines the success or failure of an organization. However, recent academic approaches investigate leadership not as something one inherently is, but rather what one does, and challenges entity-based views with team-based or process-based propositions (Uhl-Bien, 2006).

However, the rise of new complexities, such as integration of techno-economical solutions to redesign business processes have left this notion of leadership at a loss in academia. Ghoshal (2005) argues that business schools, and the academic research they conduct in order to claim business theories as science, has led to badly formulated business frameworks. These tautological theories, by ignoring complex social phenomena, inevitably lead to self-fulfilling prophecies that add very little value to global businesses, as they disregard any social effects of humanness, choice or judgement. Management theories, therefore, focus on clear-cut, functionality-based processes through partial analysis, and neglect case based, empirical approaches. As researchers, it is crucial to challenge these set ideas and assumptions to re-legitimize pluralism in academia. Rather than discarding learnings from empirical evidence that do not fit the preconceived frame of science, research must be reframed to build on collective knowledge.

Indeed, these techno-economical solutions, namely intelligent systems, such as Artificial Intelligence (AI), that businesses integrate into their strategy, can have both a beneficial and a detrimental effect. Regardless of the costs or benefits, however, they undoubtedly have a tenacious effect on how businesses run and are led. Even though we are currently in the midst of Industry 4.0, meaning putting smart technologies in the forefront of businesses, it will be challenged and inevitably succeeded by Industry 5.0, a full integration of the human touch of business and intelligent systems. The combination of the latter elements will merge the potential accuracy of full automation with critical and cognitive skills of business leaders. Today, nearly 85% of businesses use some form of intelligent system in their business operations, but only 63% of employees are acutely aware of this (HubSpot, 2020). This paradoxical effect of automation through Artificial Intelligence, highlights the core issue: it is both a unifier and a divider in the future of the workplace. Working towards the beneficial effects of technological integration, while simultaneously utilizing it to the maximum value for long-term success has become the core challenge. According to experts, Industry 5.0 is inevitable, and we must take a step back and revisit our predisposed notions of leadership and technology in order to be prepared.

Industry 5.0 calls for more transparency in business processes, yet the prevalence of the concept does not include techno-economic parameters in academia that take AI for what it is. Main research on transparency falls under the umbrella of auditing, control or productivity, and carries a strong positivistic undertone where the more we see, the more we understand about the organization that leads to increase in productivity (Bernstein, 2012). Visibility and observability, often used interchangeably with transparency, however do not take deeper analysis of decision-making processes into account and create another paradoxical situation where determinants of decision-making are either taken for granted, not understood or deliberately ignored.

1.2 Problem Discussion

The growing integration of intelligent systems, namely Artificial Intelligence, in both businesses and our daily lives, creates a multitude of challenges and opportunities for the future workplace of Industry 5.0, what the authors of this thesis will call the new normal. Questions regarding job (dis)placement, economic status quo, developing and redefining crucial skill sets, as well as potential of unlocking unimaginable economic profits must be addressed by leadership of successful organizations. Identifying new problems, such as technology challenging the human touch of business processes, increased consciousness and responsibility of techno-economic integration, transparency in complex decision-making must be the center of any C-suite discussion.

These exponential changes in the business landscape mean preparing both the role of leadership and future workforce for the new normal, and the hypothesis these researchers operate under is that the role of leadership *will* change in the near future. Although the existing literature on the implications of Artificial Intelligence on business operations carries a positivistic tone, outlining benefits and cost reductions, there is some reason to be skeptical, as literature based on empirical research on its effects on the role of leadership is lacking. Research on AI has been conducted in academic silos, with taking only a part of organizational behavior or process in focus, and lacks insights on how technology affects organizational behavior on decision-making levels, trust and transparency, while maintaining pluralistic integrity.

It is essential to investigate the perceptions, concerns and demands of leaders, future workforce and practitioners for the new normal. The base of integrating the human touch of business and AI has been established by industry leaders, with great promise, but a deeper dive must be made into how current and future organizations can share the benefits of AI equally and what determinants must be in place for its success. The potential of collective learning through merging primary research with industry shapers and future workforce with academic literature can provide essential guidelines for the future preparedness of businesses for the new normal.

1.3 Aim of the Thesis & Research Questions

This thesis aims to explore the role of Artificial Intelligence in the new normal of moving from Industry 4.0 to Industry 5.0, a change that will put more constraints – or potential – on how managers and future workforce define and carry out leadership, in order to draw broader conclusions of the challenges businesses face. With a more significant integration of intelligent systems in business processes, the context of day-to-day work is ever-changing, and therefore, this thesis aims to answer the following research question:

How will Artificial Intelligence impact the role of leadership in the new normal?

By incorporating empirical, managerial and theoretical perspectives, this thesis has been designed in a threefold approach. Firstly, we set out to identify the business processes that AI will inevitably influence, analyzing the *role of AI in the organization*. Secondly, conceptualizing the growing focus on transparency, and its incorporation into decision-making processes, offers the researchers an analytical lens – and highlights the extent to which *Artificial Intelligence can assist as a tool*. Finally, we build on this knowledge to determine the interplay of the *role of AI* and the *role of leadership*, and how this will affect the techno-economic reality of organizations today and tomorrow. The results of this research will provide insight into the changing and contextual nature of leadership, and contributes to both the conceptual as well as practical implications for companies and future leaders. Furthermore, by contrasting current expectations and attitudes of future workforce to leadership tendencies, we can draw conclusions on the preparedness and techno-economic maturity of companies, reflective of the temporal nature of this research. As a consequence, the results of this thesis will determine a set of guidelines based on the collection of primary data that will help us frame the role of leadership in the new normal, and draw upon the importance of coherent strategy and design of business processes.

A set of sub-questions (SQ1-SQ4) have been established in order to help us answer our primary research question.

SQ1: How do business practitioners define Artificial Intelligence and its processes, and what are the costs and benefits of its implementation?
SQ2: How does AI affect transparency in the workplace?
SQ3: How will the combination of technology and leadership affect decision-making in the organization?
SQ4: How do employees define the future of the workplace?

1.4 Outline of the Thesis

This thesis has set the starting point with the above discussed section, and is followed by:

Section 2: Methodology outlines the methodological considerations for this thesis. The section among others, includes discussions of research philosophy, design and data collection methods, and why they were specifically chosen. Conceptual organization of 1st and 2nd order codes through data structure is presented. Furthermore, issues of research ethics and confidentiality are taken into focus to draw implications for validity and reliability.

Section 3: Literature Review and Theoretical Considerations critically reflects on the literature on key concepts of processes, transparency and leadership in the context of Artificial Intelligence, and their interconnectedness, to form an understanding of current literature and the gap we, as authors, aim to fill. We conclude with delimitations regarding key concepts and constructs we work with throughout the thesis and construct the model for analysis.

Section 4: Findings presents the results from primary data gathering and displays the analysis. The outline of the chapter follows themes of the coding method outlined in section 3, and is divided into sections based on themes. Analysis of qualitative and quantitative data is presented.

Section 5: Discussion deals with the findings in the relative context of the literature review and our delimitations, and primary data, and is divided into two subsections. Theoretical Implications aims to discuss the theoretical approach to the issues at focus of this thesis while Managerial Implications outlines the practicality of the thesis and offers guidelines for decision-makers in businesses in Industry 5.0 to maximize the value of the strategy. These subsections in combination meet the aim of the thesis.

Section 6: Limitations outlines a discussion on contingencies that the researchers have taken into consideration. These include both methodological (including data collection and analysis) as well as theoretical considerations and will conclude with suggestions=s for further research.

Section 7: Conclusion will revisit the logic of the thesis, and answer the research question.

2. Methodology

This section looks into the methodological processes and aspects of this thesis, following the systematic approach of the Research Onion Model (Saunders, Lewis & Thornhill, 2016). This model functions as a funnel to reflect on and understand main paradigms and philosophical positions in business research. The model departs from the philosophy of knowledge creation, and covers approach to theory development, methodological choices, strategy and design, time horizon and techniques and procedures of data collection and analysis in an orderly fashion. By providing a structural framework that is built on decisions on research, this model is easily adjusted to any form of research that builds on logical progression and justifies how this research has been conducted. The chapter ends with a section on ethical considerations, taking into account our data collection, and discusses reliability and validity in order to critically assess our own research processes.

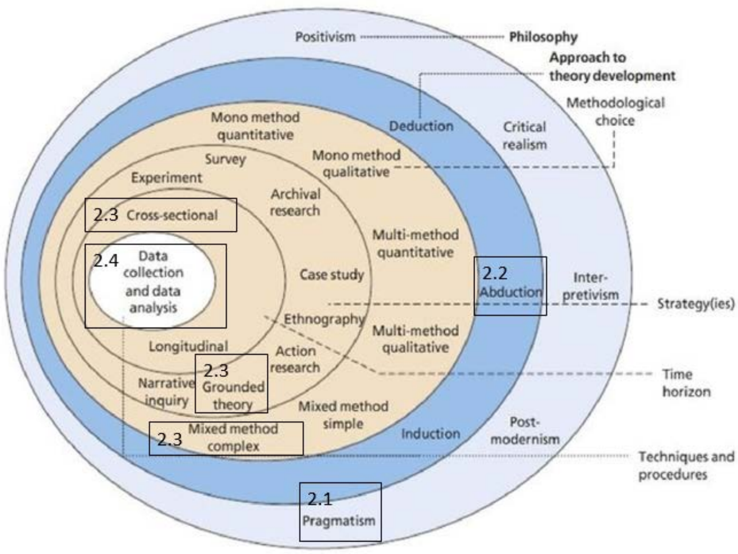


Figure 1: Saunders et al., 2016: Research Onion Model.

2.1 Philosophy

In order to answer our research question and interpret our findings, certain methodological assumptions must be made that, in a consistent combination, will constitute a credible research philosophy and aid us in development of knowledge (Burrell & Morgan, 2016; Crotty, 1998).

Ontologically, for this thesis, we consider the nature of reality in the organizational context in cause-effect relationship and procedurally, meaning that reality is only created through practical applications of ideas (Kelemen & Rumens, 2008). We see theories, concepts and constructs as instruments to explain contextual situations (Watson, 2011). This research starts with a complex and *surprising problem*, and aims to contribute practical solutions that inform future practice in organizations, maintaining the possibility of multiple realities (Saunders et al., 2016). Considering epistemological assumptions, this research focuses on practical applications, where knowledge is valuable and acceptable only if it enables actions or advancement, as opposed to constructing truth through politically or socially dominant views or equating theories to carry the same importance (Bristow & Saunders, 2014). The contribution to knowledge we make through our research will be practical in nature and focuses on problems and informed future practices. Regarding axiology and the assumptions we make, this research is built upon and reflects on the authors' values and beliefs, aiming to address the doubts and complexities the research question brings – the progression where each actor creates new values and solutions to deal with novel issues (Biddle & Schafft, 2014).

Pragmatism as a research philosophy was chosen for the abovementioned reasons. Furthermore, Saunders, Lewis and Thornhill (2016) outline that pragmatism as a philosophy allows for the notion that meaningful data is constituted from critical, practical and experimental engagement with the world, rather than focusing purely on measurable metrics. Rather than focusing on pre-determined thought learned by objectified knowledge, pragmatism aids the authors to focus on knowledge development through emergent logic of relations whilst maintaining social integrity (Glassman & Kang, 2010).

The research question suggests a connectivist approach, also prevalent for studying digitalization, where understanding of core issues must materialize through social interactions, the logic of dynamic thinking processes and how information is organized and processed (AlDahdouh, 2017). Pragmatism not only gives the tools to find meaning in how interviewees see problems in a socially constructed way, but also how they organize complex knowledge for decision-making. This philosophy allows for the freedom of understanding the language and terminology interviewees use to work with conceptualization of theories and non-linear problem solving (Dewey, 1916; Glassman & Kang, 2010). We as researchers acknowledge that our research question must take multiple realities into consideration, see results in a non-abstract form, and thus consider our findings in the context of practical considerations.

Pragmatism commonly follows the research problem and question through a range of suitable methods, allowing for plurality of data collection and analysis, legitimizing multiple method approach within one study (Glassman & Kang, 2010). The chosen philosophy allows us to select the methods that result in the most credible and valuable outcome, ensuring coherence. As the researchers take a problem-solving and non-linear focus, as opposed to institutional, top-down approach, development of knowledge and new information must take into consideration the context of both the interviewees' and researchers' own logic and architecture (Glassman & Kang, 2010; Saunders et al., 2016).

2.2 Approach

As this thesis process starts from collecting data to explore a phenomenon, identify themes and explain patterns to challenge existing theories and bridge the gap, with constant iteration, an abductive approach was chosen (Saunders et al., 2016). As the conceptualization of AI in business operations is a topic that has only become prominent in the last decade, theory on the relationships between intelligent technology, leadership, transparency and consequent processes is lacking. By moving in a continuous feedback loop from theory to data and working with concepts (a general idea formed by similarities of characteristics) and constructs (a complex idea, formed by many smaller concepts), value in research can be created through meaning-making (Peirce, 1934; Timmermans & Tavory, 2012). Peirce (1934) argued that meaning-making, the process of forming explanatory hypotheses, practiced throughout research repeatedly, will allow to see and analyze the situational fit between observed rules and facts. The meta-hypothesis for these researchers was that the role of leadership will change in Industry 5.0.

The authors of this thesis aim to analyze and explain Artificial Intelligence not as a stand-alone technological innovation, but as an actor which interacts with other theoretical concepts, such as leadership and transparency. The novelty of this technological breakthrough, which among other notions, has the cognitive ability to act on its own behalf in decision-making will change how leadership in organizations is and will be perceived, and what characteristics will change regarding transparency. Triangulating between theory, practitioners and data gathered from future and recent graduates will allow a multiple layer approach, meaning that both explanatory and exploratory mindset can be taken in order to understand surprising facts (Saunders et al., 2016; Timmermans & Tavory, 2012). The role of theories, however, should be understood: iteration and movement can only happen in a meaningful way, if the scope and sophistication of theories is holistically constructed. Surprising observations can only be made if researchers are sensitized to their potential relevance (Timmermans & Tavory, 2012).

Abductive reasoning allows the authors to move back and forth between observations and theory, and construct our understanding of leadership, decision-making and transparency that is grounded in the notion of techno-economic solutions, namely Artificial Intelligence. Furthermore, as opposed to inductive or deductive reasoning, the role of theory serves the purpose of both inspiration and goal (Timmermans & Tavory, 2012). Theoretical inspiration, in line with pragmatism, is a way for researchers to ask more informed questions, while the role of theory as a goal focuses on creation of better theories that allow for an understanding or broader phenomena (Timmermans & Tavory, 2012). Artificial Intelligence, as an emerging concept provides a challenging notion to conventional leadership theory, but one that will become more prominent in our daily lives in the years to come – and complexity should not be ignored but embraced.

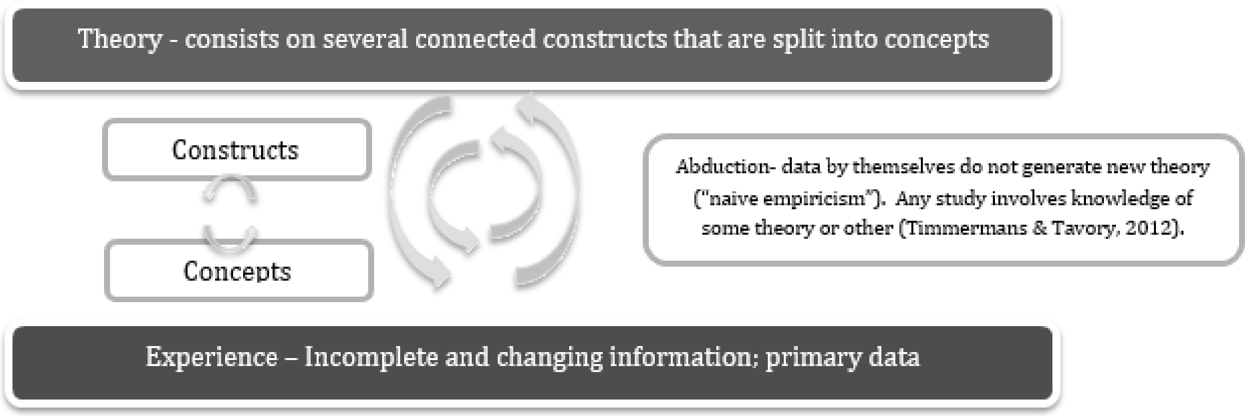


Figure 2: Logic of the Approach of this Thesis Inspired by Hernes (2014) & Timmermans & Tavory (2012).

The outcome of this thesis generalizes from the interactions between the specific and the general (Saunders et al., 2016). This means that we have chosen an area of interest, through primary data collection observed surprising facts, researched theoretical literature to make meaning of our findings, collected further data with increased richness to allow us explore the phenomena, identified theoretical themes of interest and built constructs and repeating this logic until saturation. Revisiting our assumptions and theoretical literature ensures that we address our own possible bias as well as reaching the same observations trans-situationally (Timmermans & Tavory, 2012). The researchers aim to counter existing theory where appropriate and include new conceptual actors, as well as address the novel challenges leadership faces in the future. Pluralism remains important, and no one answer can be given to any complex social notion without sacrificing the richness of data or context (Ghoshal, 2005), therefore the thesis focuses on guiding principles that can offer a broader appreciation of interactions of various concepts and constructs.

2.3 Design & Strategy

The methodological choice made for this thesis has been a mixed method complex choice (Saunders et al., 2016), as to ensure the coherence of our philosophy and approach. Our research question: *How will Artificial Intelligence impact the role of leadership in the new normal* requires clear importance of taking a holistic approach, as purely qualitative or quantitative research cannot answer this question. In line with pragmatism, we include a multitude of positions to help us undertake the research and find meaning in the context (Tashakkori & Teddlie, 2010). Mixed method choice further follows the abductive approach as we constantly iterate between theory and data to test our assumptions, and gather more data of any significant nature to develop a richer theoretical understanding (Timmermans & Tavory, 2012).

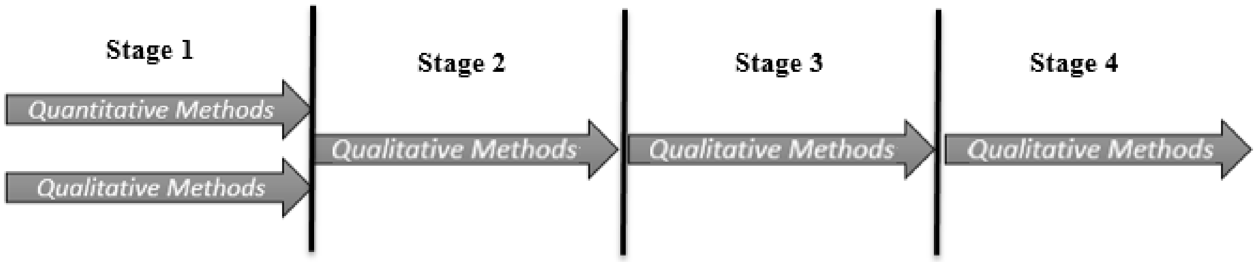


Figure 3: Mixed Method Research Design: Concurrency and Sequence, Inspired by Saunders et al., 2016.

The combination of qualitative and quantitative techniques have been concurrent in the initial stage of data gathering to ensure that both data sets have been interpreted together to provide a richer comprehension of the research question and area (Stage 1). However, after the initial data gathering process, a sequential multi-phase mixed method design has been followed (Stage 2 to 4), as more data was gathered from different sources, both primary and secondary to test our assumptions and uncover significance in correlations. The choices made have been to ensure a) the dynamic nature of the research, b) coherency in integration of different data into the research and c) the flexibility to consult and reevaluate theoretical literature on the chosen subjects, making sure we have a fully integrated mixed method research (Nastasi, Hitchcock & Brown 2010; Saunders et al., 2016; Tashakkori & Teddlie, 2010). Firstly, we have conducted a set of interviews with an array of qualitative open-ended questions, in parallel to an online survey to collect quantitative data on future workforce (Stage 1). After analyzing the gathered data, more interviews were conducted with both industry experts (Stage 2) as well as consultants (Stage 3) to understand leadership and transparency processes within organizations and to elaborate on our initial set of findings. Subsequently, a last set of interviews (Stage 4) were conducted to test our assumptions. The sequential multi-phase design was both the result of availability of the interviewees as well as a deliberate choice, especially in the later stages of the research. The use of both qualitative and quantitative methods has also defined the scope and scale of our thesis, as this research is focusing on companies that are industry leaders, who define the concepts of AI and process automation that trickles down to all organizations, and new insights previously unknown to researchers have been observed and further followed up on, and allows for diversity of views. Finally, mixed method research in AI and leadership research is appropriate, as the aim is to ascertain if the findings from one method mutually corroborate the findings from the other methods – and secondary data was further collected for the same purposes.

Complementarity of the findings has been one of the key aims for the researchers due to the need for holistic explanation of concepts and constructs through iteration of qualitative and quantitative data. Purpose of this research is both exploratory and explanatory (Saunders et al., 2016). Furthermore, we have taken precautions to eliminate both our own bias as well as bias of collecting data from a single method design. The different methods of data collection are highly contingent on our research question and sub-questions. By interviewing leading consulting firms who are working in AI implementation plans, we have aimed to outline the core challenges the industry and society face, as well as gaining the understanding of process automation. Companies who are top-tier performers in AI development have been interviewed in order to understand the complexities in the practicalities for automation of business processes, as well as leadership challenges. Finally, the third leg of data, both a qualitatively and quantitatively designed online survey, distributed to future or recent graduates who are entering the future workforce, was analyzed to investigate the maturity of expectations and attitudes towards working in the future of Industry 5.0.

Grounded Theory was selected as a research strategy, as we are interpreting and following a process where we analyze, interpret and explain the meanings social actors construct to make sense of their everyday experiences (Charmaz, 2006; Glaser and Strauss, 1967) as well as develop theoretical assumptions on complex contexts in business (Gioia, Corley & Hamilton, 2012), however this research uses Grounded theory in a loose method (Saunders et al., 2016). Using Grounded Theory loosely means that we will refer to the methodological considerations that theory is grounded in data, which are analyzed simultaneously through development of analytical codes that emerge independently through primary data – but in line with abductive approach, theoretical literature is taken into consideration when making meaningful connections between codes and aggregated dimensions (Gioia et al., 2012). Furthermore, Grounded Theory is predominantly linked to purely qualitative research, however, Saunders et al. (2016) argue that the aim for methodological choices and strategy formulation is not rigorously following predetermined rules, but rather making meaningful connections between data and theory. The authors apply the same methodological principles of concurrently collecting and analyzing qualitative data to data of quantitative nature.

The history of development of Grounded Theory has been ambiguous, and there have been numerous subfields (Corbin & Strauss, 2008; Gioia et al., 2012; Saunders et al., 2016; Suddaby, 2006), where each academic has pursued their own interpretation, but due to the nature of this research, the authors of this thesis follow Charmaz (2006), who argues that only constructivist grounded theory is based on interpretive approach, where surprising facts are not discovered but constructed. With regards to Artificial Intelligence and its novelty in business processes, as well as previously mentioned ambiguity in constructs such as leadership, the interaction of these theoretical and data-driven actors must be constructed through data to carry meaning. Ideas and research areas have included theoretical literature, and the author's understanding of it, however codes are created through data and thereafter researched in theory. However, being guided by preexisting theoretical literature cannot be fully eliminated from the process, as the researchers require background knowledge to ask meaningful questions from the interviewees (Bryant & Charmaz, 2007). Suddaby (2006) further acknowledges the importance of theoretical background knowledge in Grounded Theory strategy before interviews take place, as to avoid testing inappropriate philosophical assumptions, or working hypotheses. Finally, Grounded Theory is a methodologically simple process (Saunders et al., 2016), and methodological rigidity should not be the goal on its own, but rather developing a frame of codes where theoretical insights can emerge from (Corley & Gioia, 2011).

Cross-sectional time horizon has been chosen over longitudinal study due to the novelty and complexity of the research area. The authors have previously conducted multiple studies on Artificial Intelligence and its relationships with different contexts (supply chain, process management, technological actors and management practices), and with every study there has been one constant: the speed and scope of the development of AI has grown exponentially. The research paper analyzes the “snapshot in time” (Saunders et al., 2016) where all companies are moving towards Industry 5.0, and even though the data collected carry some capacity of change, the core focus lies in studying a particular phenomenon at a particular time – a phenomenon of developing leadership for greater preparedness for the promise of Artificial Intelligence.

2.4 Techniques & Procedures

In order to answer our research question, both primary and secondary data were collected, and the relevance of both will be outlined in the following sections, as well as methods of analysis. Considerations on both qualitative and quantitative data are included in this section. The logic of data collection has followed the sub-questions to the research question.

The nature of different sub-questions for this thesis require different primary and secondary data in their scope and nature (For a full list of unit codes, refer to Table 1):

- SQ1: How do business practitioners define Artificial Intelligence and its processes, and what are the costs and benefits of its implementation? This question draws on interviews conducted with consultants (CON-1 to CON-4), and leading companies in development of AI (CMP-1 to CMP-7; RCON-1 to RCON-2) as well as secondary data in the forms of peer reviewed literature and trade reports.
- SQ2: How does AI affect transparency in the workplace? This question relies on data gathered from AI implementation and development specialists (CMP-1 to CMP-7) and secondary data for background information in the form of peer reviewed journal articles.
- SQ3: How will the combination of technology and leadership affect decision-making in the organization? This question draws on interviews with consultants (CON-1 to CON-4; RCON-1 to RCON-2) who work with decision-making processes with clients in various industries.

- SQ4: How do employees define the future of the workplace? This question draws its scope from a survey conducted with future and recent graduates who will be the workforce of Industry 5.0.

Further analysis of the purpose of different data are discussed in this following section.

2.4.1 Data Collection

In order to answer our research question, negotiating access to companies that both work within the umbrella of Artificial Intelligence as well as companies that are the trend setters and developers of the newest technologies, has been crucial. Issues of feasibility and sufficiency are considered when selecting companies that we have wished to interview, as they inevitably impact the content and process of answering our research question (Saunders et al., 2016). Due to the nature and design of this research and physical constraints regarding geographical locations, a hybrid access has been chosen as a level and type. This means that we have included sources from both traditional access levels (face-to-face interviews, telephone interviews) as well as Internet-mediated access for interviews (the Web, email, instant messaging) and survey (social media platforms). For 7 of the companies selected, physical access has been granted, and one of the researchers has gained contacts in companies through this process, and establishing credibility of this research project. By following up on those contacts, cognitive access, meaning access to interactions, opinions and experiences of participants has been established. For the 6 remaining companies, access has been granted by referral from various institutions including but not limited to: Copenhagen Business School, CBS Blockchain Society, CEMS Club Copenhagen, CEMS Club Dublin and UCD Michael Smurfit Graduate Business School, however the role of researchers has been defined as an external one in all situations, to provide maximum flexibility. Secondary data gathered include, but are not limited to, peer reviewed journal articles, technical literature and recent theses on some of the aspects of this research.

2.4.1.1 Primary data

Following the logic of abductive reasoning and Grounded Theory, primary data collected is used to investigate a phenomenon, analyze and identify patterns and themes, collect codes in order to create theoretical aggregated dimensions, set them in a conceptual framework and test this through subsequent data collection (Gioia et al., 2012; Saunders et al., 2016). Primary data specifically gathered for the purpose of this research include 14 interviews with 13 companies as well as a survey conducted with 139 participants. Even though a mixed method approach was taken, a greater leverage is on qualitative data, to assess themes and constructs. Qualitative data is crucial for this research to capture temporally evolving phenomena of techno-economic change in rich detail in order to understand the underlying cognitive processes (Langley & Abdallah, 2011). Furthermore, data was gathered in multiple sessions, for the intent of moving responsively and reflexively between assumptions, theory and concepts (Gray, 2014; Langley & Abdallah, 2011).

2.4.1.1.1 Interviews

Interviews were conducted through a semi-structured interview guide, allowing for both open ended questions as well as the use of probing questions when necessary. Semi-structured interviews were needed, as the focus of this thesis lies in the techno-economic paradigm, therefore it was necessary to have some structure in place to keep the interviews in the appropriate direction (Bryman & Bell, 2011). Questions were deliberately broad in the interviews, in order to gain an understanding of how respondents define concepts of leadership, transparency and processes in the context of AI, and the questions have remained the same in exploratory and explanatory structure. Two interview guides were constructed: 1) Interview guide for companies that work in the realm of AI development and implementation (Appendix 1) and 2) Interview guide for consulting companies that focuses on overall industry changes (Appendix 2). The interview guides have been divided into 4 thematic sub-sections: a) introduction of the research topic and background of the interviewee and the company, b) questions related to leadership, c) questions related to Artificial Intelligence and d) questions related to future expectations on the business world. This classification has allowed the researchers to both analyze the conceptualization in a stand-alone context, and through open-ended questions, allow interviewees to themselves outline how these concepts interact while establishing the level of techno-economic literacy of the respondents (Bryman & Bell, 2011). Not all questions have been asked from all the respondents due to time constraints or due to interviewees themselves covering multiple questions in one answer. Finally, by using Saunders' (cited in Saunders et al., 2016) framework for semi-structured interviews and allowing for open discussion, new relevant topics and concepts have emerged, which then have been researched in theory. These new concepts are scarcely covered in literature, and rather defined by industry experts, yet allow for more richness in analysis for this thesis.

A method of purposeful sampling was used for selecting these interviewees (Patton, 2002) in order to ensure relevance and value of the findings. Patton (2002) highlights the key advantage of this method – collecting information that is challenging to obtain from other sources. However, in order to deliberately choose the most optimum sample, the target population needs to be defined (Sekaran & Bougie, 2016). As the overarching umbrella in our research problem is the effects of techno-economic change, specifically the influence of AI, a base knowledge in this field is desired. This means that in each company, researchers aimed to interview an individual from either a level of middle management or experts with experience and daily application of AI, and tenure in the company was taken into consideration for the purpose of establishing applicability of opinions. For the above-mentioned reasons, three companies have been excluded from this research. Furthermore, theoretical sampling was used in line with Grounded Theory (Gioia et al., 2012; Saunders et al., 2016) to ensure the correct number of interviews. In this thesis, this means that interviews were conducted until patterns in conceptualization and construction were visible and aligned (Sekaran & Bougie, 2016).

14 interviews in 13 companies in 4 different countries have been conducted. The interview respondents, including the codes assigned to them, location codes, and interview reference abbreviation codes, time frame as well as the industry they operate in have been outlined in the table below. Codes have been assigned to ensure the highest level of confidentiality, and the thematic coding system was used (Miles & Huberman, 1994).

Company	**Location Code**	**Interview Reference**	**Time (Minutes)**	**Industry- needs to be finished**	**Work area of the interviewee**
CON-1	L1	I1	30	o Industry: Management Consulting o Employees: ≈3500 o Location: Global o Revenue: $1.4+ Billion	IT Consulting
CON-2.1	L2	I2	30	o Industry: Consulting, Audit & Tax o Employees: ≈310 000 o Location: Global o Revenue: $46+ Billion	AI Consulting

CON-2.2	L2	I14	60	o Industry: Consulting, Audit & Tax o Employees: ≈310 000 o Location: Global o Revenue: $46+ Billion	RPA Consulting
CON-3	L2	I3	30	o Industry: Strategy & Consulting o Employees: ≈510 000 o Location: Global o Revenue: $43+ Billion	Automation Consulting
CON-4	L3	I4	30	o Industry: Management Consulting o Employees: ≈27 000+ o Location: Global o Revenue: $10+ Billion	Digitalization Consulting
CMP-1	L3	I5	40	o Industry: Software and Hardware o Employees: ≈150 000 o Location: Global o Revenue: $143+ Billion	R&D Software Development
CMP-2	L2	I6	30	o Industry: Social Media o Employees: ≈52 000 o Location: Global o Revenue: $70+ Billion	R&D AI Area
CMP-3	L2	I7	45	o Industry: Internet-Related Services and Products o Employees: ≈115 000 o Location: Global o Revenue: $66+ Billion	Business Support
CMP-4	L4	I8	30	o Industry: Software and Hardware o Employees: ≈135 000 o Location: Global o Revenue: $39+ Billion	Cloud Solutions and Business Development
CMP-5	L2	I9	30	o Industry: Cloud Computing & Software o Employees: ≈49 000 o Location: Global o Revenue: $17+ Billion	Business Development
CMP-6	L3	I10	45	o Industry: Social Media o Employees: ≈15 000 o Location: Global o Revenue: $8+ Billion	Marketing Operations
CMP-7	L2	I11	30	o Industry: Software o Employees: ≈3000 o Location: Global o Revenue: $670+ million	Business Development/ Marketing
RCON-1	L4	I12	30	o Industry: RPA & Software o Employees: ≈1000 o Location: US, UK, Australia o Revenue: $68+ Million	Business Development & Support
RCON-2	L4	I13	30	o Industry: IRPA & Software o Employees: ≈350 o Location: US o Revenue: $50+ Million	Support Management

Table 1: List of Companies Interviewed, Their Information and Corresponding Codes.

All interviews have been recorded and transcribed, and names, locations and distinguishable features that could be linked to the company have been coded. Recording was undertaken consensually with the interviewees, and contextual note taking took place to control bias. Recording the interviews has provided researchers with a number of advantages: concentrating on listening to the answers and identifying where probing questions are required, allowing researchers to learn from their own question formulation, ability to re-listen the interviews in case the tone and context has been ambiguous, allowing the usage of direct quotes. Transcripts have been done verbatim through text-analysis software for audio files, and taken as is in situations where emails or instant messaging was the medium for interviews, with a degree of data cleaning, meaning removing filler words, correction of grammar etc. (Saunders et al., 2016). Transcripts created from audio files have in some instances been summarized, meaning the researchers have compressed long statements into briefer ones that carry the main ideas and answers to questions. Medium for interviews has been highly dependent on the wishes and preferences of the interviewees, due to Covid-19 pandemic and the subsequent restructuring of their work, and therefore, time. Most of the scheduled interviews (9 out of 14) had to be rescheduled, and in some instances multiple times, meaning the researchers had to pertain to flexibility in literature review and data analysis. However, the researchers have done everything in their power to mitigate this constraint it has placed on time, resulting in the non-traditional research timeframe (discussed in Figure 3). Instances where interviewees preferred either instant messaging or emails for communication have not affected the quality of the data, as clarifying questions were able to be asked. Full transcripts have been attached as a separate appendix (see Transcripts 1-14).

2.4.1.1.2 Survey

Referring to data gathering for primarily SQ4 (but to a limited extent for SQ2), an online survey was conducted to gather first-hand data on the opinions, expectations and preferences of recent and future graduates who will be part of the future workforce in Industry 5.0. The survey was conducted concurrently with interviews for a) triangulation of data and b) help researchers evaluate what a representative population sample of the future workforce considers important in leadership, transparency and their own skill development. Survey was deemed an appropriate method, as it allows for a voluntary participation of people representing any age, gender, geographical location and background in an economically feasible and standardized fashion, allowing for easy comparison. Further, according to Saunders et al. (2016), the likelihood of contamination or distortion of answers is very low when the survey is distributed online. Before the survey was launched, a pilot test was concluded with 2 people outside of the realm of academia, and their feedback on question formulation and clarity was included. The survey was kept open for respondents for 3 weeks, ensuring enough time for the researchers to analyze and revisit the gathered data and find statistical correlation. The self-completed survey was created through a survey program (Qualtrics) and standardized to be used for both computer and mobile screens.

Designing the questions has been a crucial step, and the structure consists of a mixed form of multiple choice questions, Likert-style rating questions on agreement with various statements, open ended questions and semantic differential rating questions that analyze opinions and underlying attitudes on a bipolar scale. For a full list of questions, refer to Appendix 3. The survey includes questions on opinions, attitudes and thoughts on current and future characteristics of workplace and workforce. Each question in the survey was required to be answered, however an “Other” option was added to all questions with an optional textbox that respondents were free to use for comments and clarifying questions. The survey was answered by 139 people, out of which 120 completed all 15 questions. The method of analysis of the qualitative and quantitative data gathered from the survey will be discussed in section 2.4.2.

2.4.1.2 Secondary Data

Published secondary data used take the form of managerial literature, company case studies, peer-reviewed journal articles, and recent theses on the subjects of transparency, process management and leadership in the context of Artificial Intelligence. Compiled data has been additionally searched through databases for comparative, contextual and explorative functions (Saunders et al., 2016). Secondary data has been analyzed with rigor, making sure that in every step of the way, invalid sources have been excluded. Professional journals are used to gain insights in industry trends as the topic at hand is a relatively new one, but used cautiously, and especially high caution is taken regarding their positivistic tone of technological development. Peer reviewed journal articles are used for theoretical and methodological purposes. A number of books about Artificial Intelligence have been studied in order to gain comprehensive background understanding. Furthermore, both of the researchers have attended a number of conferences where the topics of this thesis are discussed at length in either a presentational or a panel mode, and notes have been taken, as well as contacts with companies established. A number of recent theses have been reviewed (see section 3.4), as this method of data collection offers the advantage of access to the most up to-date research on specific topics (Saunders et al., 2016).

2.4.1.3 Ethical Considerations

There are certain ethical considerations we have taken into account as researchers in both data gathering and analysis. Silverman (2006) highlights the core principles that can assist researchers to conduct ethically just and sound research.

Firstly, all participants in this research in any stage have been informed and consented to being interviewed, and the integrity of voluntary participation is maintained. All interviewees have been briefed on the topic of the research in broad terms, in order to not corrupt our data by inserting ourselves to the conceptualization process.

Secondly, we have made data confidential to protect people from harm, in order to ensure full openness of the interviewees in regards to sharing data and opinions. As the nature of this research looks deeply into leadership tendencies in broader industries, but also takes into consideration the interviewees' experiences with clients or other companies, as well as the companies that employees themselves are and subjected to, extreme caution was taken in anonymity. All company, product and employee names, locations and, in some instances, comparisons to competitors have been coded throughout this thesis, including transcripts to ensure the well-being of interviewees due to the sensitive nature of this research.

Finally, ensuring trust between the researchers and interviewees has been key in order to design this thesis. Interview guides have remained broadly the same for two reasons: a) keep the open-ended questions as they are for us to be able to draw upon statistical consistency and rigor and b) not revealing any data received from previous interviews.

In addition to Silverman's (2006) considerations, the attention has been drawn to the following:

a) We do not have to manage any interviewees or the companies they represent as a stakeholder, meaning the researchers do not have to exclude any sensitive material from the analysis, and all data gathered can be analyzed and included.
b) Besides coding all names, introduction to context of the industry they represent is given in a broad manner.
c) No funding or conflict of interest has taken place, meaning researchers are independent from contingencies of the companies

d) All interviews have been conducted in the time, place and medium (online / chat / phone call) of the choosing of the participants. Researchers have been flexible with rescheduling when necessary.

2.4.2 Data Analysis

Qualitative data analysis, meaning analysis of thick and rich data, which are based on words and meanings they carry, require categorization into themes and conceptualization (Saunders et al., 2016). Since words and contexts can have multiple meanings, an iterative and reflective process is necessary, and these non-standardized data have been analyzed thematically. In addition to this, codes have been assigned. As an abductive approach has been undertaken, a clearly defined framework has not been in place, and the relationship between data and theory has been of focus. Furthermore, the researchers have taken measures to not be sensitized to theoretical coding in the first round of thematic analysis.

Therefore a Grounded Theory analysis has been undertaken. However, there is much disagreement among scholars in regards to method of coding (Bryant & Charmaz, 2007; Charmaz, 2006; Gioia et al., 2012; Glaser and Strauss, 1967), specifically the rigor and logic behind it. Saunders et al. (2016) suggest that there is no "right" way of approaching this issue, and a method should be chosen and followed based on the preferred outcomes of the research. Through an abductive approach, pre-existing theoretical concepts play a significant role in this research, and Gioia et al. (2012) argue that not only is it crucial to understand the voice of the informants, but also the researchers, and the theoretical knowledge gained by those who undertake academic research. This understanding has led to the utilization of first order codes, meaning primary data specific, informant-centric in vivo codes, and second order codes, researcher-centric codes, themes and dimensions. This system of coding enables the researchers of this thesis to a) carry out qualitative analysis to show links between data and theory in a highly conceptualized manner and b) build on the researchers' interest and background knowledge to further show insight into the research problem.

The interviews were conducted in a semi-structured manner and in multiple rounds, allowing for additional in-depth questions, once patterns started to arise, and each further interview was conducted to explore theoretical and analytical ideas from codes of the previous interview (Saunders et al., 2016). The researchers aimed to conscientiously use the terms and language of the interviewees

(Gioia et al., 2012). Interviews were transcribed and coded in two rounds. The first round coding was done by exploring themes, patterns and ideas, and adhering faithfully to terms used by interviewees. As we conducted more interviews, the researchers were looking for similarities, differences and patterns among first order codes, and categorize them under labels and phrasal descriptors that use informant terms in order to reduce the number of codes to a more manageable structure. Thereafter, the researchers considered themselves as *"knowledgeable agents"* (Gioia et al., 2012, p. 20) and structured these codes into second order codes. Second order codes consider the informant centric first order codes as well as theoretical abstraction in order to classify terms and find deeper structure.

Once in the theoretical realm of second-order codes, outlined in the Findings section, we aimed to focus whether the second order codes suggest concepts that help us explain or describe the phenomenon we are researching. In this step of the coding process, theoretical literature is considered to help us make sense of the findings and to confirm new concepts have emerged. Aggregated dimensions, meaning distilling the second order codes into overarching analytical umbrellas of core constructs, allow us to formulate the data structure to answer our research question. The data structure is not only a visual aid or a methodological tool, but also represents how we moved from raw, unprocessed primary data to concepts, and thereafter constructs to conduct our analysis. The data structure aids the researchers to analyze data both methodologically as well as theoretically. Abductive approach in this coding method is key, as we are rarely fully uninformed about previous work as well as maintaining the premise of novel research and constant consulting of existing theoretical realms shows that there is no framework currently in place to help us answer our research problem. Literature review has been conducted in a back-and forth method, aiming to see what theorists say about the phenomena, to make sense of what we have observed and challenge our clusters of codes (Sekaran & Bougie, 2016). Data structure of this thesis has been outlined in Table 2. Finally, word frequency analysis was conducted to support selected core findings.

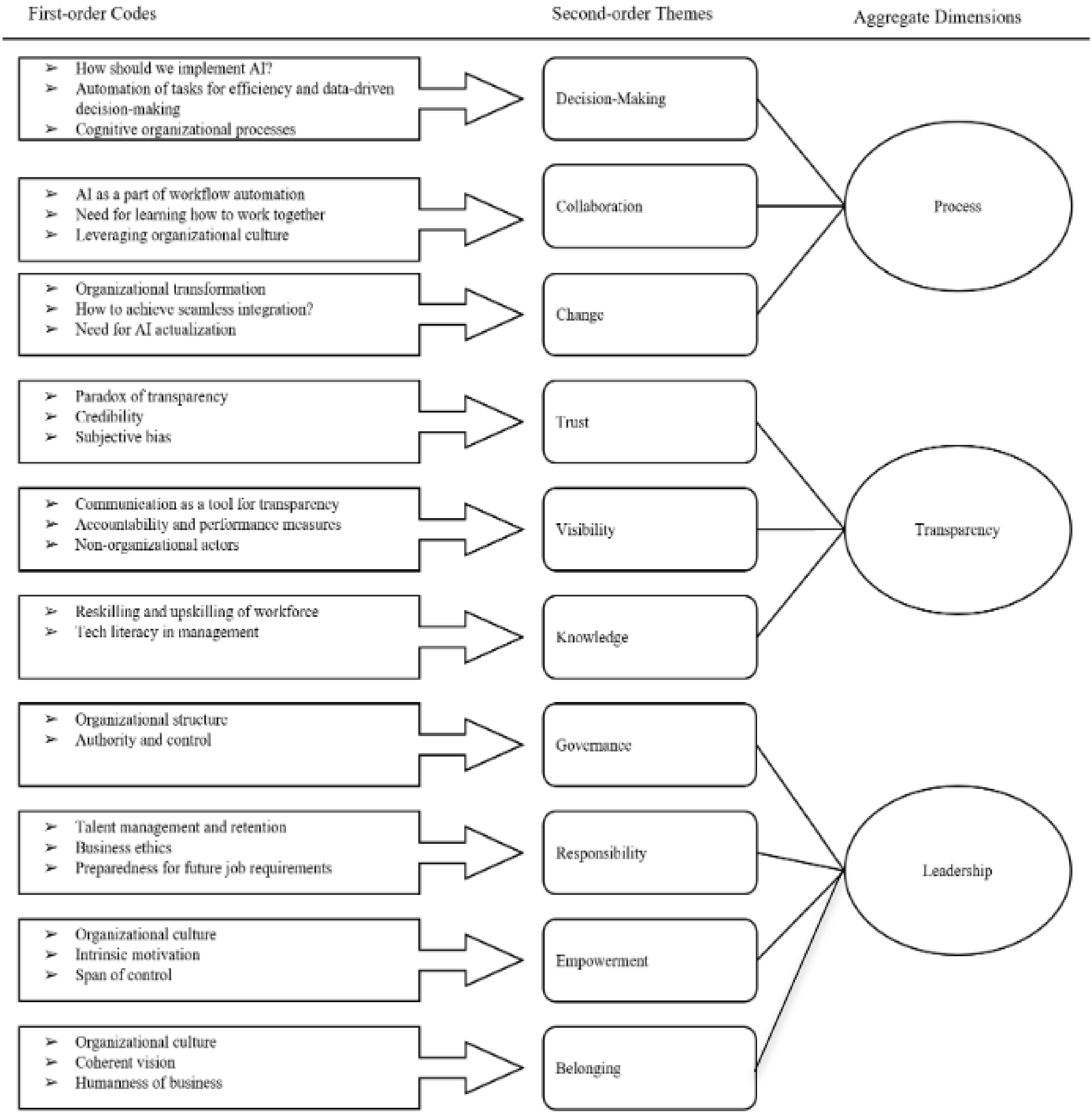


Table 2: Data Structure: 1st and 2nd Order Codes & Aggregated Dimensions.

The quantitative data gathered from the survey was analyzed by using descriptive statistical tools, as the questions were focused on agreement with statements, opinions and open questions. Focus has been placed on expectations for the future work environment, understanding of technologies and respondents' own personal understanding of core skills that they have and think they need to develop in the future. Survey platform Qualtrics, and the integrated data analysis tools were used for variance, mean and deviation calculations, and for open questions, word frequency analysis was conducted.

Analysis of secondary data has been systematic and carried out for explorative, comparative and contextual purpose. Background information about the companies has been used during the interviews in order for the researchers to be well informed and prepared for the interviews. Only relevant secondary data has been included to ensure that we limit our scale and scope to ensure the feasibility of this thesis. Secondary data has been further analyzed through a theoretical lens to make sure we are not bound by company specific context or take a descriptive stance, as well as to ensure that we do not miss any underlying or recurring theme in data.

2.5 Reliability & Validity

Reliability in the quality of the research design considers the extent to which the results of this thesis can be replicated by another research team in a different time in a consistent manner (Saunders et al., 2016). A number of steps have been taken in order to mitigate the risk of researcher and participant error and bias. Firstly, the survey was shared through social media platforms online, meaning that any participant was free to choose the time, place and how much time they wanted to spend on answering each question. Secondly, for all the participants in interviews we have conducted, a suitable time, place and medium was selected. Researchers met all participants with highest flexibility with scheduling and rescheduling, time differences, duration and whether they preferred an online or a face-to-face medium, ensuring a comfortable mindset for all interviewees.

For researcher error and bias, measures were taken as well (Leung, 2015). An internal briefing before every interview was conducted to go through the interview guide, and any theoretical considerations were discussed. We acknowledge that researcher bias cannot be fully eliminated, however, all interviews were recorded, transcribed and both of the researchers took notes during the interviews.

After each interview, a structured debrief was conducted, and notes were compared in order to ensure that no subjective view was integrated into interpretation of participants' response. Furthermore, in line with maintaining internal consistency, multiple companies were used to gather data (Leung, 2015).

However, all interviews and the survey were conducted in English, a language that is not the mother tongue for either of the researchers, as well as some of the interviewees and/or survey participants, and a language barrier may affect the interpretations of the subjective opinions of the participants. The researchers have however aimed to give plenty of time for all participants to answer and leave comments, reducing this flaw in design of data gathering.

Internal validity in this research design was ensured through gathering data from multiple companies in key industries that work with the concepts and constructs of this paper on a daily basis, ensuring both factual knowledge and experience in this area. Nevertheless, in regards to past or recent events and instrumentation, meaning impact of change (Saunders et al., 2016) do pose a threat to this study: recent events in global scale regards to Covid-19 pandemic and the subsequent growing rate of digitalization and technological upscaling may place the context of this research more prominently in the minds of participants, resulting in artificially inflated opinions on the significance of Industry 5.0. The researchers have aimed to address these threats through minimizing the mentions of Covid-19 as a topic in the interviews, as well as comparing the results with interviews conducted in pre-pandemic times. Furthermore, when need has arisen, the integrity, interpretation and analysis of statements has been checked with participants in order to ensure credibility in qualitative research (Guba & Lincoln, 1989).

Finally, the method of triangulation has been used, collecting data from multiple independent sources simultaneously to confirm the validity of interpretations and analysis (Saunders et al., 2016; Timmermans & Tavory, 2012).

External validity in this thesis is of highest importance and deals with the question of generalizability – can the results of the research be applicable in broader scope (Leung, 2015; Saunders et al., 2016). The nature of Grounded Theory and the coding and conceptualizing of research areas, such as leadership, transparency and processes, affect all organizations regardless of size and industry.

However, not all organizations aim to embrace technology, namely AI into their systems, and therefore questions of technical excellence may become irrelevant. Nevertheless, this thesis aims to offer guiding principles for any organization that correspond to issues of techno-economic change for a long term strategy, and are not only rooted in one particular industry. Interviews were conducted with multiple organizations, departments and representatives of different roles to increase external validity (Sekaran & Bougie, 2016), however, regardless if the data does not show strong deviations, we cannot be definitively sure that they do not exist.

3. Literature Review and Theoretical Considerations

This section critically reviews the literature on the academic realm we are working in for two main reasons: 1) to provide the context and outline the limitations of theoretical discussions in the situations the promise of AI creates (Saunders et al., 2016) and 2) to outline the gap in literature and place our findings in a broader body of knowledge in this area (Gioia et al., 2012). By critically reviewing existing theories on processes, transparency and leadership within the context of AI, we outline the role these have in the changing worlds of businesses and for the future workforce. The literature review has been further refined in line with thematic coding and an abductive approach, in order to generate relevant search terms and to relate our findings in discussion to previous research (Corbin & Strauss, 2008). However, one crucial consideration must be made: the topic of AI is relatively novel, and therefore connections to theoretical realms vary. However, we aim to review what is and what is not known about our research question (Wallace & Wray, 2011, as cited in Saunders et al., 2016). The separation of these relatively intertwined constructs is done artificially, as to narrow down the complexity of analyzing them. This section will conclude with our definitions on key concepts and how we see them in interaction with one another, providing a theoretical lens that will put our findings in perspective as well as considerations that must be undertaken for discussing AI.

3.1 Process

Commonly, organizational design is conceived as structures, processes, and roles that help an organization carry out its strategy (Daft, 2012). Conducting a critical literature review on the topic of processes, meaning the series of steps or actions taken to reach a goal (Merriam-Webster, 2020), we must take into consideration which processes in organizations can be optimized through AI driven automation and where the overlap for future implications is. This means that the researchers have both through desk research and primary data collection from industry experts gathered information on the potential and limits of AI *at this current time* to find the "sweet spot" of organization-driven and AI-driven processes that are of focus for this thesis.

The recurrent theme in AI automation of processes in its full potential, and the focus of this thesis, is decision-making, which in itself is a complex process, affected by a number of determinants, e.g. bias, sub-consciousness, emotion, experience, knowledge, motivations and these are ultimately interconnected (Miranda & Aldea, 2005; Shepherd & Rudd, 2013). AI is not only about building machines that perform processes intelligently (Burrell, 2016), answering Turing's (1950) original question: *can machines think*, but rather taking a much more cognitively structured view (Miranda & Aldea, 2005). Process management has been in the core of Artificial Intelligence as a field of study, as the development and implementation lies in breaking down different tasks (McAfee & Brynjolfsson, 2012; Myers & Berry, 1999; Ramaswamy, 2017) and by doing this actually aims to analyze what makes a machine intelligent (Russell & Norvig, 2020; Zerilli, Knott, Maclaurin & Gavaghan, 2018). However, only in the recent decade we see organizational studies integrating these academic fields that involve domains of active control of technically complex entities in businesses (Zerilli et al., 2018) and build on the overlap of objectives, requirements or approaches (Shepherd & Rudd, 2013).

Simon (1982) makes the argument in his bounded rationality model that humans are not rational in the process of decision-making, and outlines that especially when it comes to management decisions, managers attempt to satisfy stakeholders in the process, and once the complex cognitive process is finalized, decision-making as a mechanism is a means to end and must only suffice. A number of other models exist that contradict this notion (Brown, 2007; Griffin, 1991; Guo, 2008; Miranda & Aldea, 2005) and outline how decision-making process can be divided into rationally bounded steps which is more in line of how AI is coded and implemented (Chander, Srinivasan, Chelian, Wang & Uchino, 2018; Russell & Norvig, 2020). Furthermore, the economically rational model, by far most commonly used for coding this process, deliberately eliminates bias and opinion, and focuses on facts, predictability and precision (Russell & Norvig, 2020). These academics all include similar first steps in any decision-making: gather and analyze available data, find best alternatives and make the decision. Being informed about outcomes and information is crucial (Bonaccio & Dalal, 2006). Irrationality in decision-making however is dependent on the framing of solutions, and more importantly, problems (Ariely, 2010). Grint (2005) argues that complex situations are made complex by leaders in order to frame a problem in a contextually specific way to legitimize their own behavior, making decision-making both rational and irrational.

The grandfather of AI, computer scientist Alan Turing (1950) focused on developing the Turing test, the method of inquiry in the system of AI that can determine whether or not a computer is capable of acting like a human being. Russell & Norvig (1995; 2020) built their approach of the humanness of

AI in decision-making on this parameter, but contradicted Turing's logic that *acting* as a human being equals *thinking* as a human being, and include two dimensions of modeling behavior humanly and capturing intelligence rationally (Russell & Norvig, 1995) and these four determinants together make a machine both artificial and intelligent. Decision-making combines all these: *thinking humanly* is the incorporated essence of cognitive modeling, where programs or systems engage in problem solving as humans do, while *acting humanly* refers to performing actions. *Thinking rationally* builds on the use of logic, where complexity of situations is heightened and modeling uncertain, while *acting rationally* indicates that maximum performance in any case where parameters are clear is performed and agency problems mitigated. Franntz (2003) challenged that logic in scientific discipline where discoveries are made in a rational and logical progression by rigorous data analysis and creative decision-making, and yet in empirical cases, no discovery has been made by AI.

Society and businesses are moving further away from intelligent human analysis to intelligent technological assistants (Frick, cited in Krogerus & Tschäppeler, 2008) and challenges institutional norms in the workplace (Canbek, 2020; Schildt, 2017). AI will be able to view realities from multitude of perspectives objectively, as well as take into account complex information and enormous data sets that humans could ever process (Schildt, 2017), and mitigate the bias towards their experiences and past. The questions regarding decision-making based on structured or unstructured data is the foundational difference in what makes a machine both artificial and intelligent (Russell & Norvig, 2020), in addition for a system or a program to be able to analyze the data it is fed based on statistical probability, it can today process complex judgement-based tasks and learn from its own processes (McAfee & Brynjolfsson, 2012). Frick (cited in Krogerus & Tschäppeler, 2008) argues in her constructed understanding of decision-making that interconnectivity of human and machine is the new causality and managers *"didn't need decision-making models any more. Causal connections are becoming less important, because intelligent machines make deductions based on data not models."* (p. 146). This notion takes into consideration the fact that decisions based on data and patterns may be highly precise, speedy and diverse but due to the lack of understanding, creates the *"paradox of plenty"* (p. 148), and does not necessarily create meaning behind data. McAfee & Brynjolfsson (2012) further outline the managerial challenges for decision-making and suggest *"muting the HiPPOs"* (p. 7), the Highest-Paid Person's Opinion, in order to be fully led by data and not bias or cognitive confusion in decision-making.

Decision-making is one of the core subjects in both organizational context as well as the realm of AI, one that is *framed* mainly as a threat to humanity and the workplace in the form of singularity (Shanahan, 2015), loss of jobs (Schildt, 2017), loss of meaningful interactions (Libert, Beck & Bonchek, 2017) or loss of culture (Liebowitz, 2014). Critics of AI in organizational contexts fully focus on lack of transparency in decision-making and coded bias (Chander et al., 2018) or tabula rasa mentality (Froese & Ziemke, 2009). However these academics fail to take into consideration that the processes in place for human cognitive decision-making are as cloudy and complex as the code behind any judgement-based AI program (Ariely, 2010; McAfee & Brynjolfsson, 2012; Ramaswamy, 2017).

In all, decision-making processes in organizations are changing rapidly (Canbek, 2020). Combination of data-driven and HiPPO facilitated decisions are already in place in number of companies, and as AI development continues, these processes will get either more automated or more integrated (Libert et al., 2017; Chander et al., 2018; McAfee & Brynjolfsson, 2012). The biggest advantage in this active process management is eliminating cognitive bias, and Machine Intelligence Research Institute (MIRI) highlights that is only possible if the coding system is itself unbiased (MIRI, 2014). However, as stated earlier, academics are taking the stance on AI development that places focus on the interactions on intelligent systems rather than singular programs (Schildt, 2017), which in essence works as a roundtable of human agents discussing the optimum outcome for a situation, at a faster pace and through more informed decisions (Ramaswamy, 2017).

Collaboration, therefore, is another crucial process that academics qualified in AI research have addressed in recent years (Chander et al., 2018; Liebowitz, 2014). Collaboration defined as working with someone to produce something (Merriam-Webster, 2020), requires interaction, exchange of information and ability to be intellectually on the same page. Collaboration is not static, it has to adjust to the ever changing environment that it operates in. Collaboration comes in many forms and functionalities, e.g. mass, instant, and functional and builds on interpersonal synergies (Gray, 1985). The notion that collaboration has to be constrained to the cognitive abilities and understanding of entities, such as human actors, has been challenged by academics (Miranda & Aldea, 2005). Collaboration models that equate AI to an actor with some human capabilities have cultivated theories that focus on the iterative communication of human-to-machine and machine-to-human (Lyons, 2013), but highlight that *"perceptions would benefit from accurate perceptions of the robot's ability, intent, and situational constraints."* (p. 49).

Context regarding what we want to achieve with collaboration is crucial, especially when AI is integrated into the process: enhancing productivity, creativity, crowdsourcing or seamlessness of collaboration processes (Canbek, 2020). Lyons (2013) further elaborates that *"having shared context between humans and robots will be a critical facet of the overall system performance of human-robot teams and this will likely facilitate "appropriate" reliance on the robotic system"* (p. 48). From an organizational perspective, it is not the jobs we should turn our focus on, but rather the tasks these jobs perform. This is the notion that Industry 5.0 will essentially challenge – and perhaps even question the dictionary definition of collaboration. Taking Machine Learning and natural language processing for productivity gains as an example, Oke (2008) claims that when it comes to application potential of automated decision-making, intelligence should be seen as something that is *"constructed by the continual, ever-changing and unfinished engagement with the social group within the environment"* (p. 24)*"*, for whatever the environment currently is or will be.

Processes change in time, and this is highlighted by the rapid development of AI even in the past 5 years, as well as the growing popularity of this topic in organizational academia (Canbek, 2020). Agility, pro-activeness and adaptability are all part of AI development and technology that can easily be used across departments and organizations – it will be of higher focus and must be met with an organizationally sensitized perspective. Chander et al. (2018) argue for the benefits for companies that push the focus of architectural change *"from "Intelligences Apart" – human and machine intelligences being separate – to true human-AI collaboration"* (p .2). These companies will succeed, but only if *"human decision-makers use alignment with their existing beliefs about AI"* (p. 4). A call for building artificial agents, which can behave in a robust and flexible manner under changing realities and conditions they create, has been highlighted (Canbek, 2020; Froese & Ziemke, 2009). Data driven processes push for further interconnectedness and responsiveness in organizations (Schildt, 2017). Christensen, Hall, Dillon & Duncan (2016) argue that these technological tools are only sufficient if they do the task they are hired for, and if they fail to do so, they will be discarded and forgotten.

Ariely (2010) argues that no matter how many decision-making models we analyze, as humans, we will always make irrational decisions, even when presented with the full logic of complex cognitive processes of how we make those decisions. Human decision-makers will always be affected by bias and experience, even when they are aware of this bias. This notion is one that through time has been the driver for AI automation, analyzing full sets of data that the human mind cannot comprehend, and carrying out probability analysis not based on bias, but contextual facts to make the optimum decision (Schildt, 2017). This only works however, if the end goal is clearly defined (Bonaccio & Dalal, 2006) in *this current time*.

3.2 Transparency

Transparency in literature carries multiple meanings and is defined in various contexts, as it is not an end state, but rather a constantly evolving mechanism in itself (Hansen, Christensen & Flyverbom, 2015). In regards to this thesis, after brief discussion of different approaches to transparency, the authors have placed their focus of the literature review on two categories: transparency in the context of technology, and transparency in the context of paradoxical situations, and these literature themselves make a distinction between transparency of a system itself, and transparency on how that system affects them, and not the combination of these – what these authors hereafter call the *transparency of reality*.

Defining transparency is a challenging task, however. The broad spectrum of the concept considers the methodological and theoretical discipline or field, and lacks tangible features or rules of thumb (Hansen et al., 2015; Harvey, Reeves & Ruppert, 2012), and should be considered an operational mechanism (Albu & Flyverbom, 2016; Schnackenberg & Tomlinson, 2014). The latter have analyzed these disciplines and narrowed it down to six core areas where transparency as a mechanism affects organizational behavior, and among these are strategy, organizational culture, leadership and (financial) markets. However, these disciplines can also include psychology, anthropology, law and political science (Albu & Flyverbom, 2016).

The discipline of technology provides very little insight to transparency, with the exception of monitoring (Francisco & Swanson, 2018), control (Smythe & Smith, 2006), pricing (Soh, Markus & Goh, 2006) or governance (Nixon & Johansson, 1999). Pfleeger (2014) and Burrell (2016) argue that opacity does not necessarily carry a negative connotation, if vendors or other users of a certain technology make that choice consciously and responsibly. There is a significant gap, however, in literature that takes Artificial Intelligence for what it is, an intelligent actor that is both able to create, but is also subjected to its own creation of transparency. Specifically, Machine Learning and Deep Learning are in essence a line of code, but how that code or program interacts with other systems whilst learning from them and modifying itself based on training data, is not easy to grasp for the majority of business professionals. Transparency as *"visibility and legitimacy"* (Smythe & Smith, 2006, p. 32) therefore is something that needs elaboration in the context of Artificial Intelligence.

Nevertheless, the context where, how and why transparency operates in, or rather, is operationalized in, needs clarity. Taking organizational studies into focus, transparency has been defined by the functionalities it carries in organizational trust (Kramer & Lewicki, 2010; Mayer, Davis & Schoorman, 1995; Schmitz, Raggo & Bruno-van Vijfeijken, 2012), governance (Albu & Flyverbom, 2016; Flyverbom, Christensen & Hansen, 2015; Hansen et al., 2015), organizational identity (Bernstein, 2012; Etzioni, 2010; Schnackenberg & Tomlinson, 2014) and control and monitoring (Latour, 1990, Power, 1996). Within these academic works, the agreement to define transparency as a variance of *"visibility, predictability, and understandability"* (Gray & Kang, 2014, p. 459) exists, but the question on how it is established, carried out and materialized brings about further debate in academia.

Transparency in the context of trust defines the concept as either accountability and effectiveness of leadership to disclose information (Schmitz et al., 2012), focuses on distrust due to the lack of visibility (Kramer & Lewicki, 2010), the legitimacy of practices that enable trust to surface (Mayer et al., 1995) or something that in itself generates trust (Schnackenberg & Tomlinson, 2014). Regarding governance, transparency interacts with control and monitoring through observability (Flyverbom et al., 2015) or employee empowerment through flexible governance practices (Hansen et al., 2015).

One condition on transparency however is underlined in most of the existing literature: transparency does not exist without actors. Albu & Flyverbom (2016), attempting to conceptualize transparency, outline this in their premise that transparency is a process where a) subjects of transparency are inherently engaged in interpreting transparency, b) material objects facilitate this transparency and c) a setting where transparency takes place exists, and these parameters must be taken into consideration combined. Theorists that focus on the creation of transparency (Etzioni, 2010; Latour, 1990; Power, 1996) take that focus from the standpoint of problem solving in the notion of power – transparency is a standalone concept to mitigate issues of accountability, visibility or trust. Yet, this work poses another challenge in their conceptualization, where transparency carries a positivistic and even innate philosophical undertone, where transparency just is, as something that someone does, and not as something that is collectively constructed in reality among actors who are subjected to it.

Controversy of these conceptualizations for this thesis lies in connection to technology, or *material objects* that facilitate this transparency (Power, 1996), as they are defined as either cameras that facilitate observability (Flyverbom et al., 2015) or similar. Artificial Intelligence even in its lowest application potential and format is not an immobile static tool, nor a material object, but rather an actor, and more importantly, a subject to that actor, and should be viewed as anthropomorphic. Industry 5.0 calls for more transparency in how machines and humanness are connected seamlessly, yet through the semi-static terminology of transparency, academia has failed to consider technology as an actor and not a medium. The complexity of these interdependencies create a valuable lens and perspective on the topic that has been present for a long time, and yet does not carry the flexibility to be transported to the modern world and its challenges.

In recent years, the terminology of Responsible AI has been used, but defining the meaning behind it lacks the dynamic connotation of transparency. Responsible AI is equated to Explainable AI, where transparency is either built into the system as design (Theodorou, Wortham & Bryson, 2017; Wortham, Theodorou & Bryson, 2016), or how that design is communicated to employees or other stakeholders (Licht & Licht, 2020; Schildt, 2017) or code-to-human and human-to-code transparency (Brauneis & Goodman, 2018; Lyons, 2013). These academics see transparency as a function of AI, rather than a construct and use the concept of agent transparency that is defined by Chen et al. (2014, cited in Iyer et al., 2018[1]) as *"quality of an interface (e.g. visual, linguistic) pertaining to its abilities to afford an operator's comprehension about an intelligent agent's intent, performance, future plans, and reasoning process"* (p. 144). Chander et al. (2018) contradict the legitimacy of AI transparency in its design stage, due to the fact that any functioning AI is interactive, and original, or first-order data sets are compared against the algorithm created by a human actor who defines results according to their own beliefs as to what the value of the algorithm is.

[1] Iyer claims this to be a definition by Chen et al., 2014, however this quote was not found in the original reference. Either there is a mistake in Iyer's bibliography (e.g. year or publication), or no reference for this quote is provided.

Consequently, these academics argue for the necessity and value of transparency for whichever function it fulfills, or how it is set up, and this is the popular tendency in academic literature. The benefits of a partial (Licht & Licht, 2020), full (Lyons, 2013) or even radical (Scott, 2009) transparency are abundant, and this reflects in the overly positive tone on its effects. Nevertheless, in recent decades, in both connection to behavior as well as technology, academia has slowly integrated the paradox of transparency in order to critique the tradition. Empirical evidence, where transparency as a concept has the opposite effect, has surfaced (Bernstein, 2012; Christensen, Morsing & Thyssen, 2009; Tapscott & Ticoll, 2003). This paradox contradicts and contrasts the overly positive tone of management literature and argues for the need for leadership to make educated decisions that are subjected to their organization, processes and management style. Licht & Licht (2020) further argue that more transparency in AI development and implementation does not necessarily mean a better outcome, as the code or model is too complex to communicate credibly. Christensen et al. (2009) make the argument that pressure to be more transparent in an organization leads to hypocrisy and misleading information. Finally, from a behavioral perspective, Strathern (2000) argues that when visibility is artificially enhanced, it creates mistrust and suspicion.

Transparency is a complex social phenomena, with a multitude of determinants, however academia is divided on how to bring these together – they rather see singular aspects that affect transparency or vice versa. Schnackenberg & Tomlinson (2014) further outline that the gaps in literature are highly dependent on the conceptualization of transparency as a dynamic actor, either as an effect or as a perception. Albu & Flyverbom (2016) state that *"conceptualizations of transparency are rarely subject to critical scrutiny and thus their relevance remains unclear."* (p. 268) and propose a framework for a three-fold structure: conceptualization, conditions and consequences and state that these *"components cannot be examined in isolation"* (p. 277), yet neglect to see the complexity of construction of transparency and how it intertwines with its effects – the *transparency of reality*.

3.3 Leadership

As an ambiguous concept (see Table 3), leadership has no universally accepted definition, nor is there agreement on what leadership means, does or is — there are as many definitions of leadership as there are organizations. Conducting a literature review on this academic discipline, therefore, carries complexities, and we must take into consideration two academic fields – traditional, entity-based leadership, and modern, relational leadership, and as we take both a situational and a temporal view on leadership, analysis on how, *and why* perspectives have changed, will be of focus. The literature review includes this academic discussion and brings in various critiques from managerial literature, specifically from the past two decades as to see how *the role of leadership* has changed – to help us unbox how the role of leadership will change in the intricacy of the modern world.

Author	**Title of Paper**	**Year**	**Definition**	**Page**
Ralph M. Stogdill	Handbook of leadership: A Survey of Theory and Research	1974	There are almost as many definitions of leadership as there are persons who have attempted to define the concept	p.7
Arthur G. Jago	Leadership: Perspectives in Theory and research	1982	Leadership is both a process and a property. The process of leadership is the use of non-coercive influence to direct and coordinate the activities of the members of an organized group toward the accomplishment of group objectives. As a property, leadership is the set of qualities or characteristics attributed to those who are perceived to successfully employ such influence	p.315
G.B Graen & M. Uhl-Bien	Relationship-based approach to leadership: Development of leader–member exchange (LMX) theory of leadership over 25 years: Applying a multi-level multi-domain perspective	1995	Despite many years of leadership research and thousands of studies, we still do not have a clear understanding of what leadership is and how it can be achieved	p.220
Michael A. Hogg	Social Identity and Leadership	2005	Leadership is a relational term—it identifies a relationship in which some people are able to persuade others to adopt new values, attitudes and goals, and to exert effort on behalf of those values, attitudes, and goals"	p.53
M. Uhl-Bien	Relational Leadership Theory: Exploring the social processes of leadership and organizing	2006	Leadership as a social influence process through which emergent coordination (e.g., evolving social order) and change (e.g., new approaches, values, attitudes, behaviors, ideologies) are constructed and produced.	p.654
Crosby & Kiedrowski[2]	Integrative Leadership: Observations from a University of Minnesota Seminar Series	2008	Fostering collective action across boundaries to advance the common good	-
Merriam-Webster Dictionary	N/A	2020	(1) the office or position of a leader; (2) capacity to lead; (3) the act or an instance of leading; (4) leaders	-

Table 3: Various Definitions of Leadership through Time.

[2] The quote was originally found in Ospina & Foldy, 2010, which references to Crosby and Kiedrowski, 2008, however the original text accredits the definition to the official definition of Center for Integrative Leadership.

Leadership is irregular in nature, and *“we still do not have a clear understanding of what leadership is and how it can be achieved”* (Graen & Uhl-Bien, 1995, p. 220). As a consequence of this passionate academic debate, unlike in other business concepts, where the old, non-sufficient approaches are substituted by new ones, we can find coexisting contradictory theories in leadership (Winston & Patterson, 2006). Although the new academic literature, covered in this section, involves a more relational and network-of-people attitude, there are still new leader-centric hypotheses made and managerial guides on how to be a good leader. The complexity of leadership comes from its tautological nature (Ghoshal, 2005) – the importance of traits, personalities, actions, agencies and processes are in essence all true in an organizational context, but focus on these has shifted. The older leadership approaches will be outlined in order to not only present the background of theory development in order to understand today’s leadership theory approaches, but moreover to showcase the concept progression which reflects the attitudes in business overall – changes in transparency with growing business organizations (Bernstein, 2012), functionalities of leadership (Winston & Patterson, 2006) and why it is complex to separate leadership as a concept from leader-based definitions (Uhl-Bien, 2006).

The traditional approach to leadership associates the notion with a leader figure, therefore outlining the special set of attributes and behavior a person should possess to be a leader. The early attempts at exploring the dependencies of what makes someone a good leader began in the 1800s and focused on analyzing the biggest and most influential figures in history. Thomas Carlyle (1840) had established the Great-Man Theory, which argues that some people are naturally born with the crucial combination of characteristics to be a leader, yet the people who are not born with these attributes, cannot become leaders under any circumstance – and therefore, leadership skills are not learned, but are predetermined at birth and inherent in a person. “*The history of the world is but the biography of great men,”* (Carlyle, 1840, p. 34) is the foundation of entity-based theory, and one that has survived to be carried through modern day due to its romanticism. Hook (1943) further built on this theory, and divided people into the *event-making* and *eventful* men. The members of the former group determine the outcome of events for the latter, and without their participation, the aftermath of any decision-making would be much different. However, this theory has been highly criticized, as a number of empirical examples throughout history have aimed to invalidate it. The so-called “Great Men” have truly influenced the history of events, but more often than not, they have brought on unfavorable consequences that have not contributed to the long term well-being of the whole nation – their role of leadership. Empirically, some historic figures have been charismatic leaders who inspired a whole nation with their ideology and ambitions to reform – but have also persuaded those countries and their people that their ideas are worth going to war for (Hook, 1943; Khan, Nawaz, & Khan, 2016). Although the "Great Men" are inherently born leaders, they are still human and therefore also have flaws of character, and this theory sees greatness of men purely in terms of societal good, not harm. Further, academics argue that the power is given voluntarily to the leaders by their subordinates, yet this power can lead to the detrimental effects for society (Khan et al., 2016).

In consequence, academia built on the leader-based focus and aimed to uncover the set of traits someone should possess to have leadership potential, and in the process, rejected the principle that leaders are born and destined to be heroic figures (Khan et al., 2016). Trait Theory has concentrated on pinpointing the set of leader-specific traits that carry the potential of transforming someone to a leader, if possessed by a person (Bono, Gerhardt, Judge & Ilies, 2002). The list of personal attributes, characterizing the leader has been undergoing constant development, and throughout history, has included physical and personality traits, which were to differ between a leader and a follower (Jago, 1982; Zaccaro, 2007). Nevertheless, there are too many variables to consider to make concluding claims (Ghoshal, 2005; Stogdill, 1948; Winston & Patterson, 2006).

Stogdill (1948) published his first extensive review of leadership literature in order to challenge the notion of trait theory, and defy any research that would aim to determine the leader's traits. His analysis of the results led him to believe that there is no consistent bundle of traits that would define leaders and separate them from followers in different situations. Dependent on the context, an individual can choose to take up either the role of a follower or a leader, even if he/she possesses the leadership traits (Stogdill, 1948) – therefore, there must be an alignment between the personality traits and what is needed for a specific situation, i.e. role of leadership. Stogdill (1948) moreover argues that leadership is not static nor inactive, and includes specific actions, such as building a relationship with the followers – and was one of the first academics to state that a person does not automatically become a successful leader simply because they possess a certain set of traits. However, Stogdill neglects the notion that enacting leadership can also be trained over time (Müller & Turner, 2010).

Undeniably, perceiving leadership as a combination or a bundle of characteristics that a person obtained, developed or was born with has not only been highly contested, but more than anything, strictly tied the mechanism of leadership to a sole entity of a leader. The above-mentioned theoretical discussions excluded group dynamics, synergies or collaboration, and the application of particular skills (Müller & Turner, 2010), as well as various extrinsic factors – and in the aftermath of Stogdill's work, this approach had to be readjusted.

Leadership activities as a form of process takes a more modern view and defines leadership as a process between the leader and followers that entails relationships and activities between the group and the individual (Jago, 1982) – in short, *"leadership is an evolving, dynamic process"* (p. 316). Jago further builds his research on the notion that roles are not grounded in a person – in certain situations, the roles between leaders and followers can be reversed and thus, a follower can become, or take on the required behavior of a leader – and multiple leaders with different roles in one group or organization can exist concurrently. However, trait-based theoretical discussions remain popular, with rewrites and modifications (Bono et al., 2002; Jermier, 1993; Maccoby, 2004; Zaccaro, 2007). Thinking about leadership in terms of traits is the most common way to express the behaviors, it undeniably simplifies any organizational analysis and sets *"significant precursors of leadership effectiveness"* (Zaccaro, 2007, p. 14).

The trait-based approach to leadership, however, observed that there is no one set of *"universal leadership traits"* and have observed the interdependency between situation and the needed behavior and/or traits (Jago, 1982; Stogdill, 1948) – the context is empirically important. Recognizing that leadership is both situational and contextual, contingency theories evolved, which stated that the leaders should take into consideration the different aspects of the situation and the characteristics of the group, and correlate their behavior accordingly (Baker, 2013; Burke & Barron, 2014; Fiedler, 1964). Moreover, contingency recognizes that in some situations, a leader does not possess the capabilities to behave in a way that is needed (Carroll, Levy & Richmond, 2008; Müller & Turner, 2010). Therefore, the role of the leader is to analyze the situations and deliberate if their leadership style would contribute to the most efficient outcome (Mitchell, Biglan, Oncken & Fiedler, 2017). Furthermore, no matter how evolved and successful the leadership style of a person is, there may be situations where the leader is not the most adept (Fiedler, 1964). The field of contingency theories can broadly be divided into a) trait contingencies, where the models focus on leadership traits that increase the effectiveness of leadership in certain situations and b) behavioral contingencies, where the models tie effectiveness to the leadership behaviors (Jago, 1982). These theories present models that try to help define the context or situation and the preferable conduct of the leader, yet they attempt to define the interactions in a very rigid manner and do not allow for the fluency of natural synergies or unexpected changes of context. Although contingency theories have contributed significantly to the body of knowledge on leadership, changing the focus from the person-centered to the more fluid and dependent on other factors, the approach could not explain the many intricacies of leadership (Winston & Patterson, 2006).

To challenge these notions only focused on the leader persona and their inborn predispositions and dependencies, a relational approach that requires looking at leadership as a process and more crucially, as a *sum* of interactions within the team has been the focus of the 21st century. The relational leadership theories, that have in some form been concurrent with contingency theories without a formal establishment, take into consideration the socio-economic context and agility of both the organization as well as the world, and define the purpose of leadership as achieving organizational goals (Graen and Uhl-Bien, 1995; Ospina & Foldy, 2010; Uhl-Bien, 2006).

Relational leadership examines how leadership is performed in a complex organizational setting, full of interdependencies and relations to and with external and internal stakeholders (Graen & Uhl-Bien, 1995). Notion of leadership as a socially constructed concept in an environment full of variables (Berger & Luckmann, 1966; Winston & Patterson, 2006) offers a more realistic view of the world. Ospina and Foldy (2010) argue that *"the potential for connectedness is always present in human beings,"* (p. 292) and that this relationship can encourage commitments, which can lead to working together in the name of a unified (organizational) goal. However, much of the relational approach has been built on previous academic body of literature and the overlap is significant. Uhl-Bien (2006) has classified relational leadership theories into two types. The first are entity-based theories, which concentrate on the *actions* – but not traits – of one person and define the outcomes of leadership in terms of the actions of said individual. The other, fully relational theories, dwell on the complexities of rich interdependencies of socially constructed leadership (Uhl-Bien, 2006).

The entity perspective approaches the concept of leadership from a setting in which the individual is in the center of the process. The entity perspective takes a realist ontological assumption of the world and thus, perceives people as independent entities (Uhl-Bien, 2006). The person and their internal "selves" are in full command of their mind and their cognition is separated from the outside environment. This individual is the designer and assessor of their environment, both internal and external – taking into consideration the personal perceptions and behaviors of individuals in the relation to their interactions with others. The synergies are created by individuals interacting with each other and those interactions have to take into consideration the set of background factors the entities are molded by. Moreover, the aim of the interaction is to assert influence or gather information about the participants (Dachler & Hosking, 1995). Thus, the relationship is performed with the "subject-object" approach.

According to the entity theory advocates, the fundamental unit of leadership is the relationship, either between the leaders and the subordinate or leader and team (Uhl-Bien, 2006). However, leadership is a process that involves both sides and thus inclusion of the followers in that process is crucial, as the follower can also exert power over the leader – leadership and relationships are put in terms of transactions, where both parties give and receive (Antonakis & Day, 2017; Hollander, 1992). How these transactions are facilitated is yet up for debate – Hollander and Offermann (1990) discuss the importance of empowerment in the leader-follower relationship and points out that managers should, instead of delegating tasks, share the responsibilities by *"engaging others'"* talents. (p. 179).

Yet, in the complex organizational world, there are more considerations to be made besides the relationships between entities. The understanding of concepts is socially constructed as the know-how, perceptions and awareness is gathered not by individuals but by groups (Berger & Luckmann, 1966; Uhl-Bien, 2006). The observations and experiences of the world are affected by factors such as culture, past experience and bias – what one perceives is therefore constructed around our relational ties to the external world. Individuals are not separate from the environment that created them, or what they created, as entity theories presume, but are rather formed by it and therefore nearly impossible to separate. The ability to distinguish between the personal cognitive conclusions and what aspects have been influenced by outside factors is difficult to facilitate. Moreover, as knowledge is "*socially distributed*" (Uhl-Bien, 2006, p. 665), which entails that the interactions and the surrounding world are the sources of our information and the society is distributing the "rules of the game" in a natural and unconscious manner (Uhl-Bien, 2006).

In epistemological terms, the relational leadership perspective regards knowledge creation as "a process of relating" and therefore it is a continuous action of constructing meanings based on our understanding of the world and constantly revisiting assumptions. Therefore, knowledge is constructed by relating observations and experiences to the socio-economic context that one is influenced by and trying to make meaning of it. Moreover, this process is continuous and has no end – and therefore has no beginning. Dachler and Hosking (1995) point out that as we perceive situations through the lens of our experiences, there is no clear line separating the experiences which are essential for understanding separate events, therefore, all experiences are an indispensable part of the meaning-making, and there is no onset time. Pearce & Manz (2005) further argue for shared leadership, where decisions are made on facts and knowledge, and through self-leadership, the detrimental effects of the ego and past experience are mitigated – allowing adjusted behavior for different standards.

In order to understand leadership in terms of relational perspective, the lens of social construction must be applied. The organizational activities are formed by the reciprocal relationships, but also by the intersubjective contexts (Bradbury & Lichtenstein, 2000). Therefore, factors to take into consideration are those of cultural and historical backgrounds that influence the framework of interaction as well as personal experiences of the individuals, which have developed and shaped those (Bradbury & Lichtenstein, 2000). *"Knowing occurs between two subjects or phenomena simultaneously, therefore we must attend to the multiple meanings and perspectives that continuously emerge"* (p. 552) therefore, any bundle of interactions should be a process of meaning-making that attempts to interrelate all the external and internal factors for the purpose of understanding the intricacies of leadership (Winston & Patterson, 2006). Furthermore, leadership is a social process exercised by the group and should be analyzed as such – the unit of analysis is not an individual but the *"coevolving group"* (Bradbury & Lichtenstein, 2000, p. 551).

The tool of leadership, meaning communication processes and what they consist of, e.g. language, dialogue, is of higher focus in relational theories. Consequently, the interactions are following a feedback loop and do not necessarily include only human actors. Therefore, leadership can also be performed including a non-human agency – technology (Bradbury & Lichtenstein, 2000).

Yet, due to the ambiguity of development of leadership theories, a clear lack of non-human agency in leadership and novelty of AI, there is a significant gap in literature that considers these aspects. A number of theorists have however attempted to tackle the issue of this change in both academia and managerial literature.

Chamorro-Premuzic, Wade, & Jordan (2018) predict that AI technology will overtake some of the more data-focused tasks as intelligent systems, and will be more efficient at carrying out the responsibilities around information processing. In turn, this will allow for more focus on the soft skills organizational leaders should possess, develop and discard (Kolbjørnsrud, Amico & Thomas, 2016). A number of theorists have called for rethinking the role – or *"essence of effective leadership"* (Chamorro-Premuzic et al., 2018, p. 3) – and what qualities are necessary to cultivate the future workforce – humility, adaptability, vision, and engagement will take over some of the traits deemed important today (Chamorro-Premuzic et al., 2018). Hyacinth (2017) further claims that more focus on soft skills and "humanism" will be the natural progression for most companies. In an organization, for the successful implementation of technology, the human actors and Artificial Intelligence should symbiotically coexist and therefore, the leaders should be curious and show flexibility (Dhanrajani, 2019). Tapscott (2014) argues that in line with increasing technical capabilities of the organization, leaders should concurrently establish a foundation for work-learning environments for oneself and employees. Sanders (2017), on the other hand, argues that this will not be sufficient in dealing with the complexity of technologies as advanced as AI, and a different leadership paradigm which takes on more *"netcentric"* (p. 2) approach to organizing actions and processes is necessary – and due to interconnectedness of AI systems, other agencies, meaning companies, governments, and leaders, will have to function in a similar manner. AI technology should be perceived by leaders as a potential co-worker or advisor (Kolbjørnsrud et al., 2016) and the power of individual agents will be reduced with the public distribution and availability of information and reduced traditional hierarchy. Thus, the leaders will have to *"leverage networks"* (Sanders, 2017, p. 2) of other actors in order to achieve optimum gains of the organization that they represent.

Dhanrajani (2019) argues that leadership should focus on three core aspects in alignment: a) the vision of AI implementation should be well prepared, b) the communication should be both vertical and horizontal and c) the process of implementation should be monitored throughout every step. For this strategy to succeed, it is fundamentally important to redefine the key performance indicators, benchmarks and criteria in order to be able to measure what success is (Kolbjørnsrud et al., 2016).

Most of the managerial literature in reference to modern technologies takes on a capabilities-centered focus. The majority of these articles however still list the traits future leaders should possess and develop in order to integrate technology and human resources, and lack the flexibility needed to become the standard. Ghoshal (2005) argues that bad management theories, meaning theories that claim one and only cause-effect situation in managerial decision-making, gives both the readers and the practitioners a *"pretense of knowledge"* (p. 76), make a business out of social sciences, and destroy good (future) management practices. There is no singular framework that can deal with complex social phenomena such as leadership in a meaningful way, as excessive truth claims based on partial empirical analysis inevitably lead to self-fulfilling prophecies. Management literature offers a practitioner perspective but is inevitably rooted in their own experience, nevertheless, challenges leadership academia in its positivism in claims to be a science (Bernstein, 2012).

3.4 Theses

In addition to critically reviewing the existing body of literature, these authors deemed it crucial to review a selection on theses published in the recent years due to the novelty of the subject. The authors of this thesis have defined the scope and scale of this research, however recent academic work on selected contexts should not be dismissed as a) they highlight the growing popularity and complexity of the issues of AI and leadership, b) challenge the theoretical frame we operate in and c) ensure that our research is not conducted in isolation. Furthermore, we aim to understand both the theoretical and methodological challenges AI in research brings about in order to avoid overlooking important characteristics of this research.

Field	Year	Author	Name
Business Information Technology	2019	Bayati	AI in Consulting
Management	2018	Björkman & Johansson	What Impact will AI have on the future leadership role?
International Marketing & Management	2019	Lønning & Kallstad	How does the Interplay between AI, Management and Organization Impact the Implementation of AI-Driven Solutions?
Innovation Management & Business Development	2018	Vescovi	Artificial Intelligence Big Data and the Human Mind: A Study on The Effects of New Technologies on Students' Decision-making Process

Table 4: Recent Theses on the Subject of Artificial Intelligence in Various Contexts.

Bayati (2019) aimed to analyze in his thesis the potential AI has in redesigning the consulting industry through data analysis to enhance, prevent growth and streamline various aspects of business. He argues that AI is too complex of a technology to fully utilize by the majority of companies whose primary value proposition lies outside the premise of technology and programming. He concludes with the statement that AI is only used in very specific situations in the consulting industry as to a high focus on people-related tasks, and that is not the go-to technology for client work. As Bayati (2009) bases his conclusion on only one interview and does not include any other primary data in his research, the authors of this thesis challenge this finding due to the contradictory statements made by multiple interviewees in the consulting industry.

Björkman & Johansson (2018) work with the same working assumptions as the current authors, and strongly argue that AI will have an impact on future leadership. However, they focus on leaders' expectations as opposed to how the role of leadership will change, regardless of their expectations. The statements of the six interviewees have been taken subjectively, asking questions on the leaders' own perception whether they are ready for the future of AI, and their skills, and conclude that leadership of current companies are prepared for AI's future implications. Issues of generalizability due to the limited amount of primary data as well as formulations of the questions that allow leaders to evaluate themselves without observations put the methodology of their research up for questioning for these authors.

Lønning & Kallstad (2019) focus on the interplay of AI, management and organization, and through their conceptual framework highlight the necessity of new capabilities and competencies that management must possess and utilize. The case studies they conducted focused on organizational resistance and structure. However, by separating functionalities of management from organization and vice versa, they analyze AI's impact to management only through value creation and competences, and management's impact to AI through AI-driven leadership and responsibility. This separation of intertwined concepts excludes possibly other impactful metrics such as cognitive decision-making, collaboration and discounts leadership as a field.

The aim of Vescovi's thesis (2018) was to understand and analyze the effects of gaining knowledge about AI and Big Data and how it affects future decision-making in implementation of technology.

The results of his work included a convergence of behavior of students who took courses in said topics as opposed to students who did not. This convergence however only affected one of the steps of decision-making process (increased data literacy led to more analysis of different variables), and has implications for designing courses. The thesis provides valuable insights into how data is analyzed with or without data literacy, however it is subjected to the opinions of students, and these authors argue that the responsibility of those decisions is significantly smaller than it is for leaders.

The theses above have all outlined the importance of Artificial Intelligence and its prevalence in modern academia, the effects it has on leadership, businesses organizations and cognitive processes. Furthermore, the research highlights the turmoil of AI and its potential as the proliferator of Industry 5.0, as it draws out the connection to humanness and agility, planning and communication AI requires. However, the theses outlined are four different pieces of a larger puzzle, and these authors aim to build upon the research previously conducted as to connect the dots for future leaders, alongside future workforce and the changes all industries will go through in the coming years. This is to say, the aim is not only to investigate the nature of AI as a unifier or divider in an organization, but also outline specific steps that allow for a better match of skills in the future workplace, and create a dialogical playing field created by AI.

3.5 Constructs and Concepts of this Thesis

The overview of the literature was critically reviewed with the purpose of answering our research question: *How will Artificial Intelligence impact the role of leadership in the new normal?* This requires the researchers to define the concepts reviewed above, as we have identified multiple gaps in literature in our review that consider AI in its theorization or context. Firstly, a definition and a short overview of Artificial Intelligence is provided in order to intertwine our theoretical delimitations, place them in context and exhibit the relevance of this research.

The definition of Artificial Intelligence is ever-changing, as new technological discoveries and advancements are made with exponential speed. AI has become a popular theme in essence in all fields of business, and each of these fields provides its own, context-driven definition. By sharing and combining the knowledge the authors know previously, academic and practical research conducted and through the collection of primary data (see Table 5), new techniques and approaches can be developed and deeper understanding gained. For the purpose of this research question, the authors of this thesis define Artificial Intelligence as a *combination of various programs or algorithms that facilitate human-like processes that are able to work seamlessly and interactively with other agents and have cognitive skills, meaning AI is both artificial and intelligent. The cognitive skills that AI is currently able to perform are reasoning, learning and self-correction* – these overlap significantly, but for the purpose of this thesis, we are limiting ourselves to this classification.

Reasoning skills refer to choosing the right algorithm (code, or data set analysis but should for the sake of simplicity be seen as *rules*), in order to reach a predetermined and desired outcome. There are multiple methods of how this works in action. An example could include a *library* of past best practices, or previously made decisions and outcomes, and an AI system is able to determine the optimum outcome for the current set standard. The reasoning skills include, but are not limited to, case-based model, linear or non-linear modelling (for structured or unstructured data), qualitative reasoning, temporal reasoning or common sense reasoning.

Learning skills refer to neural networks that have been created in Artificial Intelligence in a loose form are designed as a human brain – specifically the section that is able to create and recognize patterns, and integrate those into decision-making. Deep Learning and Machine Learning are the main research areas here, and by far the most popular topics in academia and practice – and carry the most potential in the advancement of AI. Examples of this in action for leadership include understanding and discarding inductive bias (when presented with new data, experience bias can be determined in training data temporally; and in near future it will include meta-cognitive introspection), strong and weak AI for decision-making and a non-hierarchical decision-making (integrating external data sets to the algorithm to draw broader conclusions).

Self-correction is a cognitive skill in AI that includes two aspects: a) (unsupervised) AI algorithm is able to learn from a mistake in data analysis if that mistake refers to the optimum outcome and the end goal is clarified *and* does not hinder the outcome and b) it is able to reconfigure some aspects of its algorithm if errors occur and the error has been defined as such (e.g. natural language understanding and processing). There is a significant challenge in determining between supervised and unsupervised learning processes, as they are highly intertwined.

How would you define the concept of Artificial Intelligence?	
Company	**Definition**
CON-1	AI is basically this transformative monster that most established companies see as a threat – and mainly due to their lack of knowledge how to capitalize on it; much info out there on how to make money by using it, and it's all in this "adapt or die"; it's mainly algorithmic usage, so Machine Learning and automation of big data and so on.
CON-2.1 (I2)	Technology that can mimic human tasks, that can be automated and works together with human capital, and not for or against. Big Data, and especially learning from Big Data; RPA, IA.
CON-2.2 (I14)	Artificial Intelligence usually involves all the more intelligent technologies ranging from the Machine Learning to the more advanced Deep Learning. There is language processing; generating; computer vision; image recognition; That would be the scope; they talk more about the problems of AI and how to connect the hardware parts so it can interact more as a human being. Then [those systems] are even more intelligent to cognitive that way. You have to adjust how you are talking about it depending on the audience you are talking to about it.
CON-3	Intelligent processing system that benefits users, an ecosystem that works in an end to end way, and then combining human judgement with technological speed; Machine Learning and everything else, so RPAs, natural language, and so on. It's a constellation of technologies, not just one thing.
CON-4	The extent of cognitive skills that can be automated, so anything to do with learning, perception, problem solving, contextual interaction… yeah, so anything from autonomous vehicles, Machine Learning, text and image processing, virtual agents, so chat bots and the like. Deep Learning.
CMP-1	There are two categories for intelligent systems, process based and cognitive based intelligence. It's the work, where you really need to make some kind of analytical work or judgment based decisions, you need to work with unstructured data and that could be anything from natural language or plain text or image recognition or anything like that. Whereas robotic automation or that we call here as "head work" it's more of a rule-based head type of work. It could be clicking buttons or filling in fields, filling out a form and it doesn't really require judgments or analytical skills as such. It's more repetitive work that's not gonna change from time to time
CMP-2	Artificial Intelligence used to be anything that resembles an intelligent program, but here's the thing, since 2012, we have moved away from intelligent programs towards intelligent systems. It is no longer one singular program that interacts with itself or with data, to whole systems that interact with each other. The idea of AI has been around since the 1950s, but really came alive with Machine Learning in the 80s, with predicting things, based on data sets, and Deep Learning in 2010s. But then there are these ideas of singularity that also fall under here.
CMP-3	I mean, it is absolutely everywhere. So, short answer, data and what we do with it, how to make decisions, and educated decisions based on it, really. Machine Learning, and RPA are the big parts of it, and that is on a pretty solid development phase. Next up is cognitive programs,(...) a code that replicates humanness and human action. So machines being able to make informed decisions.
CMP-4	To me it is this system of seamless operations in the background, automation, speech recognition, programs that interact with me, and are able to learn.
CMP-5	Machine Learning and NPLs, computer vision.
CMP-6	Any technology that is able to learn from itself, or through processing data. Machine Learning, Deep Learning, algorithms… profile augmentation, recommender systems, but then also logic networks, cognitive reasoning systems, computer vision.
CMP-7	The three pillars we stand on here are Big Data, AI and Machine Learning, but it's all AI really, but if you look at it the Machine Learning and Big Data make up like what, 80 percent of what AI is today. But then, we put Machine Learning in a separate box, because it's just so big, and then we say AI is recommender systems, and data….data based decision-making… and then a lot of it practically means making decisions, and SEO strategy.
RCON-1	Intelligent programs or systems that deal with complex problems that need to process multiple streams of data or skills, mainly then Machine Learning and Deep Learning. Structured, unstructured data analysis. Turing's question was can computers think, but that's now changed to "what makes computers think", and if pure intelligence can be obtained, possible singularity, but we are far from that, now it is still in the cognitive areas, but most value for majority of companies comes from structured data analysis programs.
RCON-2	Systems that enrich the data sets, and act with it, by including it in the processes or suggest actions. System that works with intelligent processes, Machine Learning, RPA, computer vision, natural language.

Table 5: Excerpts from Primary Data: What is Artificial Intelligence?

These cognitive functions are crucial for the understanding of what AI can and cannot do for organizations in a broader context. Our primary data outlined the term *new normal* and *Industry 5.0* which the authors use interchangeably. Industry 5.0 refers to the shift from humankind using machines for productivity gains to an organizational context where the lines between human and machine are blurred, they work seamlessly together. Nevertheless, we cannot fully ignore the notion that there are aspects of AI automation that do refer to supervised learning processes and lack cognitive functions such as RPAs – Robotic Process Automation, as an example that refers to customizable software automation that is highly rule-based and lacks judgement-based aspects.

This will naturally change how we conceptualize processes. It is clear that value-driven methodology stays in place, but the broader conceptualization must include how AI and process management is *framed*. The aim of AI is to build on the premise and the existing value proposition of an organization, to optimize and operationalize processes. These constructed processes can be either broken down to very basic sections (cognitive and non-cognitive processes) or concepts (decision-making, collaboration, change management) and must be context-specific. The question for researchers is how these processes are *framed* and communicated down in an organizational level, and which variables are key. Finally, analyzing processes must consider the agency – who is collaborating, who is making decisions and who is managing the uncertainties of change. Both human and technical agency will change the approach to and of AI development. Processes in the context of AI will essentially focus on **the role of AI in organizations**, in connection to decision-making, collaboration and change.

The method of framing AI in an organizational context connects to transparency of design, communication and knowledge. Yet again, both technical agency and human agency must be considered – literature discussed above claims that trust is the optimum outcome of transparency in organizations, yet a gap exists in regards to Artificial Intelligence. The paradox of AI being more cognitively transparent in its process management than human agency creates, in theory, more organizational transparency – but its complex nature, unfathomable to most business practitioners, can create opacity in practice. The authors here argue that transparency is not static, it is not inherent in a system and must be actively managed – and contextually. *Transparency of reality*, where AI as an actor not a medium, is transparent, creates transparency and is deeply affected by it needs a constructed balance for an organization to create value, to understand **how this role of AI affects transparency**. Nevertheless, human agency plays a key role here, e.g. decision-makers who have gained the responsibility of constructing transparency must gain better technical fluency in this realm. In literature, this notion of transparency is in this constant struggle due to this polarization, while we propose to see it as a prism: the transparency of reality is a collectively constructed notion, rather than a top-down monitoring or governance mechanism, or a concept that lies solely in actors for them to define by themselves.

This will no doubt trickle down (or up) to leadership. For the purpose of this paper, the authors define leadership as a *socially constructed organizational function that is relational and actively managed and is something we perform and do as opposed to something a leader is.* However, some contingencies exist with regards to trait theory – leadership must be able to incorporate agility, and one could argue this is a trait of a leader. However, the authors take the stance that the semantics of this do not – and should not matter in the bigger picture – we do not reject behavioral or trait attributes but rather insist that they are not necessarily grounded into one person. Furthermore, even though we acknowledge the difference between management functions and the role of leadership, the interviewees use these terms interchangeably throughout the interviews – and we do not separate these significantly. Given what we know and have gathered from primary data on the past and current roles of leadership, we aim to explore how the combination of AI facilitated changes in processes, changes in transparency and changes towards Industry 5.0 **will change the role of leadership**.

Lastly, the context of current and future employees must be taken into consideration – it is not enough to analyze businesses and their process automation in silos – especially when core focus lies in the future premise of Industry 5.0. External and internal flows of the future workforce (SQ4) must be considered when discussing leadership and its implications.

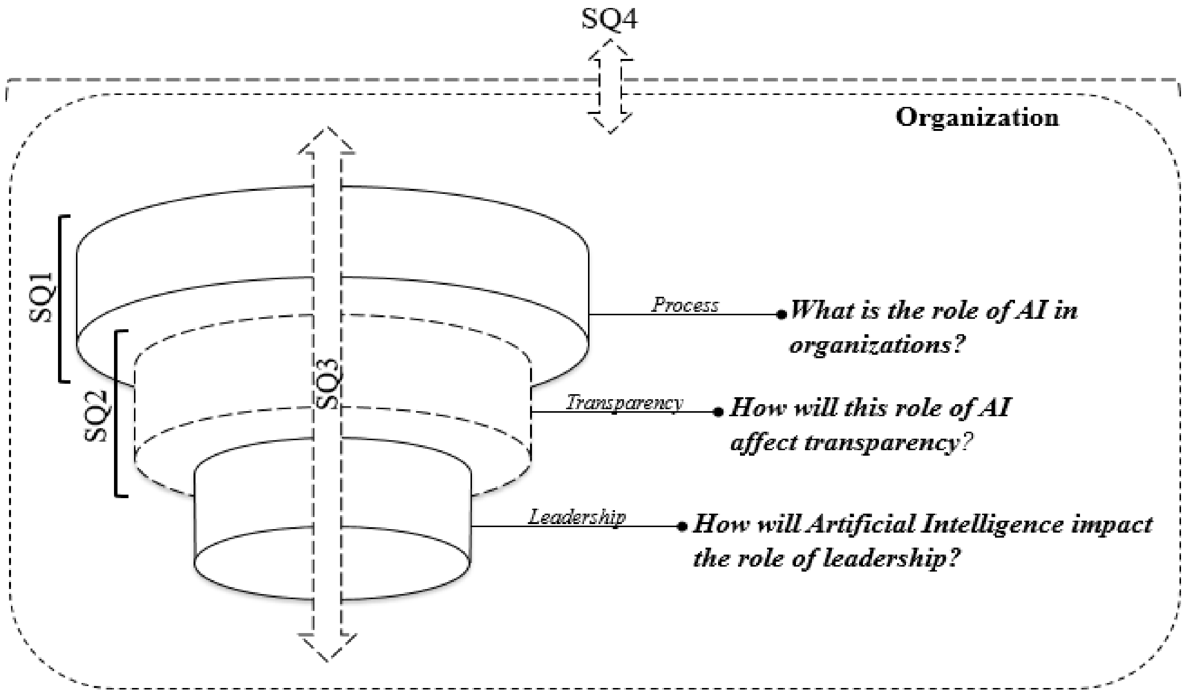


Figure 4: From Data to Constructs – Conceptualization of Processes, Transparency and Leadership in the Context of Artificial Intelligence.

4. Findings

This section follows our data structure (see Table 2) and presents our key findings on 1st and 2nd order codes which are grouped systematically based on our aggregated dimensions. Excerpts from primary data are provided in text, for full transcripts, see separate appendix (Transcripts 1-14). As there is thematic overlap within these aggregated dimensions (See Figure 4), the somewhat artificial segmentation is necessary to form a logic progression and highlight the transgression to leadership level.

4.1 Findings on Process

Departing from an organizational standpoint, some clarity regarding the conversation around AI is necessary in order to a) highlight the expertise of our interviewees and contrast and compare this with survey respondents; b) analyze the advantages and disadvantages of AI from a practitioners' and implementers' perspective and c) present a contextual narrative that focuses on the business side of implementation of technologies such as AI.

The development of technology is always trying to address certain issues or inefficiencies in the world. AI is already capable of processes we did not think possible a decade ago, and performing tasks that are time consuming and exposed to human error. Over 90% of the respondents of the survey conducted by the researchers have ranked AI as quite or extremely beneficial for businesses. As most of the respondents are part of the new or future workforce (90.8%), this indicates that the general perception of AI technology is that it is necessary for both business and personal competitive advantage, as well as reaching strategic goals through organizational design. Therefore, the landscape of businesses is in an accelerated change curve, and business processes must adapt – leadership in cooperation with the workforce should be able to prepare their workflow and process automation for Industry 5.0.

Nevertheless, the consequences and application of AI powered automation are not always clear, nor carry the same gravitas for all agencies. Processes are everywhere – and the challenge is to find the overlap in organizational and AI-driven processes. Therefore, in the following paragraph, the researchers have outlined some of the use cases of AI in the daily operations of the companies interviewed.

Taking **process automation** through AI as the foundation for analysis, the majority of interviewees have determined cost-cutting either directly or indirectly to be one of the core advantages, and this is further reflected in the survey, where **productivity** and **cost reduction** (58.3%) were rated as the third highest in *"association to AI."*

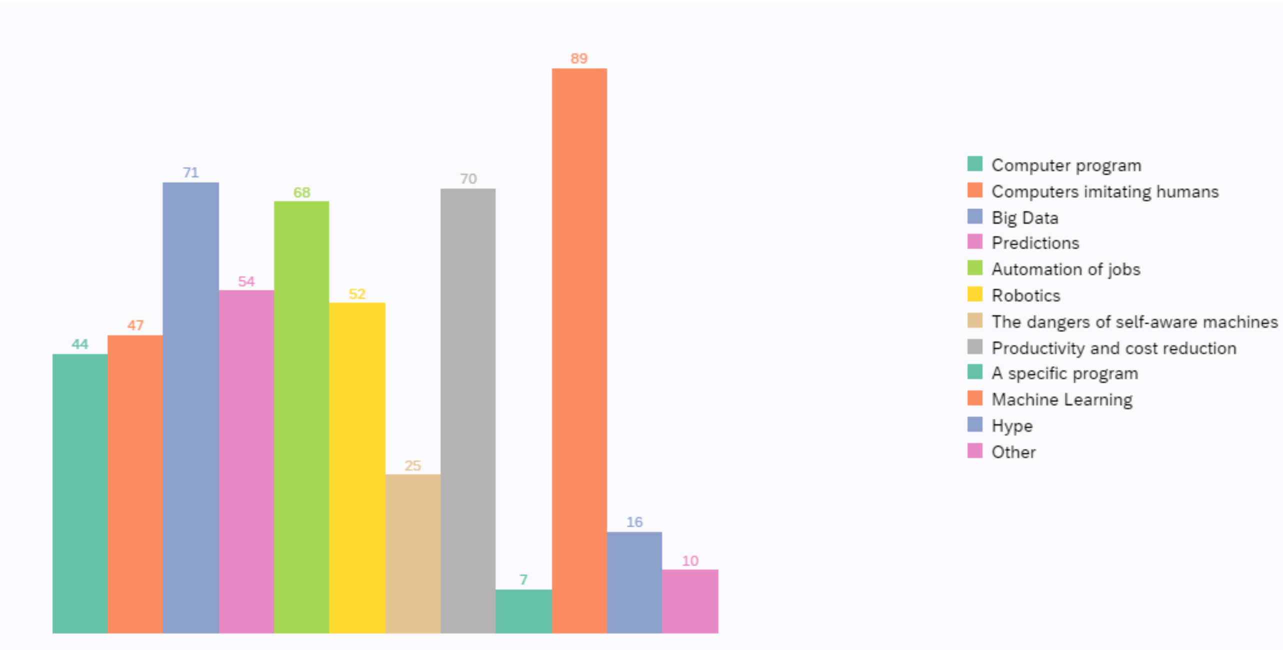


Figure 5: What Comes to Your Mind When You Think About Artificial Intelligence?

There is an undeniable gain for companies who implement AI successfully, both financially but also regarding performative measures and internal Key Performance Indicators (from hereinafter, KPIs). I7 said, *"it [the cost reduction of automating processes] could be anything from about thirty to sixty percent per automated process, and how skillfully it is fitted in the business processes."* Additionally, some interviewees have made the point that the programs and systems do not get tired or need no vacation (I7; I12). Moreover, both the safety of the data stored and embedded and the automation of the tasks potentially increases the security of the system as a whole – and in consequence, companies can assure a higher level of compliance (I1; I2; I12).

When it comes to Artificial Intelligence in practical applications, it is important to understand that the context of the technology is novel and continuously advancing, thus, the processes surrounding its implementation are still being developed. As *"AI is becoming more important for the companies and is higher up on their agenda*" (I4), the question of what Artificial Intelligence is and stands for in and for the organizations should be the center of discussion. This is specifically highlighted when we take **decision-making** into focus, as it is both a process that can and is automated as well as understanding the contexts of which decisions need to be made.

All of our interviewees have mentioned **automation** as the main goal when referring to AI (I1-I14), moreover, the survey respondents have picked automation as the fourth most identifiable element of it, after Machine Learning, Big Data and productivity. Automation fulfills the purpose of creating a system to perform some tasks that are usually repetitive and do not necessarily involve critical thinking – and decision-making, in its bounded rationality, often falls under this category. In regards to automation, the interviewees include keywords such as *"Big Data, and especially learning from Big Data, RPA, IA*[3]*"* (I2), *"process-based [automation]"* (I5) and *"Machine Learning, and RPA"* (I7). These areas of AI are mostly algorithms fed by data, which is enforced by recognition of patterns. With time, AI will be able to take on more complex tasks by design, such as learning from unstructured data like speech, which will expand the possibilities of AI usage. This second category of AI was described as *"cognitive programs, … a code that replicates humanness and human action. So, machines being able to make informed decisions"* (I7). These two categories are intertwined as such, but the key differential is whether processes involve structured or unstructured data. Structured data refers to clearly defined numbers, structures or groups of words that can be categorized, while unstructured data can be everything else. There are limitations to AI – it is "*not a one-size-fits-all solution"* (I2) or tool, and distinguishing between these categories is crucial for implementation.

However, both above-mentioned functions overall describe technology that aims at helping with the automation of tasks – and decision-making especially, as employees are required to make decisions on a daily basis that involve both categories of data. An advantage of AI implementation is that as it is automated and based on data and statistics as opposed to opinion, it allows for more *"accuracy and*

[3] Robotic Process Automation (RPA) and Intelligent Automation (IA) are two sides (among many) of AI – While RPA focuses on structured and rule based automation, IA is the area of cognitively advanced AI, and often includes Machine Learning, Deep Learning and Natural Language Processing.

consistency in decision-making" (I12). Decision-making, therefore, can become more data-driven and reliable when broken down into rationally bounded steps.

The usage of AI in decision-making provides the ability to have a **constant overview** of both singular and integrated actions and its analytics (I3). Every employee, in theory, has access to the goals and progress of their team, department or even whole organization, which allows for vertical and horizontal communication (I6). Undeniably, this ability stimulates **agility** and flexibility of any business, especially in the era of ever-changing trends and market conditions. Similarly, this process works vice versa: any change on the market can be quickly diagnosed and translated into a decision, which, due to this interconnectedness, will reach the bottom-line in no time (I6).

I2 has explained that AI *"helps to make strategic decisions across the organization, and it's scalable and flexible,"* therefore it can be adjusted to the needs of any company process and can grow together with the company workflow. Process automation can be root-level RPA, that Machine Learning can eventually be built on as processes regarding decision-making become more complex and cognitively dissonant. What is important, however, is that with AI, innovating the company can simply build on top of the existing technology and data sets, therefore unlike with most technological products, one does not have to regularly purchase new systems, nor make systems more complex – "*All processes, if you break them down to smaller and smaller tasks, can be automated"* (I7). Therefore, most processes, even cognitive ones, can reach a certain level of automation of domains of **active control**, but only through defining goals and methods.

The company and specifically the decision-maker and decision-implementer of the process should have appropriate **knowledge** about the activities in the company and its direction in the strategic canvas. I6 elaborates that finding the right aspects of the business to automate is not an easy task as *"you have to know your business very well, and what every department is really doing."* Yet, the paradox becomes clear – the higher in the hierarchy, where one is in a position of power, the less there is knowledge about the specifics of bottom-line operations.

I10 believes that the implementation of AI will allow for making processes leaner, as AI will be able to analyze them and point out bottlenecks and inefficiencies, therefore, *"streamlining [the processes] to the fastest extent."* For CMP-9, AI use cases include internal chatbots, which by having access to all the necessary information, organizational structures, and job descriptions, can easily match the employee with the document or person they need. CMP-6 is already using and developing AI in its daily activities and uses RPA for customer data streamlining, data organization and notification systems – meaning tasks that do not require critical thinking, but rather manual data entry. The system utilizes the unlimited processing power of machines for data analysis and is able to see any abnormalities and will inform the employee if his/her attention is needed, allowing the system to keep learning in the process. These are some of the examples of decisions based on structured data, and require no, or very low levels of **cognitive judgement**.

Although companies would like to increasingly use AI in the process of decision-making, there is the potential issue of **systematic bias** when decisions become more complex. Systematic bias refers to a situation where algorithmic processes are created by humans and the data fed into the algorithm is possibly subjected to bias (e.g. racial profiling in classifying resumes), meaning, there will always be the possibility of some kind of process skewness. I6 explains that *"algorithms are working on data sets, and if your scale is biased, it will confirm that bias into decision-making."* In cases of both supervised and unsupervised learning, this can pose serious threats for branding, communication and external affairs.

I6 elaborates by saying *"we like to think that humans do a lot of critical thinking, but that is not necessarily true, we are very much guided by our culture and background and bias in our lives, and that doesn't add value to decision-making."* Rationality is necessary, however difficult to obtain or define. When decision-making is classified into steps and begins with analyzing available data, rationality and meaning-making can only ensue when bias is actively managed.

Bias as a topic in decision-making is and will always be contested, whether we talk about technological or human actors. Some interviewees believe that AI automation, and specifically Machine Learning will allow for less bias compared to decisions made solely by human agency (I4) or accept that there will always be a certain level of bias (I12). Other interviewees believe that the solution is not absolute due to specific natures of bias and believe there will eventually be some form of technological advancement in the form of a review process that will allow for removing all bias (I5). Nevertheless, decision-making is bounded in experience, emotion and subconsciousness and in order to train an algorithm, we need to be aware of outcomes and framing of problems. *Thinking* *rationally* through incorporating logic must also be accompanied by *acting rationally* for **agency problems** to be addressed and mitigated – and must apply to human agency as much as it is expected of AI.

Decision-making is in itself a process and a goal of processes, and success can be created by data analysis – but meaning is created by **alignment of human and non-human agency**. Previous section focused on how this process is framed and which variables matter, while the following section focuses on the agency – and what decisions have to be made in practical contexts.

In order to be valuable to process and workflow management, AI *"has to be tailored"* (I6). I3 has pointed out that *"only 20 percent of companies have scaled AI in a meaningful way [in HR as an example]."* Most companies follow the **AI hype**, rather than actually deliberating its scalability in the business model, nor its specific purpose. It is an interesting phenomena, as we as rational beings would not hire a human actor to do a task he/she cannot do – yet lack the same critical thinking when it comes to technology implementation. The general understanding of AI potential and optimization is fairly low (I1; I3), yet people are subjected to the advantages of it and wish to be innovative and forward-thinking (I14). However, without the understanding of limitations of AI or the systems they want to implement, they *"will end up making decisions not based on long term value, but rather short-term hype"* (I4).

CON-2 performed a survey where in *"nearly half of the businesses"* the company interviewed, the respondents pointed out the importance and expectations they tie to AI, however the fast-paced changes in their workplaces were still surprising and their *"businesses are really just not ready for it"* (I2). Companies are aware that AI will cause certain modification to the way they are organized, yet a) do not fully understand it and how can it improve their business (I1; I3), b) fear the transition and the risk of big investment (I9; I14) and c) do not have strategy and understanding of their business to the point it would be successful (I2; I7). I12 further elaborates that many companies have **no aligned understanding** of the benefits, possibilities and disadvantages of AI and therefore are not realistic in their expectations. I13 builds on that by saying AI is often undergoing *"a hype based implementation, and that will only increase cost without any scalability."* Therefore it is crucial that the companies **plan before they execute**, taking into consideration the whole organization, from processes to workforce. Often the organizations, due to the lack of knowledge, underestimate the impact of AI and therefore their strategy is not premeditated (I2). I1 described the frustration: *"Companies want to invest big in this, without taking the small steps first – and it is hard to convince them."* In consequence, organizations that do indeed want to implement AI should prepare a detailed plan of action and remember that a radical transformation will only bring failure and therefore they need to proceed with an incremental evolution in mind. I4 and I13 have also stressed that a key to success is a scalable solution that can be implemented and grown gradually. Moreover, I4 emphasized that in order for AI to be successfully carried out, all parts of the company have to be aligned.

The aspects of how to **frame** AI for and in organizations should also be considered. Communication is crucial and gives a chance for leadership to align on how they want to portray it (I4). Practitioners in CON-1-CON-4 all share the notion that they are all very careful about the **narrative** and wording used when presenting their solutions and strategy. As was pointed out, framing AI systems as *"this program [that] will help you have an overview of every client, and make better decisions, or [as opposed to] here's a tool that makes 90 % of your job redundant"* will make a big difference to the client (I5). I3 underlines that when CON-3 talks about AI with their customers, they take into consideration the audience and adjust the language.

When it comes to adopting AI decision-making **internally** as a company, and the framing of the situation, CON-2 has a department for internal automation which is *"putting humans in the technology loop,"* and is concentrating on creating the strategy and narrative for their company. I2 has stressed that AI implementation *"is core in [their] value chain,"* and incorporates *"experts that are top in the world."* All in all, this creates an image of a company focusing on digitalization and it is framed strategically. CMP-6 also has a designated department assigned to AI, which they are *"really heavily investing in"*, however, I10 also underlines that simply having the department is not enough: *"change is driven from within but ... we have a strong culture here, of change, and because most of the employees are on top of what is popular in our professional network, we are advocating for it."*

Regarding companies interviewed that create and execute AI applications, two approaches have been mentioned. One of them is to **invest** heavily in R&D in general and allow for many different projects to go on simultaneously (I8). The advantage is that projects, which do not seem feasible at first, might get a chance at reaching the development stage through trial-and-error of inhouse or open sourced platforms and succeed through new approaches where innovation can foster (I12). On the other hand, as a multitude of projects are being researched at the same time, the cost is considerable and can only be feasible for large multinationals with designated Data Science departments (I8). CMP-4, which represents the other approach to innovation, says that *"[m]ost companies don't have that luxury [of investing in all feasible ideas], so your strategy has to be on point and you need to know what value AI is going to bring you and your clients."* Therefore, the projects that do reach the development phase are often low risk, and thus exclude some of the most disruptive ideas.

I14 says that an approach recommended by consulting companies to their Small and Medium Enterprises (hereinafter SMEs), is to start with "*plug-and-play*" platforms and **outsourcing**, which will help with automation of core processes that can be later built on, and more importantly, this forces deliberate decision-making in process breakdown analysis. Furthermore, by automating basic processes through AI, employees have the opportunity to onboard with less friction, and therefore ties to the narrative of incremental change.

Nonetheless, *"there's no doubt that decision-making will be changed, or at least challenged"* (I1), and he/she continues with explaining that the challenge will not come from the threat of substitution, but rather the possibility of combining technology and humanity, the high computing and data processing abilities and human approach.

Decision-making in organizations rarely happens within one agency and implementation of AI will undoubtedly change the **collaboration** processes within any organization. It will "*differentiate the way that we interact together, how leadership interacts, how we collaborate.*" (I9). Therefore, companies and employees will have to redefine the relationships with both human and non-human actors, the iteration between human-to-machine and machine-to-human.

Firstly, as AI will overtake more and more of repetitive or cognitively low tasks, there may be an increasing number of situations where people will have to deal with the system, i.e. human-to-machine collaboration, instead of human actors, which can be a detrimental change for some employees. I5 talks about "*not having … our collaborators at work [is] really scary for us to imagine, and it feels like something very unnatural."* Not only do companies internally have to prepare people for increased application of technologies, but even society at large, especially once technology assimilates in some industries, the disruption will spread through other industries as well. I9 said: *"I think it [AI] will be a super good thing for the world, and for a lot of industries, but only if you are* *really prepared to embrace the change, and not necessarily internally, but also just in the society, and be in the loop."* The burden, therefore, does not lie solely on the companies, but all actors involved, such as governments, public institutions and individuals. The companies will be responsible for onboarding their employees how to collaborate in the new workflow automation and create synergies with AI, moving reflexively towards machine-to-human, and with time, people will begin to work with AI harmoniously (I2; I7). I2 said: *"Leadership is about creating this ecosystem, and companies that fail to 'combine'* [emphasis added] *humans and automation will not win in the long run."*

Collaboration also occurs in a machine-to-machine and machine-to-human loop, especially in the last decade. I6 describes that *"it is no longer one singular program that interacts with itself or with data, but a whole system that interacts with each other."* Therefore, the technology and its own collaboration process can still be further advanced, and companies should consider this as they debate over the organization of AI and their workforce (I4). Organizational actors have to think through how they want **these two agencies to work together**, how they will design the new work "network" and how they will transition employees to new tasks (I4). If there is a lack of clarity in collaborative processes, businesses will reach a point where the outline of the responsibilities and goals of different actors is blurred, might be unclear, and overlap. Therefore, companies will have to define the context in which they operate (I13). Many factors can affect the adoption rate such as culture (I12) or adaptability to change (I5; I12; I14), and thus should be analyzed as the constructed reality of the company must be contextualized within AI processes in order to understand all aspects that will influence implementation (I5). Therefore, leadership has to analyze how their employees and AI will *"socialize with one another in different landscapes"* (I9) and "*leverage the possibilities."* (I4). I3 draws attention to the fact that *"the future collaboration [is] not through technology, but more 'with' technology"* and AI will become an actor on its own as an equal collaborator in the company culture. However, leadership should consider how to keep the most valuable attributes of both sides and maximize competitive advantage through **division of cognitive labor.** I7 points out that the *"obstacle is hitting that sweet spot where all human tasks are truly human and necessary to the value of the company, and all other tasks are hardline automated, and these two parts work together – and seamlessly."* The companies that can achieve seamless integration will be the market winners and will gain a competitive advantage over companies that will not have it (I7).

Over 87% of the survey respondents have agreed that AI will change the workplace of the future either extremely or quite a lot. This change is not a stand-alone phenomenon and must be actively managed. In broader terms, **change management is both internal and external** and variables that play a role differ. Internally, change management requires processes that support agility, adaptability and alignment about and within beliefs towards techno-economic systems. Task performance as a process on its own is subjected to change as defined KPIs and outcomes must be aligned. Externally, when we discuss AI, governmental policies and practices have a great deal of impact on the practical and theoretical applications.

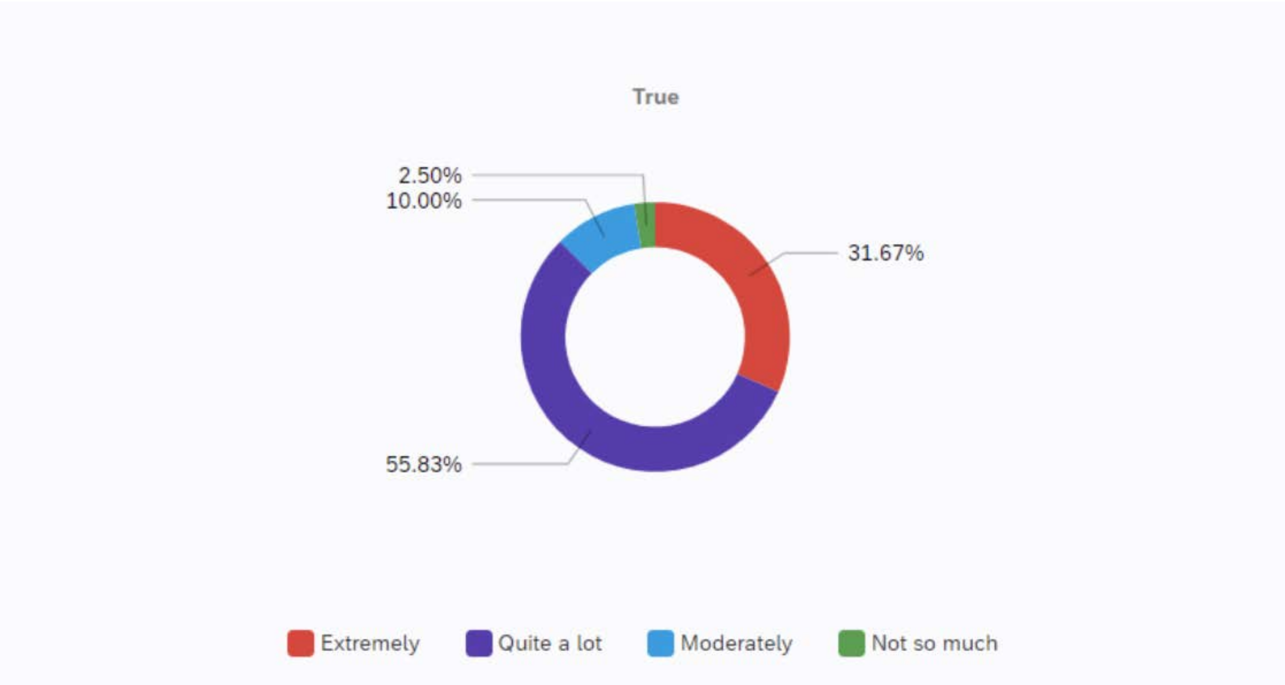


Figure 6: How Much will the Development and Usage of AI Influence the Workplace of the Future?

The companies that decide to implement AI vary – I1-14 and I14 stated that there is no one type of company that decides to undergo that digitalization. It however does matter how change is tackled and led through (I2; I4). Often, implementation is driven by somebody from inside, but they use the services of other companies to help them with the transition (I3; I12). Both the companies that focus on organizational change through consulting services as well as those companies who are selling AI-based solutions, then make sure to get all the stakeholders in the company on board – especially C-suite and decision-makers in the company (I1).

From the perspective of practitioners, whose competitive advantage lies in assisting with organizational change, the transition from idea to the final execution regarding AI is very structured. For example, CON-2 has an established **framework** the consultants follow which includes steps such as a) assessment of technological maturity; b) building the burning platform for a narrative; c) research and solutions and d) facilitating the implementation and onboarding. They stress the importance of leadership throughout the process, both in terms of top managements' approval and process of communication, and company-wide cooperation during the implementation phase (I2; I14).

For AI process and workflow automation to reach its maximum **efficiency**, there has to be a clear understanding of what the actualized goal of the workflow is. Expectations and pain points vary significantly, yet companies fail to consider these and struggle throughout the transformation and organizational change. I7 elaborates: *"you see companies now painfully implementing solutions that just do not make sense in their scale or product and fail"* (I7). **Fit between technology and strategy, organizational culture and performance must be planned.** In order to adapt to new technologies, companies must understand the way they do business and their processes. *"I don't think most companies think about their processes that much, they just do stuff like they always have"* (I10). However, change can be operated successfully only when it is managed consciously and proactively. The company "*needs to understand how you do your daily work, and see it as more than a job"* (I9). Therefore, for the change from manual task management to automation to happen, there must be a clear, structured outline of all activities that make up the process (I5; I14) – only then it is possible to see the activities that can be and would make sense to be automated.

Once processes are structuralized, the companies can analyze if the **human or non-human agency** is the most efficient at each step of the way and begin *"zeroing in on value creation and seeing how the same business can be done in new innovative ways"* (I2). The transformation into AI will thus *"fundamentally change how we do business"* (I3) as the companies must be organizationally sensitized to "*see and accept the value technology brings"* (I8). Instead of considering it in terms of digitalization or action management, they need to consider it as more of a **platform or system** that works across many technologies already implemented (I3).

In addition, change management often influences **organizational structures** – and this must be managed. Although automation of certain activities will make some job roles redundant, it will also create a need for new jobs. I5 states that *"it also creates different jobs within different sectors,"* meaning that a need for new skillsets will emerge in sectors previously destitute of it.

Furthermore, organizations will also have to change their approach to Human Resources (HR), both in terms of **agency** hired, as it is crucial to select the optimal facilitator for each task, but also what **skill** they are in need for (I11) – *"an investment is needed [for upskilling employees] and a certain timing has to be ... considered here"* (I10). For companies, educating their employees and investing in the workforce should be a part of strategy planning and not a sporadic investment into availability of new courses for employees (I10; I11). Taking into account that AI will be further developing and gaining importance, skill development needs to become a long-term strategic initiative of the organization. The survey conducted by the researchers has shown that most of the new and future workforce does not feel fully knowledgeable when it comes to AI and its usage – over 74% would describe themselves as slightly or moderately knowledgeable, and less than 4% would describe themselves as experts. There must be a reasonable overlap of knowledge between organizations and future workforce and the benefits of this are clear – the companies that can achieve seamless skill integration will be the market winners and will achieve competitive advantage (I7).

CMP-1 expects that in the next few years automation will increase workforce capacity by about 27% – equivalent to 2.4 million extra full-time employees (I5). Yet, the survey points out that on average only 50% of the respondents trust technology and a little more than 50% feel prepared for a work that incorporates intelligent systems. Moreover, over 17% of the respondents feel uncomfortable when thinking about working with intelligent systems daily. Thus, **change management** in organizations must make a conscious effort to lower friction through upskilling of the workforce and framing the technology in a collaborative manner. I3 highlighted that for smooth adoption of intelligent systems, onboarding as a process should be utilized.

Not all pressures for change should lie in companies and leadership – the process is actively managed by a multitude of **external factors** that inevitably affect business landscape. An important element of the socio-economic environment is the attitude of governments towards AI. As I6 has outlined, governments currently *"create laws that just do not fit the industry, don't help it grow in any way,* *and just inhibit us."* There is still a big gap in policy and the lack of regulations can be challenging for HR as I7 portrays: *"if there's a big gap, and this is not taken seriously by policymakers, then people could end up losing their jobs, because of no upskilling."*

"I think technology will be the single most important thing for companies in the next decade, you either get on board or you are left behind" (I7). AI implementation and adoption will increase with time – this is inevitable. There is a strong affirmation towards incorporating AI into business practices – and those who do not, risk losing customers and market share (I9). Moreover, the organization may move towards a more AI oriented business or strategic decisions due to pressures from not only its competitors, but also its network of suppliers and partners (I4). Not participating in that trend might affect the company's economic bottom line (I14). The mentality of *"adapt or die"* (I1) is forcing companies to look for technical solutions, and adapting for the sake of adapting. The threat of weakly planned implementation is however prominent – nevertheless, any AI agency incorporation should be **process based**, rather than succumbing to market pressures. I11 clarifies that *"the upfront cost is so small compared to the benefits [of AI],"* however, without proper planning, it will not achieve the expected scale and can affect the company and its culture unpredictably (I11).

4.2 Findings on Transparency

There is significant debate over AI and its effects on transparency in organization. The previous section outlined process and workflow automation through AI, but a deeper organizational context must be taken into consideration – it is not only important to identify processes, and how organizations must incorporate technology, but also how **non-human agency integrates into both cognitive and strategic organizational identity**. The interdependence is rich and complex and strategic direction is not only necessary on a global or industry level (I1), but also on the company or even department scale (I14; I5; I8), as seen from both the survey respondents as well as interviews. By nature, technological systems such as AI should permit more transparency as the systems are based on clear rule based structure (I3), however, the implementation phase can mishandle the advantages of change by lack of proper communication (I4), inadequate education (I4; I10; I11), and fallacious leadership (I6).

The techno-economic solutions *"will break down how we see decisions and the effects they have on a long-term scale"* (I3). Therefore, it will make the processes more transparent through **creating this**

transparency and will make it easier to make high-value decisions and manage multiple stakeholders. Moreover, AI can facilitate a more transparent communication in the company (I13).

AI implementation allows for transparency of processes and activities within a company, simply by its rule-based nature, however subjected to the different work of various departments, workflow automation is not strategically simple by design – **automation maturity** across departments differ (I12). However, clarity and understanding of processes it brings cannot be circumvented – I11 has described the ability of systems to calculate a success rate of different marketing activities with regards to the customers' response, allowing for cross-department information exchange.

Moreover, setting up a **clear performance overview system** was highlighted by practitioners in CON1-CON-4. I4 said that one of the initial key steps is to establish KPIs and define expectations to not only monitor the progress and whether any issues occur, but also to measure the return on investment of the project. I3 confirms that KPIs are highly important to keep employees accountable for their work and process automation. Consequently, AI by creating transparency in processes could increase the overall efficiency of any business.

However, **AI is also subjected to transparency** and is strongly affected by it. Both internally and externally, a debate remains on how AI is, or rather is not, framed by governments and policies. Although an active topic, governments tend to fail at framing AI in a positive manner, nor do they focus on preparing guidelines that encourage growth and innovation of techno-economic solutions (I6). In the process, a lot of unanswered questions and unspecified policies that constrain the growth and application potential of AI remain – *"A lot of regulations and governmental questions around [AI is] also something that needs to be addressed today"* (I4).

When asked about the predictions on how AI will influence the transparency of business processes, the survey respondents had contrasting opinions. Most (41.7%) of the participants agreed that it will make it more transparent, yet over 33% claimed that the business processes will become less transparent, and 25% estimated there will be no change. The opinions are highly contested and considering the fairly young age of the respondents, these results show confusion. Although the benefits of technology are clear to survey respondents, **subjective pessimism** regarding transparency remains. This may pertain to other aspects of transparency – such as trust or technical knowledge.

In some cases, the implementation of AI has decreased the transparency in the organization. I1 says that *"some of the companies I have worked with, that have automated their processes, have actually become less transparent because people don't understand the technology."* Therefore, some areas of AI, such as dataset analysis and segmentation, Machine Learning Optimization or RPAs, which in theory should increase transparency in how data is handled, have a **paradoxical effect**. The employees who do not necessarily understand the technology, and therefore do not **trust** its merits, affect the organization through their own subjectivity and perception of a more elusive and concealed workflow (I1). Although process and data is accessible and visible, the process of implementing techno-economic solutions results in less transparent activities as employees have no understanding of what happens *behind the scenes.*

Two main concerns that create this **distrust** towards AI are singularity – referring to heightened cognitive abilities of AI that becomes a threat to humankind – and fear of job loss (I5; I6). I5 said: *"AI really triggers people, it's the thing that challenges or threatens humanness,"* and this idea of singularity is an active subject in society at large. Moreover, I6 has elaborated on the topic by explaining that the way AI has been framed since the beginning of its existence[4] has strongly influenced the perception of AI today and programs such as Alpha Go[5] *"confirmed a lot of the fears that were already present,"* and have introduced the notion of *"AI as something that can beat humans"* (I6).

Thus, framing, whether it is done by organizational actors or society at large, matters – even if the distrust is based on **lack of knowledge** or credible sources. I1 confirms that most of their customers perceive AI as a *"transformative monster that [they] see as a threat."* The distrust towards technology is hard to overcome. One reason for this could be that as humans behave in a disorderly and unpredictable fashion, people struggle with accepting that AI behaves mainly in a structured manner (I2). Therefore, they pass their own bias of being human onto the technological actor which is *supposed to act in a human-like manner*, which in turn fuels the fear (I6).

[4] See Turing, 1950
[5] AlphaGo was designed to play the game of Go against human players and is rooted in Deep Learning. It is based on pattern recognition, however Go as one of the most complex strategic games requires learning from the opponent.

Over 36% survey participants do not believe they use AI on a regular basis, however, AI technology in one form or another is applied in most of the widely used applications – people often use AI without acknowledging that it is indeed AI. At the same time, over 66% have responded that they trust technology. Considering people are not always aware when they use specific technology, how can the trust endure? The opinions formed without the appropriate knowledge can affect the opinion about any technology, and consequently, the adoption rate (I6). This lack of awareness might explain why less than 1% of the survey respondents think that AI technology will be harmful for the businesses. There is a distinct connection between knowledge of the subject and trust, and **AI is *subjected to it.***

The general distrust of AI technology has a detrimental effect on its adoption and success, and **organizational culture** (I2; I14). Although technological transformations tend to be easier to embrace in a business environment than on a societal level (I4), the perception of AI *at this point of time* is not benefiting the transition. Transparency is not static and aspects affecting it must be contextually managed. Firstly, some people are "*concerned about security*" (I8), and its subjectiveness to security breaches. Secondly, some employees are apprehended by the 'unknown' aspects of the process. As part of the tasks of a job are automated and the process is not visible or tangible, "*it kind of becomes a black box, just gives you a recommendation*" (I4). Therefore, as people are not technically literate (and one could argue not literate enough in processes), they distrust the tangible outcomes of AI automation. This paradox of plenty creates opacity in itself. In order to prevent that, there must be a higher level of understanding of AI technology in the company, but also generally in society.

In order to raise trust in AI technology, the primary data points to **knowledge management** in the company (I2; I4; I9). Lack of knowledge is a barrier to proper adoption of these techno-economic solutions. People undeniably have to have a certain degree of understanding of how AI works, as it is already present in many technologies used daily and will affect all industries eventually (I9).

I1, who works for a consulting company, says that most of his/her time is spent educating the top management and explaining the potential value of AI in the business model. The **technical literac**y of the C-suite is indispensable for the implementation of AI, not only due to funding and approval of projects but also, aligned expectations. Whether to automate (and to what extent and technical level) requires breakdown of processes and connecting these activities with the agency that provides the highest value.

Technical literacy is also important for making informed decisions. I1 says that many companies reach out to CON-1 and would like to implement AI but do not understand the workings of the technology and what it could do for them specifically – and often there is not much value that AI could add. Therefore, the companies must have consciousness about the technology, and not neglect comprehending the functionality of it and weaknesses (I4).

I2 and I14 in CON-2 have underlined the importance of educating the companies on the mechanics of AI functionalities early on in the **onboarding process** in order to achieve any significant results. It was stressed that often companies have low technical literacy and although beginning implementation processes can be smooth, at the later stage of implementation the lack of knowledge catches up and there is a lot of push back and friction from the employees. In some instances, the projects of implementing RPAs had to be halted due to the above-mentioned reasons. It is important to underline that implementing AI *"it's not a one-size-fits-all solution"* (I2) and the onboarding, upskilling or reskilling of the employees will have to include that aspect. There is a need for a continuous and agile approach to it in order to always be up to date.

Reskilling and **upskilling** is not only a responsibility of the leadership – at the same time, it lies equally on the shoulders of individual employees. *"If you are not willing to learn, your job won't be taken from you – you are just giving it away yourself"* (I7). Therefore, people have to become more proactive and learn about the techno-economic solutions and operating them. As AI will not affect jobs but rather individual tasks, every employee has to understand what the mechanisms regulating it are. I1 presented an example:

> *"If you work on a task-board that's automated, and it prioritizes your daily tasks throughout the organization, like, in your own work, your team's work and so on, if you don't understand the logic behind the prioritization, or where these decisions come from, it can definitely become frustrating for some people."*

In consequence, AI cannot be omitted by avoiding certain job roles because it will be present in every aspect of the company and *"you need to understand the technology, whether you like it or not*" (I7). The expectation of the future workforce will, therefore, include the possession of certain tech fluency (I4). The survey conducted by the researchers has shown that the workforce has *some* understanding of AI, as the top associations included Big Data and Machine Learning, although the respondents mostly belong to Generation Y and grew up surrounded by technology. However, when asked about their expectations about what skills will be most needed by the future workforce, the respondents placed higher focus on **flexibility** and **adaptability** – and these skills are not isolated from technology – nor leadership.

4.3 Findings on Leadership

As seen from primary data as well as theory, the concept of leadership is highly ambiguous and often approached by individuals and organizations in different ways. The question about definitions, of what leadership is and how it is performed in the companies, often confused the respondents and therefore, the researchers needed to ask probing questions. The topic is complex in nature but as the interviewees pointed out, of great importance. The development of AI and the pressure it will put on the organizations will create an undoubtedly difficult challenge for the leadership of tomorrow – *"[AI] will definitely put into perspective what leadership actually is."* (I7).

The approach and understanding of leadership differ across organizations, but one of the main roles rooted in the understanding of leadership is **governance**. The researchers observed, however, that interviewees refer to leadership as a process or structure rather than behavior or singular action – specifically when they refer to leadership roles *within their own* organizations. However, to analyze the data, the authors have grouped these definitions and perceptions into two sub-categories: a) leadership as management function and b) leadership as an organizational structure.

The first approach distinguishes between an archaic definition of leadership as a management and a more modern approach of relational leadership. The former category sees the role solely in terms of a management, responsible for increasing shareholder value and **controlling** the performance of subordinates, and people as solely human resources to achieve that goal (I4). Consequently, the employees who perceive leadership as such, understand leadership in terms of transparency of job tasks and expectations, therefore base this understanding on company goals and key performance indicators (I4; I5; I7). When asked about what constitutes leadership in the company and if it is transparent, both I5 and I7 answered: *"I guess so ... I understand my KPIs, and I know what I have to deliver"* and *"here is a clear understanding of progression, priorities, how work is distributed and how bonuses are determined."* Thus, leadership is understood in terms of control and overview of actions.

When asked about leadership style and if it is constructed through empowerment or reward and punishment system, I7 talks about different methods of evaluation between departments, and although he/she concludes by saying that both techniques are used, does not mention communication of empowerment at all. None of the interviewees who defined leadership as management have mentioned teamwork or encouragement of innovativeness in daily jobs. It insinuates that in these companies, tasks are assigned from the top, evaluated by predefined rigid measures and the acknowledgment is demonstrated by financial measures. Researchers have noticed that the people who understand leadership only in terms of management are often coming from highly technical backgrounds.

In contrast to the former, the latter approach showcases more **network-of-people** style leadership. The goal of leadership in these organizations is creating a vision for the company (I2; I6; I8; I9; I11), leading people towards success (I4; I7), and is a reflective and dynamic process (I2). Many of the interviewees (I1; I2; I6; I8; I9; I14) stressed that leaders are responsible for giving the direction and creating an environment that helps achieve the goals through **empowerment** and good company **culture**. I5 has described the transition from manager to leader in regards to expectation of what should happen in Industry 5.0 as *"being able to let go of the need to control every small bit in the chain, but focus on the bigger picture."* – the concept of leadership is understood in terms of teamwork, vision and **collaboration**. *"Definitely group-driven"* (I2) and *"very collaborative"* (I6) were the descriptions used by some interviewees. They perceive leadership as a **process of cooperation** in the team, where the leader is a dynamic member of that group. The researchers have noticed that interviewees belonging to the latter group rarely talk about their manager as separate from the group, only mentioning the leader/manager in situations of struggle or friction, and they rather use terms such as "team" or "department" as pronouns (I6; I8; I9; I11). In consequence, those employees describe the atmosphere within their department and how the activities are organized instead of focusing on KPIs, delegation of tasks or division of labor. As an example, I6 describes the work environment in his/her company as "*collaborative*" and adds "*we work together and share knowledge quite easily.*" I10 adds *"we are also a very diverse team, very different backgrounds, so it is really nice to just sort of [do] crowdsourcing within the team*", therefore putting the focus on his/her team diversity as an advantage for **collaboration**.

The respondents often mentioned **empowerment as a mechanism of leadership** in their team or company. I6 has described his/her working environment as *"complete freedom to choose our projects and research, but then funding and timeline has to be agreed with [Department Head], and he decides and advises us on how to proceed."* Employees feel *freedom* as they choose projects that inspire them, and therefore can devote their time on something they deem important and value-adding – and focus on context-driven value creation. The manager is performing the role of a guide who, due to experience, can give recommendations and leads. In CMP-5, the employee described his/her work as *"basically whatever you want it to be"* and it is also possible to *"focus on the areas or industries we care about."* Employees who co-create this type of leadership have a more positive and motivated attitude towards their work. For this reason, empowerment leads to a more inspired workforce, which is motivated not only by financial gains but by the satisfaction deriving from meaningful work.

The second approach the respondents take when talking about leadership is **equating leadership traits to the organizational structure** of the company. In many instances, when asked about leadership in their company, the interviewees have retorted by describing the department or company leadership as *"flat"* (I9). Although the organizational structure nor span of control translates into leadership style by itself, the respondents, due to the probing questions, explained their meaning – I11 firstly answers with *"it is very flat, and relaxed"* and then continues explaining that within their department they *"work as a team and motivate each other."* It is worth underlining that leadership in a flat structure is meant more as assisting than controlling function, however, this does not mean that management is not in control of the organization or there are no consequences of low performance. There is still structure in the company that is needed (I9).

Although we have grouped the definitions of leadership given by our interviewees into a) leadership as management function and b) leadership as an organizational structure, it has not covered all the divergences. Some interviewees have pointed out that the leadership style in their organizations differs between departments (I5) or between the levels of the organization (I8). Most corporations that have a global presence, and especially if company revenue is brought in by sales, have some level of **fixed hierarchy** in their organizational structure. It is undoubtedly hard to function across borders, time zones, and departments without a framework for clear decision-making and accountability. In some companies, there may be a diverse approach to leadership originating from the **nature of the department's activities** (I1; I7; I8). As the activities of some departments are more performance-based, leadership style tends to be more top-down due to high focus on results. On the other hand, departments with more creative tasks, that require collaboration and intellectual deliberation, would have a more flat structure (I5). For example, I7 describes *"the BS [Business Support] and coders are more team-driven, and sales and marketing are more top-down, they have to constantly show the numbers."* When companies can implement some level of a flat organization and management into their ranks, employees often associate it with a more relaxed environment – I8 said *"it's very flat actually, at least in my team. People are rather chill."*

Moreover, I1, when asked about leadership approaches within the company, responded, *"my company is internally competitive,"* and followed by explaining that although they cooperate, the culture in the company is to compete with each other, and therefore, every employee is responsible for themselves and their abilities.

I8, when asked about the transparency of leadership in the company answered: *"I mean, decision-making is communicated rather well within the organization, but I wouldn't go as far as to say it's transparent."*, **equating transparency of leadership role to decision-making function**. On the other hand, I9, whose company is rather flat and focused on empowerment, replied to the same question, *"in the way that we are all friends and so, yeah, we call each other by first names here, and it's pretty clear cut."*, **equating leadership roles to collaboration**. Transparency in the role of leadership therefore includes both vertical and horizontal communication. On one hand, it is tied to the clarity of communication and unconcealed motives. On the other hand, I9 has connected the transparency to the 'flat' leadership in the team, speaking more about the atmosphere in the group than how transparent the activities are. This person has automatically associated transparent leadership with group decision-making and thus, approached leadership in a very egalitarian, group-based manner.

I3, who works for CON-3, however, has noticed that over the years there has been a decline in **long-term leadership**. *"Because there is so much change and risk, and it's hard to tackle complex problems"* many companies resort to short-term rather than long-term solutions. It is clear that leadership is contingent to internal organizational context. I8 has stated that *"we have tried hard to lose the ancient feel of the company"* and that there has been a visible *"new wave of openness"* in leadership in recent years. I6 has described that in his/her organization one *"can easily send a message to anyone higher up, and bounce it off, and if it gets the attention of anyone, you can move quite fast in the company,"* stressing the direct communication in place, which strongly empowers employees and does not hinge on hierarchical bottlenecks. Emphasis is placed on **work-learning** and agility, allowing once again for both vertical and horizontal communication –*"Compared to past [there is] more focus on things other than shareholder value and micromanagement, they learn faster and adapt better"* (I4). Therefore, as leadership function is already changing, the question is not if the advancement will happen but what will it transition into.

When asked about the expectations on how leadership role will change in the future, most of the interviewees have mentioned **agility** (I4; I5; I8; I9; I10; I11; I14) and **soft-skills focus** (I1; I2; I11; I9; I12) – and these terms overlap significantly in the interviews, as they are not mutually exclusive, nor should be taken as such. Agility was explained as the ability to respond quickly to the changing environment. *"AI will change all companies... Impact will depend on agility, and will happen regardless,"* said I2. Therefore, agility must also be present in leadership function as well as development, for both control and maximizing the impact of AI. I5 has called it the *"entrepreneurial spirit"* of the company, which does not allow for stagnation and losing the potential of innovation in the midst of bureaucracy.

AI has already changed the way employees view leadership – the continuous process of distributing the role allows employees of a company to take on this **flexibility of changing roles**. Therefore, *"an internal attention"* (I4) about the various processes in the company is essential for leaders as it will allow them for fast decision-making and implementation of changes – a function they must be contextually sensitized to. I9 adds that leaders should have a *"more change-driven behavior"* and should be *"empowering employees."* This response is highlighting different processes of agile leadership such as change management and empowering subordinates. To conclude, I12 said, *"leadership has to be able to deal with this uncertainty, leaders need to adjust to intersecting data* *and keeping a healthy work culture to not burn out when the only constant is change."* Not only is this role and function **socially constructed**, it requires certain **personal attributes** from leaders to be successful in this role.

On the other hand, the survey respondents did not rate agility as a highly important aspect of leadership, placing it in 6th place – and it might indicate that there is already a change of expectations on leadership and agility will be perceived rather as a standard.

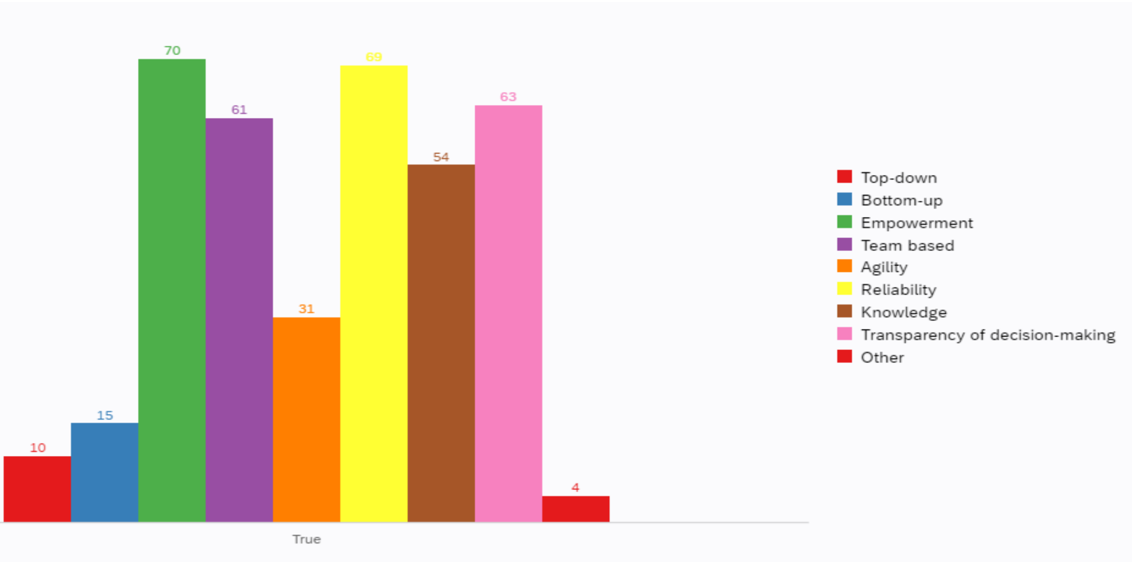


Figure 7: What Is Important to You in Leadership?

Primary data outlined a second role and function of leadership – the **focus on employees** and the development of soft skills throughout the organization. With AI taking over more and more of the repetitive and time-consuming tasks, leadership should focus on being more *"people-centric"* (I1) and "*people-oriented and move away from task management*" (I8). With process and workflow management that does not require an allocation of human agency, employees will be able to delegate their time to tasks that involve strategy, creativity and complex critical thinking. In order to be successful and efficient, employees (and leadership) will need to possess skills such as teamwork (I9) and abstract thinking (I14). Moreover, *"empathy might be more emphasized in the workplace, because … it's not easily replicated by Artificial Intelligence"* (I5). I11 states that soft skills will become more important because *"some things [...] are for the human brain [...] to solve."* Leadership skills will also be increasingly valuable as it *"belongs to the human mind"* (I11), and leadership should devote resources to developing those.

The belief that companies should consider putting more effort into both **hiring** and developing employees on soft skills has also been highlighted by interviewees. Yet, technical knowledge also plays a role, as I7 has underlined that building automation is *"a competence that most companies just don't sit on top of."* Leadership should be *"identifying and nurturing"* (I11) the employees with developed interpersonal skills in order to create a workforce of the future. One of the measures a company can take is for the leaders to pay more attention and take a greater part in HR activities. I10 says the *"hiring processes should come closer to leadership, especially at senior manager level."* Therefore, leadership needs to not only *"bring people together"* (I8) but also understand the future changes and create a *"strategy for the long term"* (I8). I12 has summed up *"by adding more meaning you automatically add more value to the company. Happy employees, happy life."*

This is one of the approaches taken by the companies where they try to *"hire the right people"* who have both technical and personal skillsets. Our respondents in majority mentioned *"investing heavily into getting top talent"* (I1; I2; I7; I12; I14), however in terms of AI advancement and progressing digitalization of the companies, the skills that are specifically needed are technology-related – I5 said that it is "*in the company's leadership's best interest to find people that want to work more with RPA, AI or Automation."*

The function of leadership further involves the **task of designing the workforce –** this involves forecasting as the leaders have to think about what kind of human resources their company will require in the long run. I2 has underlined that future leaders should be more *"purpose-driven"* and therefore involved in strategic and vision-oriented planning. It is clear that the importance of AI development and implementation will grow over the years, but the availability of workforce that carries these personal and professional attributes may be scarce. Therefore, some companies focus on internal upskilling and reskilling to gain competitive advantage through high-skilled workforce (I1), however, it poses a risk of training employees who then decide to leave for another company, as their skill set is in high demand and the market conditions are competitive (I14). However, through proper **investment into the current workforce**, loyalty and shared leadership functions can be leveraged. As I14 stated, the companies should ask themselves if *"we really need these highly skilled superstars* *within or can we work with the developers that we have and train them in these already existing, easily managed AI systems?"* The trade-off is clear – the question lies in whether any company has the capital to develop tailored solutions in the inhouse Data Science departments, or solutions development must be outsourced. Regardless of the company size or capabilities, the organization must still possess and nurture a culture of **continuous learning** – *"they have to understand the changes and bring people together and have a strategy for the long term."*(I8). Techno-economic systems are no longer static, and can be tailored and built upon. I8 said, *"[they should] either hire engineers in house, and optimize processes, or buy cloud services from CMP-4 or [Competitor]."*

AI systems implementation does not only require nurture of workforce skillset, but also **communication and framing** of change (I6; I12). Therefore, leadership takes on an important role in introducing and fostering a company-wide perception, or culture of AI, by the narrative they choose. Braiding together company vision, culture and AI systems, leadership must consider negative connotations in communication, which may lead to a lower adaptation rate and consequently, disadvantage on the competitive market (I14). I1 said, *"we need to work on acceptance and naturalization of the technology"* and one way to do that is to introduce it to the organizational culture in a positive and value-adding frame. This framing of AI, during and after any technological implementation, as discussed above (see section 4.1), is deemed highly important by the interviewees (I1; I3; I14). They highlight that leadership has a strong influence on how AI will be accepted by the employees (I1; I2; I7; I14). Both communication and attitude have been mentioned (I5; I6; I3). *"The core challenge is really about how you define the processes and what kind of mentality you have as a leader,"* I6 added. Therefore, leaders should consider how they want the future of their workforce and technology to **interact** and deliberately adjust and **manage the perception** of AI in the company to *"convince people to be on board with all of this"* (I3).

To achieve any leadership function tied to a measurable goal, it has to be **well communicated** throughout the organization. The survey respondents rated the transparency of decision-making as the 3rd most important aspect of leadership, rating only empowerment and reliability higher (see Figure 7). The process of communication is deemed important by the majority of the interviewees and unquestionably substantial for any company's activities. Yet, communication as a concept is constructed in a multitude of ways by both survey respondents and interviewees.

Clear communication is often tied to a transparent leadership function by our interviewees (I1; I9; I11). By communicating openly and clearly, the leader seems to act more transparently, and therefore is perceived trustworthy in their behavior and motives. I1 and I2 both, basing their attitudes on their own experiences with SMEs, said that in order for AI to be adopted successfully, the method of communication and internalizing information would have to change in most companies to encourage trust. Moreover, communication was mentioned as a key tool for preparing future leaders for the changes (I10).

However, AI can take up a role in itself as a non-human agency for supporting communication of information. I6 said that *at this point in time* AI will *"really make a difference, in how we deal with knowledge, and knowledge management."* Data analysis through Machine Learning or Deep Learning requires human-to-machine and machine-to-human collaboration – and communication. This process of inter-actor transmission of information also requires framing.

Responsibility has been the second broader theme in leadership discussions in our primary data. The interviewees have raised the question of **ethics** in implementing some technologies. Firstly, the challenge of responsible coding should be already considered, and not only by the developers or data scientists, but also by those who implement it (I7). Artificial Intelligence's cognitive abilities are created by the supplied data and understanding of patterns[6], which is often consciously or unconsciously fed with human bias and values (I5; I6). In line with pragmatism, people's psyche is constructed by the socio-economic factors that have affected their development, and are not able to separate the influences from self, therefore perceiving the world only through the lens of their personal background and past experience. It is generally agreed in the AI sphere that bias will always be a part of data processing, as long as AI is trained by **human agency** (I6; I7; I12). However, the responsibility often falls on leadership *function* to be able to consciously prepare and actively manage these situations and be able to isolate the cases of technological bias and intervene appropriately (I12).

Therefore, it is natural that in order to fulfil this role, a certain level of tech literacy is necessary to comprehend the **interdependencies** in the systems and organization (I1). It is necessary not only due to the responsibilities of bias management but for the overall preparedness for the reality of business

[6] In reality, this notion is far more complex and would require a discussion of structured and unstructured data processing – however this is not in the current realm of this thesis and for simplicity, the researchers follow the explanations of primary data sources.

(I1; I3). Although it is granted that the employees creating AI technologies, integrating or operating them understand it, I14 underlines that leaders should also possess those skills: *"You can't just be a believer in things, you can't just approve and think that is it."*

The **responsibility of understanding automation technologies** in order to make informed decisions about various business activities does fall on the function of leadership. As I7 said, *"managers who don't have programming backgrounds, they don't really understand how that kind of work is done, and what kind of timeframes are needed,"* therefore the responsibility of understanding all aspects of **workflow and process management is a crucial function of leadership**. I3 pointed out that *"usually the lack of understanding of what [managers] need and what is feasible or simply lack of knowledge, is the single impediment of AI implementation."* With the growing importance of technologies such as AI, technical literacy is not an additional skill but a baseline requirement for the role. *"No one will follow a leader…who is reluctant to tech,"* said I13. There is rarely a good leadership relation when subordinates do not trust their leader. I4 concludes: *"We can talk about the benefits of AI all we want, but if leadership is not able to include these notions into…meaning if they see it as complicated rather than complex, they won't see the full value."* Therefore, suitable knowledge about the topic of AI is undeniably necessary and can allow for a more adequate framing of AI and better leveraged leadership. However, knowledge is not the only aspect to consider as **ethical issues** persist.

The perception of AI is often negative and associated with **replacing human agency**. As discussed above (see section 4.1), the automation of repetitive processes and tasks has been the aim of Industry 4.0 and can support a multitude of structural organizational activities, however it must not be framed as a dystopian threat, rather as the reorganization of activities and positions (I6). Our interviewees underline in many instances that although the purpose of those new technologies is cost-cutting, it is not aimed at human agency (I4; I14). The aim is to unburden the workforce from the time-consuming tasks that do not require heightened cognitive ability and allow for more time spent on strategic and creative tasks (I14). Thus, thinking about AI implementation in terms of cost-cutting through reduction of human capacity is *"not the conversation that you would usually have"* with companies (I4).

Most companies throughout industries are currently in a transformative state, where automation is contingent to departments and only occurs **sporadically** (I3). However, there is no doubt that full integration will be happening within the next decades, towards Industry 5.0 (I12). As stated above (see section 4.1), the companies that will be slow in adapting or will not take that leap, will not be able to compete and thus suffer from potential productivity losses. Consequently, there must be a change of perception on how the workforce is developed and retained within companies (I7; I11; I14).

Most of our respondents working in tech companies have linked their department tasks with other departments in terms of cooperation, creating a **shared sense of leadership** and responsibility. However, in many cases, it was mentioned that departments such as Sales or Marketing, which are contingent on consumers, require Business Support or IT department assistance due to the lack of sufficient knowledge about the technical solutions. Thus, often, when employees do not understand AI or are unaware of its features, they communicate with the *supporting* departments. This shows a potential bottleneck in the operational strategy, and expectations for the future – technological literacy is still crucial.

Integrating technical literacy and preparedness for technological change through workforce development was the most common theme when discussing future roles of leadership. Leadership functions must be involved in the process of *"reskilling and upskilling"* of their employees (I9; I12). As the technology progresses at an incremental rate, market demands, job roles and tasks are changing, and there is a high probability that professional development of employees will become a higher priority (I9). Leadership will have to engage the employees and provide the training (I12). Active reskilling and upskilling of the employees is the responsibility of leadership, not only because they are cultivating their future talent, but also because they have certain obligations as part of a society, (I12; I14). Preparing employees for this future should be a shared responsibility between companies and governments – and both should be accountable.

Moreover, as I12 has pointed out, leaders should be *"hiring **skillset** and not skills,"* therefore, further highlighting the importance of soft-skills and work-learning. Consequently, flexibility and adaptability as behavioral traits should be of focus to have *"a rounded-up skill set [to] thrive and be critical in our work"* (I5). Another responsibility placed on leadership is to preserve the humanness within the company despite, or rather in line with automation and digitalization. As I3 mentioned *"there is always the risk that with automation, there is a loss of collective EQ*[7]*"* and therefore, leadership's role is to create a platform to nurture this.

I9 when asked, about how the CMP-5 is preparing for changes in the role of leadership said: *"you pass down the knowledge and these tips and tricks you learned when you started out, and then after two years they will do the same, so it's this continuous loop"* (I9). This mentoring program, where training is performed by word-of-mouth, builds on the experiences of the managers in the company, therefore, there is no need to update any material as it is naturally amplifying with each new mentor. However, due to the subjectivity of this method, there is possible misalignment in both the quality of mentoring and the information or approaches shared. Therefore, although one could argue that the training is contextual and grows with the developments in the technical environment, the organization will be saturated with miscellaneous knowledge and potential subjectiveness from their superiors. Some companies prepare by having leadership training available for all the employees, for example, I1 has mentioned, the company has an online Leadership Academy where various training modules are available and employees are free to access it. Although this approach is very popular and useful for contextualizing leadership and rooting it in organizational culture, it **does not give a clear picture of the direction organizations are heading towards**.

In order to build on engagement of employees and future workforce, organizations should not only provide development opportunities but also, **empower** people. When asked about the expectations for the future workplace, I2 has replied *"empowerment will become more important as well as team-building."* Moreover, it was pointed out that *"leadership will be more about inclusiveness"* (I11). The survey respondents also determined that empowerment is the most important aspect of leadership for them.

[7] EQ refers to Emotional Intelligence, and focuses on managing emotions and empathy.

Figure 8: Top Ten Words Used to Answer the Question: What Expectations Do You Have For Future Companies And Leaders?

I10 has described the internal working environment as *"bottom-up empowerment"* which he/she then defines as *"work[ing] with a mindset that encourages to challenge ideas and solutions."* Therefore, empowerment can be interpreted as the freedom and **incentive for critical thinking** and questioning processes. I10 also added that *"sparring off of each other really works well for coming up with complex solutions."* Thus, empowerment of employees allows for more employees to feel **responsible** for processes and streamlining them, which in turn allows for innovation and advancement of the company, highlighting this dynamic process of taking ownership.

Motivation is often tied to empowerment – I9 underlines that *"empowering management style"* in his department helps to feel *"motivated here."* The organization allows the employees to focus on the areas they are interested in, therefore encouraging them to influence the work they are performing and following through (I9). I11 highlighted that empowerment lies within ownership of the tasks. The company is heavily using empowerment and personal responsibility as the basis for organizational setup – there is a general target that should be achieved but the employees can plan their work individually, and asynchronous work is encouraged. Therefore, the employee is empowered by the lack of constant supervision or monitoring.

Furthermore, AI by itself has the ability to empower, through process and workflow management – AI has a bigger calculative ability and can with ease analyze huge quantities of data – a mundane process that is not worthwhile for human agency. Ultimately, AI helps by *"unlocking the potential that your employees carry"* (I12).

There is no one-size-fits-all solution or cognitive process for carrying out empowerment – **but it is a function of leadership**. How empowerment is coordinated might differ between those various organizations but can also change over time, similarly to the changes in leadership needs (I7; I11). I2 has stated that *"leadership must be able to realize the value and evaluate what makes sense,"* therefore, every manager is faced with the task of organizing their team in a method that is relevant in the current time frame. Managers have to remember that the way his/her team is formed should be evaluated constantly, as there might be demand for alterations (I1).

An important aspect of leadership, although often underestimated, is to create a feeling of **belonging**, or a sense of identity through organizational culture and vision. Organizational culture is socially constructed by the actors in it – and must be managed, especially in times of change or high friction to adaption to new ways of working. The feeling of belonging can be understood as having somebody to count on in your team, as I5 explained: *"Everyone here supports each other,"* creating a shared sense of responsibility, or seeing oneself as an inherent part of the company through ownership of processes (I1; I2; I14).

The modern approach to leadership often refers to **creating vision and culture** in the company, highlighting the importance of **workforce retention and attraction**. Subsequently, culture enforces the feeling of belonging to the company or the department, as there are often sub-cultures present in the companies. I4 developed that thought by saying that in the future "*creating this sense of culture that is inclusive and trickles down loyalty to the organization"* will be an important aspect of leadership. In the face of technological change and AI, leadership will be faced with a *"challenge [that] is in creating a culture that people want to stay in, want to be retrained and can afford it"* (I9). The culture of the company affects not only the attractiveness of the workplace but in some instances the innovativeness and success of the company (I7). *"You can and will have to build a strong company culture that your employees want to be a part of, otherwise you just will not survive,"* advocated I12.

Consequently, it is highly important to **cultivate a culture** that will ready its employees to embrace technology (I3). The implementation and adoption rate of AI will also be affected by the culture of the company (I5). The challenge for leadership functions will be to navigate the transformation which will be a continuous process and not a singular event. Thus, the organizations will be responsible for not only finding the balance between the 'humanness' of the work their employees perform and technology as two separate actors working next to each other, but rather as colleagues, coexisting and developing together. *"Leadership is about creating this ecosystem, and companies that fail to combine humans and automation will not win in the long run."* (I2). I5 further adds *"the dream here is that there is rather a cross-development and not a balance, that they are not separated as such, but, [...] work together seamlessly."*

Currently, many of the market leaders in AI technology development are known for very competitive **work environments**. The interviewees confirmed that working in their companies is very much performance-based and heavily monitored. The KPIs are hard to reach, and burnout rate of employees is high (I5; I7). I7 says that CMP-3 "*is sort of known to be a harsh company to be in, and people do burn out quite fast."* However, the majority of respondents have connected good leadership with a flat structure and empowerment (I1; I6; I9; I10; I11). More empowered employees are more engaged in the company activities and thus bring more value to the company. According to the survey, the future workforce values empowerment the most. The companies, therefore, have to adjust to the needs of the employment market as well as to the new technologies.

AI implementation allows employees to focus more on the **human side of the business**. The interviewed companies are already predicting the need for more soft skills and comprehensive training for their employees (I7), yet the treatment of the employees as workers is often very contested. "*We shouldn't choose our work over our families and lives, especially if we are all going to be expected to be more human in the future workplace"* states I7. Consequently, the companies should consider if their vision is aligned with the actual processes of the company and if it is not, what kind of consequences that will bring (I2). Companies can hardly expect more humanness of the job to emerge when employees are not empowered to do that. I12 claims that the *"whole spirit of working is not attached to the office anymore."* Therefore, organizations will have to be ready for those new demands and consequences of it, managing organizational culture more vertically and horizontally, as questions concerning advocating and performing culture arise, and preserving and cultivating belonging. Moreover, efficiency and sustainability of processes will be of higher focus, allowing people who need human interaction in order to work to have that possibility without them feeling the pressure to conform (I4; I11). I4 confirms *"the human touch [of business] will also change,"* meaning human and non-human agency will have to develop concurrently.

5. Discussion

Throughout this thesis, the aim has been to analyze the changes in the role of leadership in the new normal. Concurrently with theoretical discussion, as pragmatists we believe that research is only valuable when it carries practical implications. Therefore, this section discusses the gaps outlined in the literature review performed in the context of our findings, and continues as a broader discussion on managerial implications for future business management practices.

5.1 Theoretical Implications

Taking process management as a starting point for our thesis, the aim was to understand the nature of processes that can and should be automated, in order to understand the performative role of AI in organizations. This required a deeper analysis of decision-making processes and how they are cognitively constructed. The findings on this area showed complexity of human-to-machine and machine-to-human collaboration in decision-making – but are clearly context-specific. Moving from task automation to process automation carries significant challenges, as any form of classification is subjected to those who create and are affected by said processes.

An interesting academic debate could be established regarding our definition that was constructed through primary data – Artificial Intelligence is defined in this thesis as a *combination of various programs or algorithms that facilitate* ***human-like processes*** *that are able to work seamlessly and interactively with other agents and have cognitive skills, meaning AI is both artificial and intelligent. The cognitive skills that AI is currently able to perform are reasoning, learning and self-correction*. Nevertheless, comparing and contrasting this definition to our primary data and previous academic discussions, one could simply make an argument that as humans are flawed in their bounded rationality and are nearly never as rational as economic reasoning claims, and further, whilst knowing that inherent bias, created by our own subjective experiences and background, exists, we should not be creating or subjecting intelligent systems to the same substandard. Human agency, however, is bound to do that – we see this tendency in decision-making, specifically when we refer to AI in calculative decision-making processes, and this further, trickles down to transparency and trust. We are not claiming that AI inherently carries bias – but rather that the data sets it is trained on can easily be. Lack of understanding on how human-driven processes and machine-driven processes can collaboratively coexist complicates adoption and increases friction in organizational change.

AI does not, and perhaps should not be designed deliberately to act as a human, but rather build on a concept in Machine Learning: Human-In-The-Loop (hereinafter HITL). HITL refers to the process in Machine Learning where certain input and output measures and KPIs are clearly defined, and a confidence rate is set – meaning human agency deciding when in the process to intervene – and through this process, the algorithm continues learning. This concept has been used to *frame* certain aspects of automation to include span of control. A theoretical approach could be taken here as to *reframe* complex technology as machine-in-the-loop when preparing for organizational change, in order to lower irrationality and independence of decision-making. It is clear from data and previous research that optimal outcomes for efficiency and productivity can only be gained when human and non-human agency intertwine.

In essence, it all comes down to design – designing organizational structures, processes, human and non-human collaboration and intelligent systems. Turing's (1950) test for intelligent systems is as valid today as it was more than half a century ago, but design of intelligent systems cannot be done purely in academic silos. In either supervised or unsupervised learning models, organizations must specify what constitutes *acting and thinking rationally and humanly* in context-specific organizational settings – and this is where academic discipline has to improve. AI is designed as a superior agent in computing and rule-based situations, yet it takes the *humanness* of any organization to find meaning behind data. Cognitive Tabula rasa also applies to intelligent systems – and organizations must find the contingencies to organizational productivity that lead to operational success.

Furthermore, collaboration is not a modular process, and requires active management, and we see from our primary data that collaboration means various things to different people, and comes in many forms. Intelligent systems may not need to be designed with humanness in mind, but Artificial Intelligence needs to be humanized to an extent, or framed as such. Designing shared context, be it organizational goals of productivity output could lead to a higher engagement rate through collaboration, but requires further academic research. Industry 5.0 will be the core driver for this, and as discussed, organizations must incorporate proactive procedures.

Transparency, as seen, further broadens the discussion. Through primary data, two tendencies were clear – firstly, AI is not a passive agency that is subjected to transparency, but also *is* inherently transparent, and *creates* transparency. We refer to this notion as *transparency of reality* and can deduct from primary data that whilst designing processes is crucial, transparency as a construct must be incorporated. Secondly, transparency must be defined and managed as to not fall for the paradox of plenty, creating organizational opacity. It is not nearly enough to rely on past academic work on benefits of transparency while refraining to define it in an organizational setting. Academic discipline has defined the dynamics between transparency and technology as monitoring, control or governance – but fails to leverage AI in an operationalized context. We see through our research that as a non-static construct, the variables that affect it are changing in organizational behavior. Yes, trust is still a crucial element of transparency, but regarding complex intelligent systems, knowledge management and visibility of workflow management are as important, if not more so. We further see that the effect and perception of transparency is gaining momentum for both those who create intelligent systems, and for those who will work with these in the new normal.

Both processes and transparency trickle down to leadership – which for this thesis we have defined as a *socially constructed organizational function that is relational and actively managed and is something we perform and do as opposed to something a leader is.* Leadership discipline is saturated with definitions and perspectives, but there is a significant lack of research regarding these novel challenges leadership must face. The demands on and of leadership are growing, and move away from traditional, trait-based perspectives to collectively constructed, yet the *function* and *role* of leadership in the context of intelligent systems needs further intersubjective analysis. Our primary data highlighted some of these roles and functions – governance, creating and facilitating empowerment and belonging, and responsibility towards the employees and organizational vision.

What is interesting, however, is that we see this role of leadership as truly socially constructed in our primary data – these variables do not only lie in one person or group – but are carried through the organization collectively. We see this even more drastically when we look at our survey respondents – future workforce defines leadership as something that is team-based, supports empowerment and is enacted through all areas of an organization. There is a distinct difference between what leadership is – control function in organizational structure, and what leadership does – which is relational and *distributed*.

5.2 Managerial Implications

One of the biggest challenges companies will face in the shift to new normal is defining these different roles of actors and *framing* these in the context of the organization – and this will require deliberate and designed leadership. Throughout this thesis, the researchers have drawn upon the gaps in literature to emphasize issues that arise from *Intelligences apart*-mentality, and what industry practitioners have to say about the possible solutions. We argue in line with Ghoshal (2005) that no one-size-fits-all framework is possible to ensure the successful integration of AI into an organization, and this thesis is not attempting to provide a conclusive guide – nevertheless, some structural guidelines for a starting point and practice can be highlighted based on our findings. Taking into consideration our aggregated dimensions and how they are inevitably intertwined, in this section we outline best practices, which should be considered temporally and contextually, as best practices are only *best for the situation* they are aimed to address.

I. Know your processes

Not every problem in an organization needs an optimized solution – AI is only as good as the defined outcome, the set goal for the organizational process – and defining the outcome in some instances, is the most difficult task. This in practice requires leadership and various departments to ask themselves *how* various jobs can be broken into tasks and how many of these (repetitive or not) tasks an organization truly needs to automate. Issues of scalability should be taken into consideration, as automation for the sake of automation will be a costly experiment. Knowing the role of AI for the organization, and the role it plays in workflow and process management in decision-making, collaboration and change management, can lead to successful automation.

II. Know your design

Whether it is inhouse design of intelligent systems, design of organizational structure and flows or design of human and non-human agency collaboration, deliberate strategy and action is crucial. In line with process management, intelligent systems need to be incorporated seamlessly for them to *operate* seamlessly. Designing a strategy that allows synergies of multi-agent collaboration will increase organizational preparedness and lower adaption friction. From an operational perspective, scalability is appealing but difficult to obtain – it is critical to assess the quality of datasets, quality of tasks that can be performed, and finally, clear outcomes must be defined. Organizations must analyze all possible use cases for AI and understand how collaboration and communication is performed in the organization. Before an organization can begin to understand *how* to improve process management and performance, one should understand *what* can be improved in the first place – and how it must be framed.

III. Know your (future) employees

Our research highlighted that AI will not take away the humanness of any job – but rather restore that humanness in daily work for many organizations. People are the most valuable asset of the future organization, and a sense of empowerment and belonging is becoming increasingly important for the future workforce. Both upskilling and reskilling are seen as leadership functions that need to be fulfilled, and this consequently allows for shift towards more meaningful tasks that involve creativity and critical thinking. Another function of leadership that needs to be fulfilled is providing vision and developing strong organizational culture. Future leadership functions must not only be agile in terms of current organizational transformation, but also take into consideration the growing demands of future workforce – a workforce that realizes the necessity of working with non-human agents. Finally, utilizing non-human intelligent systems *as employees* that have been hired to perform a specific task or job must be framed as such – there must be transparency in algorithmic processes to encourage collaboration.

IV. Know where you stand

Expectations on leadership may be collective and socially constructed, but leaders must be sensitized to the traits and behaviors expected of them. Our primary data outlined the vast importance of technical knowledge and understanding of the potential of non-human actors. It is no longer enough to be equipped with inter-organizational literacy. Technical knowledge, which does not mean developer or data scientist expertise, but rather as a strategic formulation, actualization and basic mechanisms in which AI operates within, is crucial. Just as if one cannot employ human agency without speaking the same language, leadership cannot expect that from implementing intelligent systems – because their intelligence *is* valuable. Furthermore, transparency in organizations is becoming a more active topic – and just as a non-static concept, transparency must be actively managed through knowledge and open communication.

6. Limitations

This section considers the various limitations of this research, which may become the starting point for future research. The authors wish to address both methodological and theoretical limitations and point out how we aimed to mitigate the effect these limitations had on this research.

6.1 Methodological Limitations

This thesis has been designed with an abductive approach in mind – meaning the researchers accepted the temporality of truth (Glassman & Kang, 2010). Consequently, the results and implications should only be taken as is, at this point in time, as further developments of these constructs and context would require a reevaluation – specifically the technological developments in the field of AI. Interviewees, who act as representatives of the companies that develop the most advanced AI in the market, have predicted the shift to Industry 5.0 happening within the next 5-10 years – yet, this is only, at best, a very educated guess.

This thesis may be subjected to some limitations in regards to data collection and analysis via interviews. The interviews were conducted by an international research team in English, and furthermore, most of the interviewees do not speak English as a mother tongue. This may pose a limitation, as the questions are highly contextual and refer to the interviewees' experience and perceptions of certain aspects of leadership and transparency. Nevertheless, rigorous steps were taken in order to mitigate the bias in interpretation and analysis of the answers – probing questions were asked in situations where clarity was necessary, and all interviewees were given the option to elaborate during and after the interviews were conducted, ensuring transparency. The researchers acknowledge, however, that even though precautions were taken, the possibility of bias regarding vocabulary and perception of context cannot be fully ruled out.

Furthermore, the key focus of this thesis has been on leadership in the *context* of AI – and we have designed this research by interviewing primarily companies that focus on technological or techno-economic advancement of the industry and companies that work with non-technological companies to address the issues of implementation. Furthermore, big multinational companies were selected over smaller disruptive startups, who may have very different perceptions of the future. This however might pose a limitation on our scope and scale, as the narrative of leadership is not necessarily the primary focus of these companies, and a broader variance of different leadership-oriented companies, e.g. education, policy makers, public relations and (e-) commerce may provide more insights. Nevertheless, the companies were selected on two premises: a) companies either in the forefront of AI development or implementation and b) the interviewees were either a leader or part of a team – in essence they do not work in silos in an organizational context.

Another limitation of data collection and analysis that the researchers faced was the complexity of the situation surrounding Covid-19 pandemic. The interviews were rescheduled multiple times putting time and scope pressure on the researchers, meaning some clear decisions of the research design regarding scope and direction had to be made and maintained, and thus some theoretical considerations had to be excluded. This further meant that we had to also rely on secondary data in the form of trade reports and managerial literature on best practices. This limitation however was seen as an opportunity to clearly define the theoretical realm in which we work in, and exclude considerations that we deem as influential – but not of primary focus.

The primary data collected and analyzed by the researchers in the form of a comprehensive survey has limitations of both the geographical location as well as size of the sample – out of the 139 people who responded, 120 completed the full survey and 95 percent currently live in Europe, making the answers possibly Eurocentric. This may pose a limitation to the perceptions of what the future workforce considers important in the context of leadership and these results may vary significantly if this research was to be conducted in e.g. Asia or North America. The researchers however have excluded this cultural notion from analysis and focused on the broader context of leadership, taking an industry perspective, rather than country paradigm. The reasoning for this decision includes multiple variables: a) context matters, but technology, including AI in the form in which it is today, can affect, but is not subjected to culture, as it is only as intelligent as the data sets it uses to train itself, b) higher focus on the generation rather than place of residence of people who will join a global workforce within the next few years, of which 56.6 percent believe that intelligent systems will be the core of business in the near future – meaning that the understanding of leadership is grounded in the development of technology rather than culture and c) country of origin and in that regards, the national culture of future workforce is (or should ethically be) irrelevant for hiring companies.

Finally, regarding the applicability of our findings, despite all efforts to triangulate our data through multiple sources and a variety of company representatives we interviewed, in line with Ghoshal (2005), we cannot claim that our findings are generalizable. In order to test our results and generate further research to achieve generalizable results, multiple case studies across industries and company life-cycles must be conducted, and it is necessary to seek examples in great academic rigor.

6.2 Theoretical Limitations

In addition to the abovementioned limitations, the authors wish to address some theoretical limitations concerning our delimitations and theoretical lenses.

Building on the academic body of literature, and lack thereof, as well as primary data, the researchers have defined the constructs of AI, processes, transparency and leadership, and how these constructs intertwine and relate to each other in an organizational context. A significant gap in literature exists which incorporates the potential and development of AI as an intelligent agent, one that does not carry a static connotation as most technologies inherently do – and by defining these constructs in the context of AI, a limitation of theoretical considerations has prevailed. Our constructs are grounded in our data and are subjected to our interviewees' understanding of reality. There is a possibility of us as researchers carrying over the bias of the interviews – e.g. interviewees indoctrinating company culture in their answers, their perceptions about the future or a narrative related to company life-cycle. Even though this limitation has been kept in mind, it cannot be fully excluded.

Due to the scope and scale of this thesis, the researchers had to focus on the interviewee-driven narrative, reduce the academic complexity of leadership to fit the premise of this paper and exclude other theoretical realms e.g. identity, culture and innovation – which is a limitation of its own. Furthermore, the authors have aimed to theorize with AI agency through a cognitive classification, highlighting its anthropomorphic nature, but acknowledge that this classification is limited in its nature – and is highly driven by *temporality*. Multiple factors can affect this topic in a short time period e.g. legislative changes or break-through innovation.

However, this can provide a stepping-stone for future research, one that these authors were unable to conduct in this scale and scope. The interplay of identity in technological revolution is a potentially contested study, if AI agency is framed as a form of singularity, a threat to jobs or as a super-human. Culture, as mentioned, could possibly affect how leadership functions or attitudes towards transparency are defined in non-European countries, and innovation management could place a much higher focus on knowledge management processes in an organization.

7. Conclusion

This thesis as set out to answer the following research question: ***How will Artificial Intelligence impact the role of leadership in the new normal?*** This research question focuses on the novel techno-economic solutions that are causing a shift from Industry 4.0 towards Industry 5.0 – from *Intelligences Apart* towards a seamless corporation of the humanness of business and Artificial Intelligence – and the practical implications it carries for leadership.

It did so by reviewing the existing academic literature and designing a mixed-method research, and through iterative abductive methodology and taking an explanatory as well as exploratory perspective, grounded our conceptualizations in primary data in the form of qualitative interviews with industry leaders and practitioners, as well as a survey answered by current and future workforce. This conceptualization was necessary, as organizations deal with and face high level of complexity, and constructs such as leadership and transparency in organizations carries a multitude of connotations – and further, no comprehensive academic literature on the notion of intelligent techno-economic systems and their effects on leadership currently exist.

Four sub-questions were formulated in order to help the researchers approach this subject in a structured and collectively exhaustive manner.

The first sub-question to aid us was: *How do business practitioners define Artificial Intelligence and its processes, and what are the costs and benefits of its implementation?* Our primary data underlined that much like concepts of leadership and transparency, understanding of AI – even by those who actively develop and implement this technology on a daily basis – varies. Importance was placed on distinction between AI applications that require structured or unstructured data, and supervised or unsupervised data. As our focus lied on AI in the organizational context, we built our definition of AI concurrently with primary data and defined the techno-economic solution as *combination of various programs or algorithms that facilitate human-like processes that are able to work seamlessly and interactively with other agents and have cognitive skills, meaning AI is both artificial and intelligent. The cognitive skills that AI is currently able to perform are reasoning, learning and self-correction*. This allowed u to take a process-based view of its applications and potential – and core processes that surfaced through data were decision-making, collaboration and change management.

The benefits of implementing AI were vast – productivity gains through automation, scalable business practices, cost-cutting, data-driven decision-making, division of cognitive labor and utilization of higher computing capabilities – but more interestingly, as discussion took an internalized perspective, empowerment, collaboration and agility were seen as long-term benefits. This reflects on the nature of our research – non-human actors are at a development stage where they *do* play an incremental role in organizational culture.

The costs however focused mainly on cognitive and systematic bias that is present in multiple forms. Firstly, as there is a certain level of human oversight and training involved, there is the potential of inducing bias into datasets and algorithms, and carrying over past experiences and behavior of human agency. Secondly, this bias, regardless whether it exists in the algorithm or dataset or not, affects organizational change and decision-making of human agency. AI stands is an odd place in an organization – human agency does not have the technical knowledge of how this solution works *behind the scenes*, yet equates its cognitive abilities and potential to that of human agency. Other costs exist as well: detrimental effects on organizational culture through lack of proper knowledge management, issues related to trust and transparency, and wasteful resource management in situations of no product-organization fit.

The second sub-question we focused on was: *How does AI affect transparency in the workplace?* The academic debate on the structure and tendencies of transparency were contested and divided in its nature – therefore we proposed to see transparency not only as something static that exists in organizations, but as a construct that must be actively managed – *transparency of reality*. Primary data outlined that AI and transparency interact as concepts and non-human agency integrates into both cognitive and strategic organizational identity and culture through the notions of visibility and trust. Trust, or the lack thereof, however is highly contingent on how knowledge is obtained, managed and shared in an organization.

Yet, a paradox of transparency emerges – by creating an open and sharing-oriented knowledge management, AI in its complexity has the opposite effect – and creates opacity in organizations, which leads to complexity in trust for them due to the lack of technological maturity of organizations and lack of knowledge. AI further involves the inclusion of non-organizational actors, such as governments, public servants and policy makers and AI-transparency paradigm calls for more communication. Therefore, it is clear that AI creates this transparency through automation of processes, is transparent as a tool for organizations, and most importantly, is subjected to transparency in organizational structures and culture. Nevertheless, all the sides of this notion must be actively managed.

The third question we aimed to answer was: *How will the combination of technology and leadership affect decision-making in the organization?* Key observations for this question include two topics – framing and design. Primary data showed that framing solutions and problems in a specific manner is highly important for success and collaboration. Framing collaboration in a form of non-human and human agency working together as opposed to purely using AI as a tool benefits the cultivation of an agile organizational culture, increasing trust and transparency in decision-making. Process of cooperation can only ensue if the groundwork for this is established.

Therefore, the fit between technology, organizational culture and strategy must be designed, planned and managed in a coherent fashion. There must be an aligned understanding of capabilities AI has in cognitive processes – as well as the limitation human agency possesses. Moving towards a data-driven decision-making process, leadership can leverage on the humanness of business and create opportunities for creativity, critical thinking and cognitively complex strategic tasks to be placed in a higher priority. Technology and humanness, hand in hand will require organizational structures to change – but change must be triggered. This will affect not only how decisions are made, but also what types of decisions become important in future workplace.

The fourth and last question we asked was: *How do employees define the future of the workplace?* This question carries gravitas as organizations do not work in silos – there is an inbound and outbound flow of employees who have growing expectations on their future workplace. Much like Industry 4.0 brought a higher focus on organizational culture and identity, future workforce a*t this point in time* value empowerment, flexibility, team-based collaboration, reliability and knowledge in their workplace. The responsibility to provide and nurture this falls onto leadership. Furthermore, it is clear that the majority of future workforce places a great deal of importance on technological development, and expect AI to be one of the defining variables of the next decade. The challenge lies in building seamless collaboration.

Industry 5.0 is inevitable – and the role of leadership must adapt. Our research has outlined various functions and roles of leadership and why they must emerge in the realm of Artificial Intelligence – and specifically how these functions and roles of leadership are socially constructed. It is worth noting, that the focus of socially constructed leadership includes both human and non-human agency.

Primary data showed that some functionalities of leadership, such as governance are still highly important, yet the notion of what governance means, is changing. Leadership is co-evolving within the organizational culture, and is contingent to the context in which an organization operates in. In the context of AI, higher focus has been placed on functions such as onboarding and designing the workforce, knowledge management, work-learning, creating and managing transparency, managing agility and change as well as collaboration and communication. It is however interesting that these functions of leadership do not lie solely in one individual, nor even human agency, but leadership is contextually distributed, taking a network-of-people perspective. Organizational actors are no longer trait-based leaders, but rather must be contextually sensitized to traits needed for successful outcomes of those processes and roles – such as technical literacy.

The theoretical definition of leadership may be ambiguous – but practical implications cannot be. *The role of AI* in the organization through process and workflow automation must be contingent to the tendencies of *transparency*. These notions, taking human and non-human agency as two sides of the same coin, collaborating seamlessly through leveraging and framing dynamic processes such as decision-making and context will impact the *role of leadership* in the new normal.

AI *will* be the defining characteristic of the following decade, of the new normal – and it will be remembered by the humanness it brought back to the organizations – and not as a dystopian threat – it will be a companion in collaboration rather than a static tool – and perhaps even challenge the dictionary definition of process, collaboration, transparency and leadership.

8. Bibliography

Albu, O.B., & Flyverbom, M. (2016). Organizational transparency: Conceptualizations, conditions, and consequences. *Business & Society, 58*(2), 268-297.

AlDahdouh, A.A. (2017). Does artificial neural network support connectivism's assumptions? *International Journal of Instructional Technology and Distance Learning, 14*(3).

Antonakis, J., & Day, D.V. (2017). Chapter 1: Past, present, and future. In J. Antonakis, & D. V. Day (Eds.). *The nature of leadership* (3rd ed., pp.3-25). Sage Publications.

Ariely, D. (2010). *The upside of irrationality: The unexpected benefits of defying logic at work and at home.* New York, NY: Harper.

Baker, J.P. (2013). Leadership theories and approaches. In D. Bhugra, P. Ruiz, & G. Susham (Eds). *Leadership in psychiatry* (pp.49-62). Chichester, England: John Wiley & Sons, Ltd.

Bayati, M. (2019). AI in consulting. Haaga-Helia ammattikorkeakoulu.

Berger, P.L., & Luckmann, T. (1966). Origins of institutionalization. In P. L. Berger, & T. Luckmann. *The social construction of reality: A treatise in the sociology* (pp.70-85). London, England: Penguin Books Ltd,.

Bernstein, E.S. (2012). The transparency paradox: A role for privacy in organizational learning and operational control. *Administrative Science Quarterly*, *57*(2), 181-216.

Biddle, C., & Schafft, K. (2014). Axiology and anomaly in the practice of mixed methods work: Pragmatism, valuation, and the transformative paradigm. *Journal of Mixed Methods Research*, *9*(1).

Björkman, I., & Johansson, S. (2018). What impact will artificial intelligence have on the future leadership role? A study of leaders' expectations. Lund University.

Bonaccio, S., & Dalal, R.S. (2006). Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes, 101*(2), 127-151.

Bono, J.E., Gerhardt, M.W., Judge, T.A., & Ilies, R. (2002). Personality and leadership: A qualitative and quantitative review. *Journal of Applied Psychology, 87*(4), 765-780.

Bradbury, H., & Lichtenstein, B. (2000). Relationality in organizational research: Exploring the space between. *Organization Science 11*(5), 551–564.

Brauneis, R., & Goodman, E. (2018). Algorithmic transparency for the smart city. *Yale Journal of Law & Technology, 20*(103).

Bristow, A., & Saunders, M. (2014). Heightening awareness of research philosophy: The development of a reflexive tool for use with students. *British Academy of Management Conference proceedings.*

Brown, P. (2007). Career coach: Decision-making. *Pulse.*

Bryant, A., & Charmaz, K. (2007). *The Sage handbook of grounded theory.* London, England: Sage.

Bryman, A., & Bell, E. (2011). *Business research methods* (4th ed.).

Burke, R., & Barron, S. (2014). Leadership theories and styles. In R. Burke, & S. Barron (Eds). *Project management leadership: Building creative teams* (2nd ed., pp.81-99). Hoboken, NJ: Wiley.

Burrell, G., & Morgan, G. (2016). *Sociological paradigms and organisational analysis.* Abingdon, England: Routledge (Originally Published By Heinemann 1979).

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society.*

Canbek, M. (2020). Artificial intelligence leadership: Imitating Mintzberg's managerial roles. In A. Özbebek Tunç, & P. Aslan (Eds.). *Business management and communication perspectives in industry 4.0* (pp.173-187).

Carlyle, T. (1840). Lecture 1: The hero as divinity. Odin. Paganism: Scandinavian mythology. *On heroes, hero-worship, and the heroic in history.* Berkeley, CA: University of California Press.

Carroll, B., Levy, L., & Richmond, D. (2008). Leadership as practice: Challenging the competency paradigm. *Leadership, 4*(4), 363-379.

Chamorro-Premuzic, T., Wade, M., & Jordan, J. (2018). As AI makes more decisions, the nature of leadership will change. *Harvard Business Review.* Retrieved from https://hbr.org/2018/01/as-ai-makes-more-decisions-the-nature-of-leadership-will-change

Chander, A., Srinivasan, R., Chelian S., Wang J., & Uchino, K. (2018). Working with beliefs: AI transparency in the enterprise. *Workshops of the ACM conference on intelligent user interfaces.*

Charmaz, K. (2006). *Constructing grounded theory.* London, England: Sage.

Chen, J.C., Procci, K., Boyce, M., Wright, J., Garcia, A., & Barnes, M. (2014). Situation awareness-based agent transparency. Aberdeen Proving Ground: U.S. Army Research Laboratory.

Christensen, C., Hall, T., Dillon, K., & Duncan, D.S. (2016). Know your customers' "jobs to be done". *Harvard Business Review*, September.

Christensen, L.T., Morsing, M., & Thyssen, O. (2009). Polyphony of corporate social responsibility: Deconstructing transparency and accountability and opening for identity or hypocrisy. In G. Cheney, S. May, & D. Munshi. *The handbook of communication ethics* (pp.457-474). Hillsdale, NJ: Lawrence Erlbaum.

Corbin, J., & Strauss, A.L. (2008). *Basics of Qualitative Research.* Thousand Oaks, CA: Sage.

Corley, K.G., & Gioia, D.A. (2011). Building theory about theory building: What constitutes a theoretical contribution? *Academy of Management Review, 36*(1), 12-32.

Crosby, B., & Kiedrowski, J. (2008). Integrative leadership: Observations from a University of Minnesota seminar series. *Integral Leadership Review, 8*(3).

Crotty, M. (1998). *The foundations of social research.* London, England: Sage.

Daft, R.L. (2012). *New era of management* (10th ed.). Mason, OH: South-Western Cengage Learning.

Dewey, J. (1916). *Democracy and education.* New York, NY: Macmillan.

Dhanrajani, S. (2019). AI for CXOs -- Redefining the future of leadership in the AI era. *Forbes.* Retrieved from https://www.forbes.com/sites/cognitiveworld/2019/07/30/ai-for-cxos-redefining-the-future-of-leadership-in-the-ai-era/#7b2edcda2b46

Etzioni, A. (2010). Is transparency the best disinfectant? *Journal of Political Philosophy, 18*(4), 389-404.

Fiedler, F.E. (1964). A contingency model of leadership effectiveness. *Advances in Experimental Social Psychology, 1*, 149-190.

Flyverbom, M., Christensen, L.T., & Hansen, H.K. (2015). The transparency-power nexus: Observational and regularizing control. *Management Communication Quarterly, 29*(3), 385-410.

Francisco, K., & Swanson, D. (2018). The supply chain has no clothes: Technology adoption of blockchain for supply chain transparency. *Logistics 2018, 2*(1), 2.

Franntz, R. (2003). Herbert Simon. Artificial intelligence as a framework for understanding intuition. *The economic psychology of Herbert A. Simon* (pp.265-277).

Frick, K. (2008). How will we decide in the future. In M. Krogerus, & R. Tschäppeler. *The decision book: 50 models for strategic thinking.* London, England: Profile Books Ltd,.

Froese, T., & Ziemke, T. (2009). Enactive artificial intelligence: Investigating the systemic organization of life and mind. *Artificial Intelligence, 173*(3–4), 466-500.

Ghoshal, S. (2005). Bad management theories are destroying good management practices. *Academy of Management Learning & Education, 4*(1), 75–91.

Gioia, D.A., Corley, K.G., & Hamilton, A.L. (2012). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods, 16*, 15–31.

Glaser, B.G., & Strauss, A.L. (1967). *The discovery of grounded theory.* New York, NY: Aldine.

Glassman, M., & Kang, M.J. (2010). Pragmatism, connectionism and the internet: A mind’s perfect storm. *Computers in Human Behavior, 26*(6), 1412-1418.

Graen, G., & Uhl-Bien M. (1995). Relationship-based approach to leadership: Development of leader-member exchange (LMX) theory of leadership over 25 years: Applying a multi-level multi-domain perspective. *The Leadership Quarterly, 6*(2), 219–247.

Gray, B. (1985). Conditions facilitating interorganizational collaboration. *Human Relations, 38*(10), 911–936.

Gray, D.E. (2014). *Doing research in the real world* (3rd ed.).

Gray, S.J., & Kang, H. (2014). Accounting transparency and international standard-setting. In J. Forssbaeck, & Oxelheim. *The Oxford handbook of economic and institutional transparency* (pp.456-476). Oxford, England: Oxford University Press.

Griffin, E.A. (1991). Interact system model of decision emergence of B. Aubrey Fisher. *A first look at communication theory* (1st ed., pp.253-262). New York, NY: Mcgraw-Hill.

Grint, K. (2005). Problems, problems, problems: The social construction of 'leadership.'. *Human Relations, 58*(11), 1467–1494.

Guba, E.G., & Lincoln, Y.S. (1989). *Fourth generation evaluation.* Newbury Park, CA: Sage.

Guo, K.L. (2008). Decide: A decision-making model for more effective decision making by health care managers. *The Health Care Manager, 27*(2), 118–127.

Hansen, H.K., Christensen, L.T., & Flyverbom, M. (2015). Introduction: Logics of transparency in late modernity: Paradoxes, mediation and governance. *European Journal of Social Theory, 18*(2), 117-131.

Harvey, P., Reeves, M., & Ruppert, E. (2012). Anticipating failure: Transparency devices and their effects. *Journal of Cultural Economy, 6*(3), 294-312.

Hernes, T. (2014). *A process theory of organization* (ch.3). Oxford, England: Oxford University Press (Ch. 3).

Hogg, M.A. (2005). Social identity and leadership. In D. M. Messick, & R. M. Kramer (Eds.). *The psychology of leadership: New perspectives and research* (pp.53-80). Mahwah, NJ: Lawrence Erlbaum Associates Inc.

Hollander, E.P. (1992). Leadership, followership, self, and others. *The Leadership Quarterly, 3*(1), 43-54.

Hollander, E.P., & Offermann, L.R. (1990). Power and leadership in organizations: Relationships in transition. *American Psychologist, 45*(2), 179-189.

Hook, S. (1943). *The hero in history: A study in limitation and possibility.* London, England: Martin Secker & Warburg, Ltd.

Hosking D.M., Dachler H.P., & Gergen K.J. (Eds.). (1995). *Management and organization: Relational alternatives to individualism* (pp.1-29). Aldershot, England: Avebury/Ashgate Publishing Co.

HubSpot. (2020). Artificial intelligence is here – People just don't realize it. – An, M. Retrieved from https://blog.hubspot.com/marketing/artificial-intelligence-is-here

Hyacinth, B.T. (2017). *The future of leadership: Rise of automation, robotics, and artificial intelligence.* MBA Caribbean Organisation.

Iyer, R., Li, Y., Li, H., Lewis, M., Sundar, R., & Sycara, K. (2018). Transparency and explanation in deep reinforcement learning neural networks. *In proceedings of the 2018 AAAI/ACM conference on AI, ethics, and society (AIES '18). Association for computing machinery* (pp.144–150.). New York, NY.

Jago, A.G. (1982). Leadership: Perspectives in theory and research. *Management of Science, 28*(3), 315-336.

Jermier, J.M. (1993). Introduction: Charismatic leadership: Neo-weberian perspectives. *The Leadership Quarterly, 4*(3-4), 217–233.

Kelemen, M., & Rumens, N. (2008). *An introduction to critical management research.* London, England: Sage.

Khan, Z.A., Nawaz, A., & Khan, I. (2016). Leadership theories and styles: A literature review. *Journal of Resources Development and Management, 16.*

Kolbjørnsrud, V., Amico, R., & Thomas, R.J. (2016). Leadership development: How artificial intelligence will redefine management. *Harvard Business Review,* 1 - 6.

Kramer, R.M., & Lewicki, R.J. (2010). Repairing and enhancing trust: Approaches to reducing organizational trust deficits. *Academy of Management Annals, 4*(1), 245-277.

Langley, A., & Abdallah, C. (2011). Templates and turns in qualitative studies of strategy and management. *Research Methodology in Strategy and Management, 6*, 201–235.

Latour, B. (1990). Technology is society made durable. *The Sociological Review, 38*(S1), 103-131.

Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. *Journal of Family Medicine and Primary Care, 4*(3), 324.

Libert, B., Beck, M., & Bonchek, M. (2017). AI in the boardroom: The next realm of corporate governance. *MIT Sloan Management Review.*

Licht, K.F., & Licht, J.F. (2020). Artificial intelligence, transparency, and public decision making – Why explanations are key when trying to produce perceived legitimacy. *AI & Society.*

Liebowitz, J. (2014). *Bursting the big data bubble: The case for intuition-based decision making.* CRC Press.

Lønning, A.P., & Kallstad, E. (2019). An investigation of artificial intelligence in the marketplace – A multiple case study: How does the interplay between AI, management and organization impact the implementation of AI-driven solutions? Copenhagen Business School.

Lyons, J. (2013). Being transparent about transparency: A model for human-robot interaction. *AAAI spring symposium series.* North America.

Maccoby, M. (2004). Narcissistic leaders: The incredible pros and inevitable cons. *Harvard Business Review,* 1 - 11.

Machine Intelligence Research Institute. (2014). The ethics of artificial intelligence. *The Cambridge handbook of artificial intelligence.* Cambridge University Press.

Mayer, R.C., Davis, J.H., & Schoorman, F.D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709-734.

McAfee, A., & Brynjolfsson, E. (2012). Big data's management revolution. *Harvard Business Review*.

Merriam-Webster. (2020). Collaboration, https://www.merriamwebster.com/dictionary/collaboration, [accessed may 2020].

Merriam-Webster. (2020). Leadership, https://www.merriamwebster.com/dictionary/leadership, [accessed may 2020].

Merriam-Webster. (2020). Process, https://www.merriamwebster.com/dictionary/process, [accessed may 2020].

Miles, M.B., & Huberman, A.M. (1994). *Qualitative data analysis: An expanded sourcebook.* Thousand Oaks, CA: Sage Publications.

Miranda, J.M., & Aldea, A. (2005). Emotions in human and artificial intelligence. *Computers in Human Behavior, 21*(2), 323-341.

Mitchell, T.R., Biglan, A., Oncken, G.R., & Fiedler, F.E. (2017). The contingency model: Criticism and suggestions. *The Academy of Management Journal, 13*(3), 253-267.

Müller, R., & Turner, R. (2010). Leadership competency profiles of successful project managers. *International Journal of Project Management, 28*(5), 437-448.

Myers, K.L., & Berry, P.M. (1999). At the boundary of workflow and AI. *Workshop on agent-based systems in the business context held as part of AAAI.* Orlando, FL

Natasi, B.K., Hitchcock, J.H., & Brown, L.M. (2010). An inclusive framework for conceptualizing mixed method typologies. In A. Tashakkori, & C. Teddlie. *The Sage handbook of mixed methods in social and behavioural research* (2nd ed.). Thousand Oaks, CA: Sage.

Nixon, P., & Johansson, H. (1999). Transparency through technology: The internet and political parties. In B. N. Hague, & B. D. Loader (Eds.). *Digital democracy: Discourse and decision making in the information age.* Abingdon, England: Routledge.

Oke, S.A. (2008). A literature review on artificial intelligence. *International Journal of Information and Management Sciences, 19*(4), 535-570.

Ospina, S., & Foldy, E. (2010). Building bridges from the margins: The work of leadership in social change organizations. *The Leadership Quarterly, 21*, 292-307.

Patton, M.Q. (2002). *Qualitative evaluation and research methods* (3rd ed.). Newbury Park, CA: Sage Publications.

Pearce, C.L., & Manz, C.C. (2005). The new silver bullets of leadership: The importance of self- and shared leadership in knowledge work. *Organizational Dynamics, 34*(2), 130–140.

Peirce, C.S. (1934). Vol. 5: Pragmatism and pragmaticism. In C. Hartshorne, & P. Weiss (Eds.). *Collected papers of Charles Sanders Peirce.* Cambridge, MA: Harvard University Press.

Pfleeger, S.L. (2014). Technology, transparency, and trust. *IEEE Security & Privacy, 12*(6), 3-5.

Power, M. (1996). Making things auditable. *Accounting, Organizations and Society, 21*(2-3), 289-315.

Ramaswamy, S. (2017). How companies are already using AI. *Harvard Business Review,* April.

Russell, S.J., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Upper Saddle River, NJ: Pearson/Prentice Hall.

Russell, S.J., & Norvig, P. (1995). *Artificial intelligence: A modern approach.* Upper Saddle River, NJ: Pearson/Prentice Hall.

Sanders, R. (2017). Book review. In B. T. Hyacinth. *The future of leadership: Rise of automation, robotics, and artificial intelligence.* MBA Caribbean Organisation.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students* (7th ed.). Harlow, England: Pearson Ltd.

Schildt, H. (2017). Big data and organizational design – The brave new world of algorithmic management and computer augmented transparency. *Innovation, 19*(1), 23-30.

Schmitz, H.P., Raggo, P., & Bruno-van Vijfeijken, T. (2012). Accountability of transnational ngos: Aspirations vs. practice. *Nonprofit and Voluntary Sector Quarterly, 41*(6), 1175-1194.

Schnackenberg, A.K., & Tomlinson, E.C. (2014). Organizational transparency: A new perspective on managing trust in organization – Stakeholder relationships. *Journal of Management, 42*(7), 1784–1810.

Scott, S. (2009). *Fierce leadership: A bold alternative to the worst "best" practices of business today.* New York, NY: Broadway Business.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach.* Chichester, England: John Wiley & Sons, Ltd.

Shanahan, M. (2015). *The technological singularity.* MIT Press.

Shepherd, N., & Rudd, J. (2013). The influence of context on the strategic decision-making process: A review of the literature. *International Journal of Management Reviews, 16*(3).

Silverman, D. (2006). *Interpreting qualitative data* (3rd ed.). London, England: Sage.

Simon, H.A. (1982). *Models of bounded rationality.* Cambridge, MA: MIT Press.

Smythe, E., & Smith, P.J. (2006). Legitimacy, transparency, and information technology: The world trade organization in an era of contentious trade politics. *Global Governance: A Review of Multilateralism and International Organizations, 12*(1), 31–53.

Soh, Christina & Markus, M., & Goh, Kim. (2006). Electronic marketplaces and price transparency: Strategy, information technology, and success. *MIS Quarterly, 30,* 705-723.

Stogdill, R.M. (1948). Personal factors associated with leadership: A survey of literature. *The Journal of Psychology, 25*, 35-71.

Stogdill, R.M. (1974). *Handbook of leadership: A survey of theory and research.* New York, NY: Free Press.

Strathern, M. (2000). The tyranny of transparency. *British Educational Research Journal, 26*(3), 309-321.

Suddaby, R. (2006). From the editors: What grounded theory is not. *Academy of Management Journal, 49*(4), 633–42.

Tapscott, D. (2014). *The digital economy: Rethinking promise and peril in the age of networked intelligence* (Anniversary ed.). New York, NY: Mcgraw-Hill.

Tapscott, D., & Ticoll, D. (2003). *The naked corporation: How the age of transparency will revolutionize business.* New York, NY: Free Press.

Tashakkori, A., & Teddlie, C. (2010). *The Sage handbook of mixed methods in social and behavioural research* (2nd ed.). Thousand Oaks, CA: Sage.

Theodorou, A., Wortham, R.H., & Bryson, J.J. (2017). Designing and implementing transparency for real time inspection of autonomous robots. *Connection Science, 29*(3), 230-241.

Timmermans, S., & Tavory, I. (2012). Theory construction in qualitative research: From grounded theory to abductive analysis. *Sociological Theory, 30*(3), 167-186.

Turing, A.M. (1950). Computing machinery and intelligence. *Mind, 59*, 433–460.

Uhl-Bien, M. (2006). Relational leadership theory: Exploring the social processes of leadership and organizing. *The Leadership Quarterly, 17*(6), 654-676.

Vescovi, J. (2018). Artificial intelligence big data and the human mind: A study on the effects of new technologies on students' decision-making process. Copenhagen Business School.

Wallace, M., & Wray, A. (2011). *Critical reading and writing for postgraduates* (2nd ed.). Sage.

Watson, J.T. (2011). Ethnography, reality, and truth: The vital need for studies of 'how things work' in organizations and management. *Journal of Management Studies, 48*(1), 202-217.

Winston, B.E., & Patterson, K. (2006). An integrative definition of leadership. *International Journal of Leadership Studies, 1*(2), 6-66.

Wortham, R.H., Theodorou, A., & Bryson, J.J. (2016). What does the robot think? Transparency as a fundamental design requirement for intelligent systems. *In proceedings of the IJCAI workshop on ethics for artificial intelligence: International joint conference on artificial intelligence.* New York, NY.

Zaccaro, S.J. (2007). Trait-based perspectives of leadership. *American Psychologist*, *62*(1), 6-16.

Zerilli, J., Knott, A., Maclaurin, J., & Gavaghan, C. (2018). Transparency in algorithmic and human decision-making: Is there a double standard? *Philosophy & Technology*.

9. Appendix

1. Interview Guide: Companies

Background questions

1. What is your role and background in the company?
2. What is the main responsibility and function of your department in the context of the organization? Who or which actors do you support/interact with across the organization/external to your department? What do you perceive your main organizational role to be and what are your expected requirements of tools for delivering on this role?
3. To what extent is your company (and you) using AI in daily operations?

Questions related to leadership:

1. How would you describe the leadership style in your company / department?
    1. Would you say it is leader driven or group/team driven?
    2. Is it based on the carrot and stick method or empowerment?
    3. Would you say the leadership style is transparent?
2. Have you noticed a modification of leadership approach over the years?
    1. If yes, why do you think it has happened?
3. Has technology impacted your leadership role/ the role of leadership in your company?
    1. If yes, what technology has had the most impact?
    2. How did it impact it?

Questions related to AI:

1. How would you define the concept of “Artificial Intelligence”?
2. How does your company use modern technologies to facilitate work? How do you use AI in your daily work?
3. In your opinion, are the transitions to newer technologies smooth or face some obstacles?
4. In your opinion, what kind of advantages and synergies will the development of AI bring to the workplace?

5. In your opinion, what kind of disadvantages will the development of AI bring to the workplace?
6. Do you believe that the development of AI will have more positive or negative influence on the processes of companies and leadership?

Questions related to future expectations

1. What do you believe will be the biggest challenges for the leaders in the future workplace?
2. Do you think that the increasing incorporation of new technologies e.g. AI will have an influence on future leadership styles? How do you imagine these will change?
3. Do you think your company is good at preparing for the demands and opportunities of the future workplace? How?
4. Would you say that your company is preparing its leaders for the changes in the leadership approach?

2. Interview Guide: Consultants

Background questions

1. What is your role and background in the company?
2. What is the main responsibility and function of your department in the context of the organization? Who or which actors do you support/interact with across the organization/external to your department? What do you perceive your main organizational role to be and what are your expected requirements of tools for delivering on this role?
3. To what extent is your company (and you) using AI in daily operations?

Questions related to AI:

1. How would you define the concept of “Artificial Intelligence”?
2. In your opinion, are the transitions to newer technologies smooth or face some obstacles- specifically in the industries you work in?
3. In your opinion, what kind of advantages and synergies will the development of AI bring to the workplace- specifically in the industries you work in?

4. In your opinion, what kind of disadvantages will the development of AI bring to the workplace?
5. Do you believe that the development of AI will have more positive or negative influence on the processes of companies and leadership?

Questions related to the leadership:

1. How would you describe the leadership style in companies that have transitioned to using AI? (top-down/bottom- up / is it transparent)
2. Where do you see the challenges and opportunities for future leaders? For future workforce?
3. What are the processes that need to change when we talk about leadership in companies?
    1. Have you noticed a change of leadership approach/style over the years?

Questions related to the expectations of the future:

4. Do you think that the increasing incorporation of new technologies e.g. AI will have an influence on future leadership styles? How do you imagine these will change?
5. Do you think your organization is good at predicting and preparing for the demands and opportunities of the future technologies? How? Do you think your company is good at predicting the future trends and needs?
6. In your opinion, is your company preparing its workers for the changes in their leadership approach?
7. Regarding the popularity of AI and technological agility in various industries, where do you see leadership processes heading towards in the next 10 years?
8. Do you think transparency in company processes will be affected by implementing AI into management of internal activities? How?
9. Based on your experience, do you think the combination of AI and leadership will affect decision-making in the organization in the future? How?

3. Survey Questions & Design

Q1: What is your age group?

Q2: What is your gender?

Q3: What region do you currently live in?

Q4: What is your education level?

Q5: How long to or from graduating are you?

Q6: What is your profession?

Q7: How do you rank your knowledge of Artificial Intelligence and its usage?

Q8: How do you rank the benefits of Artificial Intelligence for businesses?

Q9: What comes to your mind when you think about Artificial Intelligence?

Q10: How much will the development and usage of AI influence the workplace of the future?

Q11: How do you think using AI will influence the transparency of business processes?

Q12: How do you think using AI will influence the transparency of business processes?

Intelligent systems include the broad umbrella of AI. As a member of future workforce:

- I would trust an intelligent system to monitor my work processes
- I would be comfortable with an intelligent system automating my work processes
- I would trust an intelligent system to evaluate my work
- I would trust the advice of an intelligent system for making business decisions in the future
- I would trust leadership that incorporates intelligent systems into decision-making
- I believe intelligent systems will be the core of business in the near future
- I want to work in an environment that incorporates intelligent systems
- The idea of optimizing artificial intelligence in my daily work excites me
- I would expect leadership of my future workplace to be open to intelligent systems
- I use intelligent systems daily
- The idea of using intelligent systems in my daily life makes me uncomfortable
- I trust technology
- I believe that the development of AI will have a positive influence on the processes of companies and leadership
- I feel prepared for a work future that incorporates intelligent systems

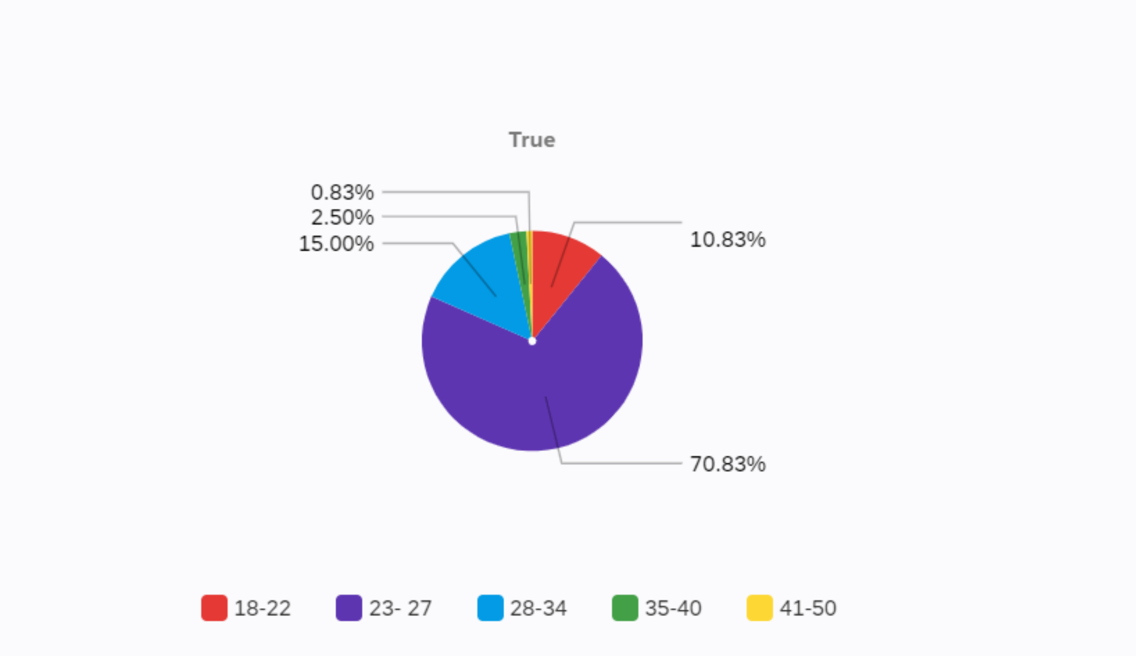
Q13: What is important to you in leadership? (Max 3)

Q14: What skill do you think will the future workforce need the most? (Max 3)

Q15: What expectations do you have for future companies and leaders?

4. Survey Results

Q1 - What is your age group?



#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	5.00	2.12	0.65	0.42	120

#	Field	True		Total
1	18-22	100.00%	13	13
2	23- 27	100.00%	85	85
3	28-34	100.00%	18	18
4	35-40	100.00%	3	3
5	41-50	100.00%	1	1

Q2 - What is your gender?

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	5.00	1.57	0.59	0.35	120

#	Field	True		Total
1	Male	100.00%	55	55
2	Female	100.00%	64	64
5	Other	100.00%	1	1

Showing rows 1 - 3 of 3

Q3 - What region do you currently live in?

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	8.00	1.18	1.01	1.02	120

#	Field	True		Total
1	Europe	100.00%	115	115
2	North America	100.00%	1	1
3	South America	100.00%	1	1
7	Africa	100.00%	2	2
8	Oceania	100.00%	1	1

Showing rows 1 - 5 of 5

Q4 - What is your education level?

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	7.00	3.77	1.03	1.06	120

#	Field	True		Total
1	Completed High School or less	100.00%	6	6
2	Currently studying Undergraduate Program	100.00%	10	10
3	Completed Undergraduate Program	100.00%	10	10
4	Currently studying Graduate Program	100.00%	76	76
5	Completed Graduate Program	100.00%	16	16
6	Completed a PhD degree or above	100.00%	1	1
7	Other	100.00%	1	1

Showing rows 1 - 7 of 7

Q5 - How long to or from graduating are you?

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	5.00	2.32	0.91	0.83	120

#	Field	True		Total
1	I will graduate and join workforce within next 5 years or more	100.00%	10	10
2	I will graduate and join workforce within next 2 years	100.00%	81	81
3	I have graduated and joined workforce within last 2 years	100.00%	18	18
4	I have graduated and joined workforce within last 5 years	100.00%	3	3
5	I have graduated and joined workforce over 5 years ago	100.00%	8	8

Showing rows 1 - 5 of 5

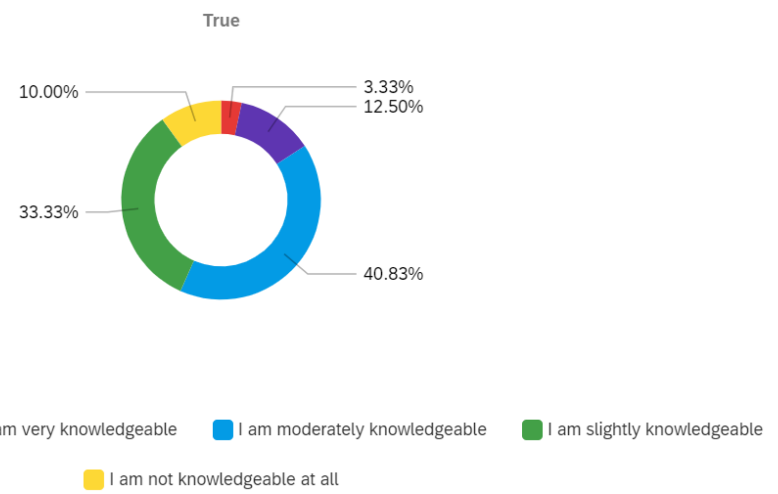
Q6 - What is your profession?

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	4.00	1.63	0.91	0.83	120

#	Field	True		Total
1	Student	100.00%	77	77
2	Part-time employee	100.00%	13	13
3	Full-time employee	100.00%	27	27
4	Unemployed	100.00%	3	3

Showing rows 1 - 4 of 4

Q7 - How do you rank your knowledge of Artificial Intelligence and its usage?

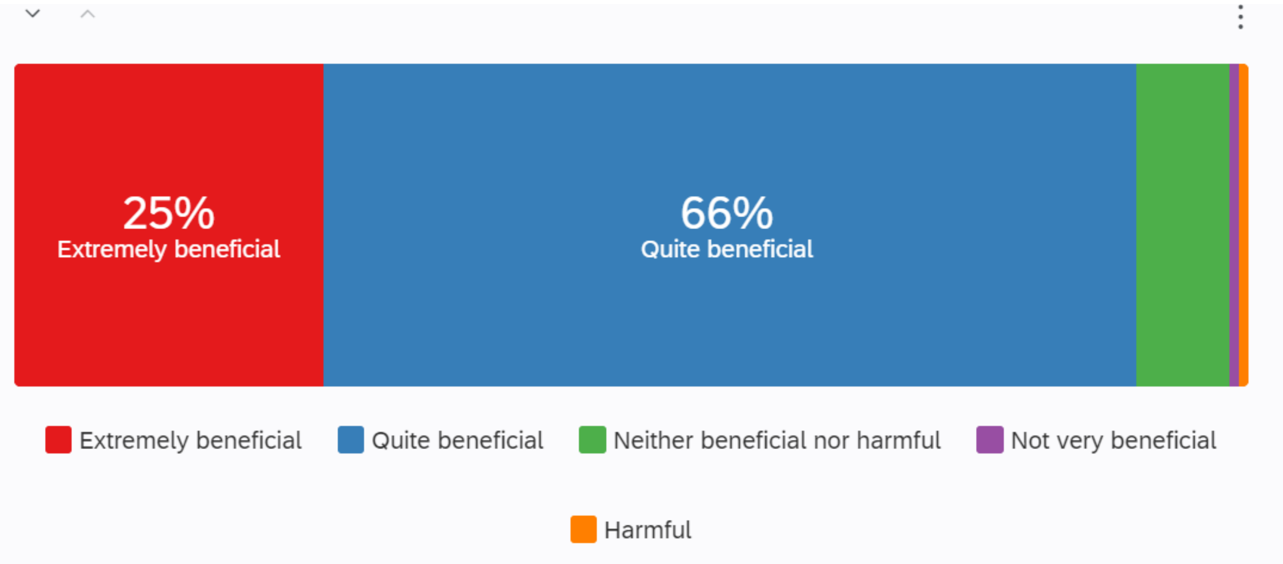


#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	5.00	3.34	0.94	0.87	120

#	Field	True		Total
1	I am extremely knowledgeable	100.00%	4	4
2	I am very knowledgeable	100.00%	15	15
3	I am moderately knowledgeable	100.00%	49	49
4	I am slightly knowledgeable	100.00%	40	40
5	I am not knowledgeable at all	100.00%	12	12

Showing rows 1 - 5 of 5

Q8- How do you rank the benefits of Artificial Intelligence for businesses?

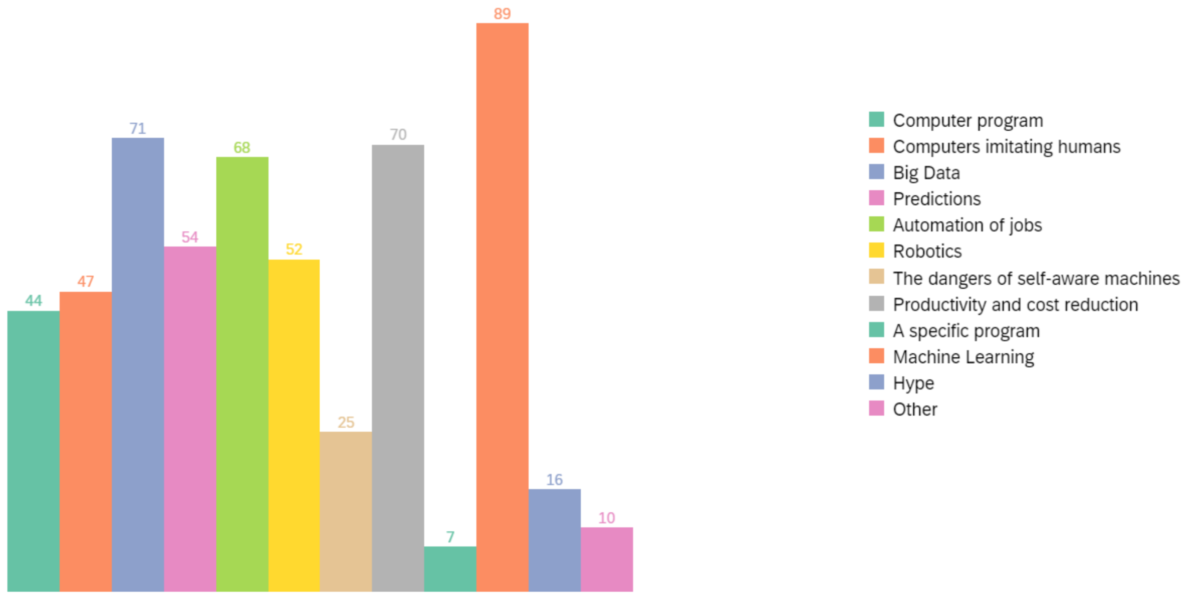


#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	5.00	1.87	0.64	0.42	120

#	Field	True		Total
1	Extremely beneficial	100.00%	30	30
2	Quite beneficial	100.00%	79	79
3	Neither beneficial nor harmful	100.00%	9	9
4	Not very beneficial	100.00%	1	1
5	Harmful	100.00%	1	1

Showing rows 1 - 5 of 5

Q9 - What comes to your mind when you think about Artificial Intelligence?



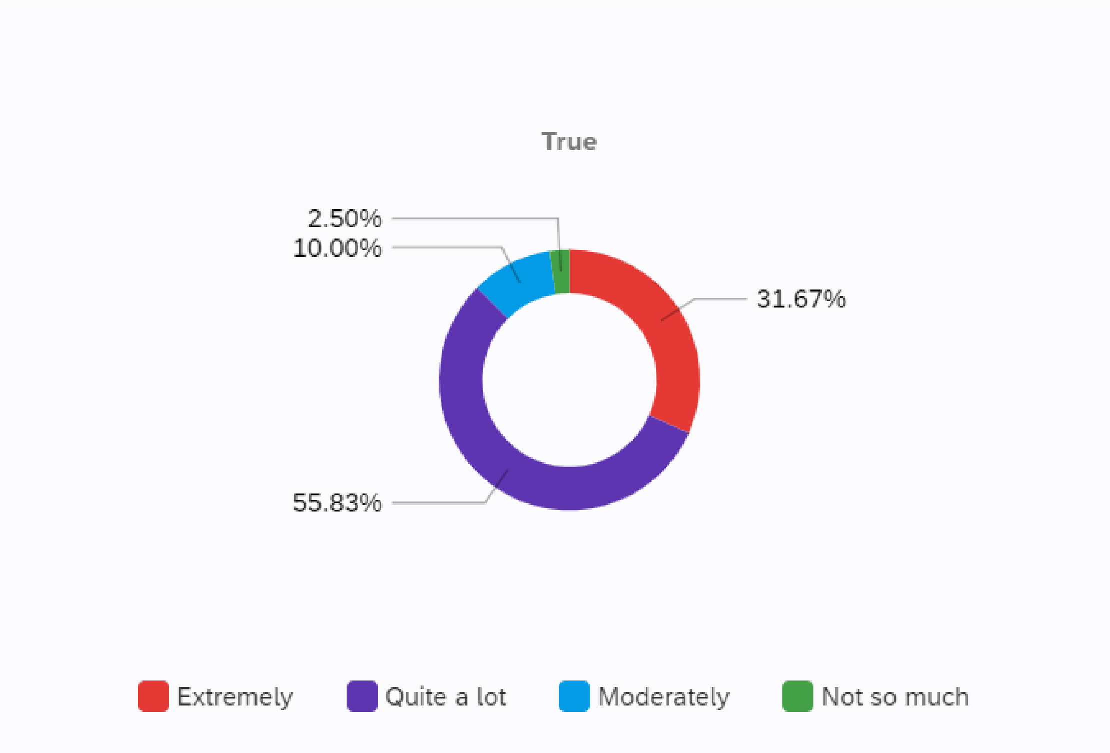
#	Field	True		Total
1	Computer program	100.00%	44	44
2	Computers imitating humans	100.00%	47	47
3	Big Data	100.00%	71	71
4	Predictions	100.00%	54	54
5	Automation of jobs	100.00%	68	68
6	Robotics	100.00%	52	52
7	The dangers of self-aware machines	100.00%	25	25
8	Productivity and cost reduction	100.00%	70	70
9	A specific program	100.00%	7	7
10	Machine Learning	100.00%	89	89
11	Hype	100.00%	16	16
12	Other	100.00%	10	10

Showing rows 1 - 12 of 12

Q9 - Other

Other - Text
Evolvement of social relations
Bad movies but hopefully sex robots soon for us girls.
Danger of vanishing democracy, humanism & self-determination
Unskilled workers loosing their jobs
A computer that can think for itself
Systems that can independebtly broaden its intelligence
reinforcement learning
All of the above
Target marketing
Robot understanding Human

Q10 - How much will the development and usage of AI influence the workplace of the future?

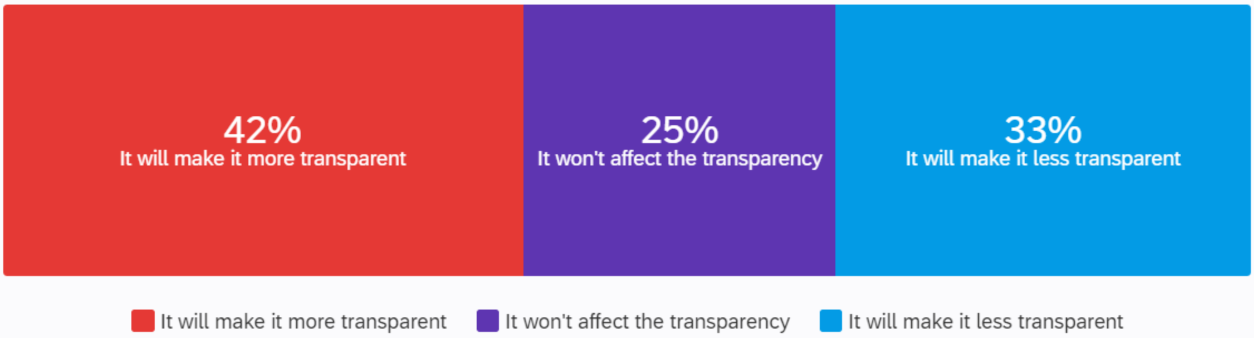


#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	4.00	1.83	0.70	0.49	120

#	Field	True		Total
1	Extremely	100.00%	38	38
2	Quite a lot	100.00%	67	67
3	Moderately	100.00%	12	12
4	Not so much	100.00%	3	3

Showing rows 1 - 4 of 4

Q11 - How do you think using AI will influence the transparency of business processes?



#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
0	True	1.00	3.00	1.92	0.86	0.74	120

#	Field	True		Total
1	It will make it more transparent	100.00%	50	50
3	It will make it less transparent	100.00%	40	40
2	It won't affect the transparency	100.00%	30	30

Showing rows 1 - 3 of 3

Q12 - Intelligent systems include the broad umbrella of AI. As a member of future workforce...

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	I would trust an intelligent system to monitor my work processes	1.00	5.00	2.67	1.13	1.27	120
2	I would be comfortable with an intelligent system automating my work processes	1.00	5.00	2.40	1.08	1.17	120
3	I would trust an intelligent system to evaluate my work	1.00	5.00	3.02	1.13	1.28	120
4	I would trust the advice of an intelligent system for making business decisions in the future	1.00	5.00	2.71	1.10	1.21	120
5	I would trust leadership that incorporates intelligent systems into decision making	1.00	5.00	2.32	1.05	1.10	120
6	I believe intelligent systems will be the core of business in the near future	1.00	5.00	2.48	1.11	1.23	120

7	I want to work in an environment that incorporates intelligent systems	1.00	5.00	2.33	0.95	0.90	120
8	The idea of optimizing artificial intelligence in my daily work excites me	1.00	5.00	2.53	1.11	1.23	120
9	I would expect leadership of my future workplace to be open to intelligent systems	1.00	5.00	2.08	0.90	0.80	120
10	I use intelligent systems daily	1.00	5.00	3.00	1.31	1.72	120
11	The idea of using intelligent systems in my daily life makes me uncomfortable	1.00	5.00	3.41	1.11	1.22	120
12	I trust technology	1.00	5.00	2.49	0.90	0.82	120
13	I believe that the development of AI will have a positive influence on the processes of companies and leadership	1.00	5.00	2.46	0.97	0.93	120
14	I feel prepared for a work future that incorporates intelligent systems	1.00	5.00	2.56	1.04	1.08	120

Q13 - What is important to you in leadership? (max 3)

#	Field	True		Total
1	Top-down	100.00%	10	10
2	Bottom-up	100.00%	15	15
3	Empowerment	100.00%	70	70
4	Team based	100.00%	61	61
5	Agility	100.00%	31	31
6	Reliability	100.00%	69	69
7	Knowledge	100.00%	54	54
8	Transparency of decision-making	100.00%	63	63
9	Other	100.00%	4	4

Showing rows 1 - 9 of 9

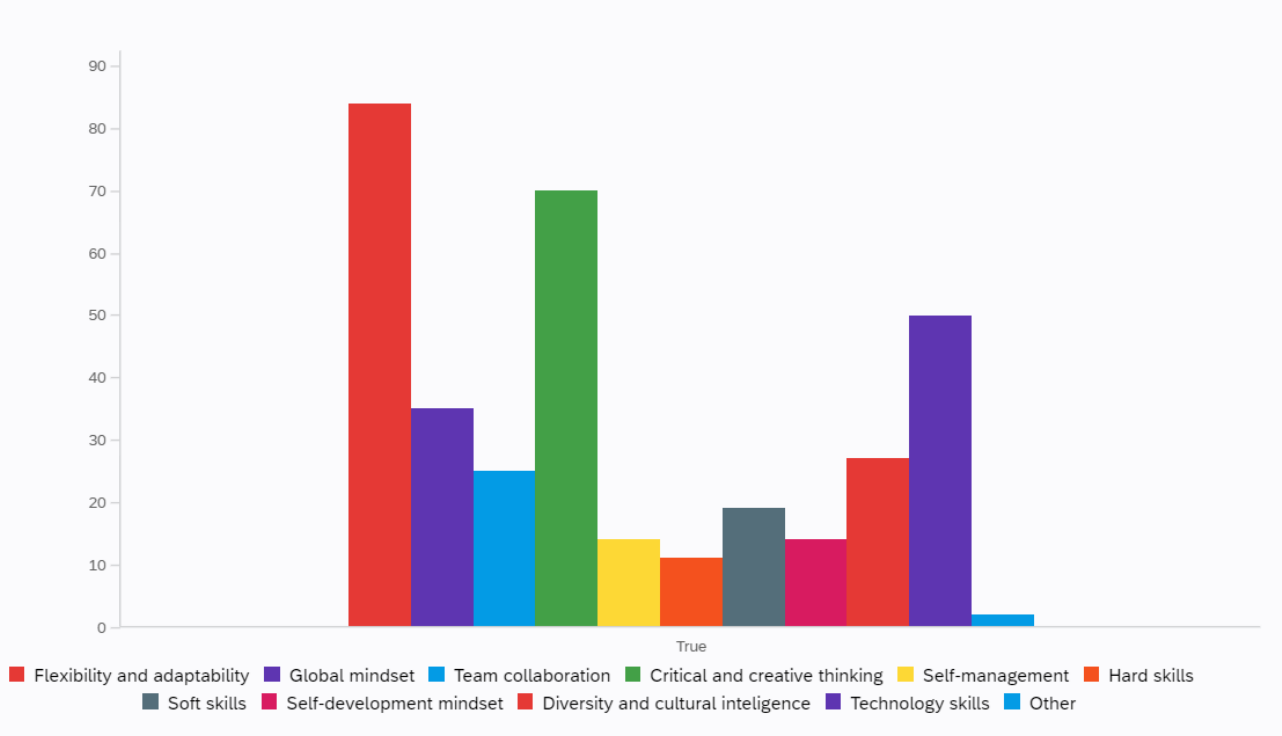
Q13 - Answers for 'Other'

True

Other
The ability to learn, unlearn, and re-learn
Emotional intelligence

Showing records 1 - 2 of 2

Q14 - What skill do you think will the future workforce need the most? (max 3)



#	Field	True	
1	Flexibility and adaptability	23.93%	84
2	Global mindset	9.97%	35
3	Team collaboration	7.12%	25
4	Critical and creative thinking	19.94%	70
5	Self-management	3.99%	14
6	Hard skills	3.13%	11
7	Soft skills	5.41%	19
8	Self-development mindset	3.99%	14
9	Diversity and cultural inteligence	7.69%	27
10	Technology skills	14.25%	50
11	Other	0.57%	2
			351

Q14 - Answers for 'Other'

Other - Text
The ability to learn, unlearn, and re-learn
Emotional intelligence

Q15 - What expectations do you have for future companies and leaders? (Visualization)

Q15 - Answers for ‘Other’

What expectations do you have for future companies and leaders?
Openness, inclusiveness, being able to manage knowledge and learn to be experts in leading complex organisations.
Unsure
x
Continues growth in a sustainable way
-
That they are more open to investments in both technology and human development
That they develop the right kind of talent
For them to incorporate AI, but still handling important decisions
Encourage flexibility, more focus on soft skills
Embrace the technological advancements & reap the benefits but be cautious of the drawbacks & privacy implications.
Not to wait for the change but create it
They will follow the evolutionary principle. Some actors will disregard responsible use of AI and seek to achieve hegemonic status. This convergence will occur eventually. The complexity, usefulness and associated power of AI is self reinforcing and exponential. With complexity, AI it becomes inimitable
.
-
Global mindsets and diverse management
pessimisticly, Considering current tendencies and the 'data revolution' i expect more companies to be increasingly mechanistic in their approach. I think AI would be able to greatly benefit many systems but i fear that many corporations will move towards cost cutting functions based on rational thinking. Optimistically, things could go the other way. Recent trends suggest that corporations are being held accountable and our "profit over everyhting" approach to business thinking might be taking a backseat to more sustainable thinking leaders (sustainable in this context does not relate to eco-friendly but to leaders priotizing long term strategies and well being of employees over short term prifits).
A strong awareness of environmental impact, sustainability in workforce
Dont know
More love between all
A lot
Be open, kind, caring and courageous.
.
Just don't fuck it up.

Adaptation to new times, flexibility
I expect them to take responsibility for their impact on the planet and its people.
Ghjkk
Y
Diversity
Trust tech, but not too much
To be sustainable
Data-driven culture, mindset and decision-making. Strategic flexibility and adaptability
Accountability for actions
A more people forward mindset then just about the bottom line.
To understand the limitations of AI and not shoot for the moon before they know how to walk.
Question is too broad to answer accurrately
no
Development. More technology
None
To focus on sustainability and not be blinded by the idea of endless growth.
For them to be trustworthy
Management of the future is about technology and data, with more tech intense companies and less people intense ones, strategy is about analyzing data.
To embrace diversity
None
Open minded
They should guve their employees an opportunity to learn and develop new skills
To recognize their role and responsibilities in the society
Being more transparent and open to new ideas
Embracing the opportunities of AI vs rejecting them
Being knowledgable about the advantages AI can bring to the way of working. Bein prepared and have an action-plan for the transition of what we define as normal now and what the future will be. Laws and Regulations to protect individual rights
Thay they are open minded towards developments as the world is changing fast
improve the state of art
I expect future companies to embrace digital options, and for IT and business to become even more interwinded.

To create a more sustainable and equitable world.
That the incorporation of AI systems would affect how companies are run and even structured.
Can't comment
Ability to learn and adapt to new technology and strategies.
...
Forward thinking flexibility
Ever changing core business
To be close to technological development and to give their employees the opportunity to upskill themselves accordingly
To be inclusive and share decision making
Flexibility, future-facing, eager to learn and develop
Dynamic
To provide a relevant vision employees can identify with.
Companies to become more responsive to change and more caring about all stakeholders, not just shareholders. Companies to implement innovative tech solutions in the day to day and with strong emphasis of tech being supportive, rather than substitutive tool; leaders to be the inspiration for the direction in which the company goes, and critical decision makers with mindsets of "doing good" for society, employees and consumers
Companies will increasingly seek to accumulate data on their customers and employees
To be less top-down and more conscious of their ethical and sustainable practices
Equality
Make it as transparent as possible
-
No clear expectations
To act in a manner that reflects their awareness of how their decisions and actions influence other entities.
Flexibility
That they will adopt a proper balance of AI and human capabilities
To incotporate AI in daily tasks but to create new job opportunties for employees with more flexibility
either would keep getting more closed
Staying informed when it comes to new trends, and change willing.
I expect that they fully understand the technology they use and from the increased efficiency and cost reduction they would be socially and envitinmentally more responsible.
Egalitarian values, Faster lifecycles of companies & employees, Less authoritative decision making
To create workplaces where people and AI can work harmoniously

.
Implementing AI
To hopefully be socially aware
Utilize technology in a way that free up ressource to focus on core strengths
-
To be responsible
To be responsible
To be agile, adaptive & innovative
Adopt AI as a tool to aide quicker and more informed decision making, and to automate certain complex background areas like energy consumption and provision, but ultimately decisions won't be very sensitive to the AI input or parameters for automated processes will be made less sensitive, but ultimately business leader decisions will still be primarily human-led.
I would expect them to be transforming their operations to include intelligent systems
.
Trustworthiness and empathy
To move beyond the technological discussions surrounding AI and focus on developing meaningful, customer-centric use cases of AI - not just implement AI for the sake of having AI, but companies are now turning towards evaluating how AI can provide a competitive edge (beyond a single marketing statement) - very happy to see this trend unfolding right now
Being open to new technolgies, being culturally aware
To be more flexible
Responsible behavior and the ability to greate sustainable growth that put the people and the planet before profits
To manage technological adoptions in a timely manner with consideration for human input.
Don't be ignorant
reinforcement learning
That they are change ready continuously
Being ethical and not knowingly raise funds on exaggerated promises that might never materialize
Balanced business processes
That the Technology dont take over humanties
.
openness, mindfulness, honesty, agility
Good ones
I expect more remote work to be more used

Giving freedom to employees, knowledge determines hierarchy
Lesss hypocrisy in recruiting and public image
Interesting
Adaptability, enabling leadership
Challenging tasks which help me grow
Don’t know what to expect :p I guess a need for more adoptable mindsets
Work hard
To be able to yield the power of technologies to create the best results but also to provide the best environment for their employees to excel (eg by doing all the boring manual work - but better)
flexibility
I expect them to understand the needs of its employees and listen to thieir opinions as well as new ideas.
Find solutions for increasing complexity + act socially responsible
Social and environmental responsibility in everything

.