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STRATEGICALLY MANAGING THE VALUE CREATION AND PRODUCTIVITY PARADOX OF ARTIFICIAL INTELLIGENCE

– The General Purpose Technology View

Kaisa Kukkonen

TURUN YLIOPISTON JULKAISUJA – ANNALES UNIVERSITATIS TURKUENSIS

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For Ompeluseura levelUP Koodarit -girls,

and all those developing AI solutions responsibly.

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ABSTRACT

This doctoral dissertation explores the strategic management of artificial intelligence as a general purpose technology and its value creation in the context of multiple industries. I study what makes AI-based value creation challenging from the management and organization perspective despite the high technological performance of AI. I analyze this through five sub-research questions, and by applying grounded theory.

Empirically, I turn to 34 AI solution developers from 18 different industries who have both technical and business understanding of using AI. The AI solution developers suit this study because of their skills, capabilities, and power position to shape the present and future through the combined use of machine learning (ML) and other AI related technologies that are already impacting our daily lives in and out of work context.

The extant literature on AI in premium outlets on general management and organizational studies can be typified into five AI use phases: 1) antecedents of AI use, 2) AI use, 3) (empirical) impacts of AI use, 4) expected (cumulative) impacts of AI, and 5) AI-related paradigm shift. The five sub-research questions of this doctoral dissertation explore the definition of AI and the use phases 1-4 by approaching AI as the subject of study. The fifth AI use phase is excluded from this study as it would require using AI also as the research method.

The main contributions of this doctoral thesis include giving an overview of AI in management and organization, and pre-theoretically identifying the technical and socially constructed decision-making criteria for AI investments, six AI use types, how empirical AI impacts have been measured, what temporal dimensions are expected to be impacted by AI, and what AI strategies organizations have already adopted to create AI-based value and overcome its productivity paradox.

KEYWORDS: Artificial intelligence, machine learning, strategic management, value creation, automation, augmentation, hybrid intelligence, conjoined agency

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TIIVISTELMÄ

Tämä väitöskirja keskittyy tekoälypohjaisen arvonluonnin strategiseen johtamiseen yli teollisuudenalarajojen. Lähestyn tekoälyä korkean suorituskyvyn omaavana yleiskäyttöisenä teknologiana ja analysoin ilmiö- ja aineistopohjaisesti sitä, mikä tekee tekoälypohjaisesta arvonluonnista silti haastavaa johtamisen ja organisoinnin näkökulmasta viiden alatutkimuskysymyksen avulla.

Haastattelin tätä työtä varten 34 tekoälyratkaisuja 18 eri teollisuudenalalla kehittävää asiantuntijaa. He sopivat haastateltaviksi, koska heillä on alan osaamista sekä teknisestä että käytännön sovellusten näkökulmasta, ja koska heillä on valta-asema kehittää koneoppimiseen ja muihin tekoälyteknologoihin pohjautuvia ratkaisuja, jotka jo vaikuttavat päivittäiseen elämäämme työelämässä ja sen ulkopuolella.

Yleisen johtamisen ja organisaatiotutkimuksen huippujulkaisuista kerätty kirjallisuus voidaan jakaa viiteen tekoälyn käyttövaiheeseen: 1) tekoälyn käyttöä edeltävät tekijät, 2) tekoälyn käyttö, 3) tekoälyn (empiiriset) vaikutukset, 4) odotettavissa olevat tekoälyn (kumulatiiviset) vaikutukset, sekä 5) tekoälyyn liittyvät paradigman muutokset. Tämän väitöskirjan viisi alatutkimuskysymystä keskittyvät tekoälyn määritelmään sekä tekoälyn käyttövaiheisiin 1-4. Viides tekoälyn käyttövaihe on jätetty tämän tutkimuksen ulkopuolelle, koska se vaatisi tekoälyn käyttöä myös tutkimusmetodina.

Tämän tutkimuksen päätuotokset luovat yleiskuvan tekoälystä johtamisen ja organisoinnin kirjallisuudessa. Empiiriset tulokset tyypittelevät investointipäätöksiin vaikuttavia tekijöitä, sekä kuusi erilaista tekoälyn käyttötapausta. Analysoin, miten tekoälyn vaikutuksia on mitattu, mihin aikaan liittyviin tekijöihin tekoälyn odotetaan vaikuttavan, ja mitä tekoälystrategioita organisaatiot ovat jo omaksuneet luodakseen arvoa ja ylittääkseen tekoälyn tuottavuusparadoksin.

ASIASANAT: Artificial intelligence, machine learning, strategic management, value creation, automation, augmentation, hybrid intelligence, conjoined agency

Acknowledgements

Growth.
Growth as opposing power to layoffs and reactive individuals scared for their jobs.

Hype.
If massive amounts of money are invested globally on AI, but no-one wants to define what is meant by AI, then what are people selling and buying when they talk about artificial intelligence?

These two premises build my personal foundation and motivation for starting this doctoral dissertation. After some reading on AI, two more fundamental premises emerged both from the theory and the empirical interviews.

1) Productivity paradox: Why is AI seen everywhere but in the productivity statistics (Brynjolfsson et al., 2017)?
2) And, Powerful technology: *"A very dangerous question to humankind is, what do you want? That is a decision humankind needs to decide, when there exists an extremely powerful technology with which we could suddenly get what we want."* (Interviewee 30, CEO).

This doctoral dissertation has been an unforgettable journey to explore the unknown for me. I started off with the question, what is artificial intelligence. This burning question got me organizing dozen AI-excursions with different cutting-edge AI-companies for 300 ladies wanting to fundamentally understand AI and to learn to code machine learning (ML) algorithms hands-on in Finland in 2018 and 2019. This quest got me inspirational support from women colleagues in AI and lifelong experiences and friends, for which and for whom, I am forever grateful.

At the same time, we started an AI meetup called AI-fest with Antti Merilehto the author of the bestselling book in Finnish, 'Artificial intelligence, a travel guide to managers'. In AI-fest, we brought together data scientists working on AI and ML solutions in AI-driven product or service startups and people working as technical consultants to discuss burning questions in their daily work.

On top of these, I attended countless other AI meetups or hackathons both in Finland and Sweden in 2017-2019. Their specific focus was on different algorithms or even replicating the AlphaGo Zero training with the newly released cheat sheets. The AI hype also enabled other great encounters such as those in the fabulous North Star AI, Applied Data Science Conference for Developers in Estonia in 2019 with keynotes and chat opportunities from leading North-European, as well as North-American, AI-leveraging companies such as Amazon and Netflix.

I even got to attend the founding meeting of the CLAIRE initiative in Belgium in 2018, where the focus was to bring together top AI researchers, experts, and policy makers to discuss and further develop the main components of a Confederation of Laboratories for AI Research in Europe (CLAIRE). The ambitious goal of CLAIRE was to found a top research center such as the CERN in European Union, but this one for artificial intelligence.

My curiosity and almost demonic drive to learn about AI from the people creating practical industry AI-solutions spurred not only valuable networks through which I found my interviewees for this study, but also valuable academic connections to understand AI as a phenomenon even deeper. I reached out to my social media contacts and their networks about good tips where to learn more.

This led me to two extremely good summer schools, one on Games and AI in Crete in 2018 that was organized by professors from New York University Tandon School of Engineering and the Institute of Digital Games, University of Malta with an impressive line-up of partner companies using AI such as Deepmind, Ubisoft and Unity, just to name a few. The other extremely useful summer school was Robotics vision summer school in Australia in 2019, that focused on lectures by professors from around the world on the fundamental and advanced topics in computer vision and robotics both theoretically and hands-on, as we also experimented and competed with computer vision algorithms that we developed on actual robotic hardware.

In 2019, I also focused my studies on industrial robotics and production automation. This was first aimed to understand robotics better as possible embodiments for the use of ML, but they ended up fundamentally influencing the focus of this doctoral dissertation on the different levels that may or may not be influenced by AI as a potentially disruptive technology.

So, a lot was happening before Covid-19 hit us from Wuhan in early 2020. Conferences were cancelled just as I was about to attend my first management and organization conference, the JMS 2020 Future of Work in Birmingham. It would have been organized by Journal of Management Studies & Society for Advancement of Management Studies. So, my transition from information system sciences minor to contribute to my major in management and organization got a slight hiccup, as getting to know my own field was not as smooth as the technical discovery journey had been. Staying alone at home silenced all the interactive wisdom and opportunities to observe, how we do things around here, when moving from information system sciences to the completely different field and research tradition of management and organization. I had to do the shift of focus from technology to humans on my own, and thus fell into a lot of pitfalls that might or might not have been avoidable in this transition. Had it been otherwise, I would have been able to integrate to the management and organization network and discuss ideas inspired by information system sciences and robotics with the senior scholars with similar interests in the field of management and organization. Yet, in 2021, tables turned. As a lot of top conferences and workshops were organized virtually, I was lucky enough to attend a paper development workshop organized by the editors of AMD, attend a doctoral colloquium in EURAM, present a paper in EGOS and BAM, as well as in one ISS conference PACIS, all from my very own living room. For a social researcher like me, I finally got the first global-scale gist, what is it that these management and organization scholars are after when I tried speaking their language in attempt to argue for my contributions in their field.

So here we are. A lot has happened. I thank all the people that I have had the joy and privilege to meet along the way, all the valuable comments, critiques, inspirations, peer reviews, rejections with valuable paper reference tips from anonymous reviewers, and most of all I thank for the great questions that enabled the required paradigm shifts in my head to get this work done.

Just to name a few, a particularly inspirational idol for me is Dr. Ella Peltonen, a hard-core technical and hands-on professional on edge-native machine learning, that I now-a-days dare to call my LevelUP-friend. Another power-woman that I "blame" for my original technical discovery scope to include not only AI but also robotics, is Christina Andersson, and of course Sara Peltola, who originally brought us together. With Sara, we've tasted the first whiskey distilled based on a recipe developed by an algorithm while watching the 2020 Fall conference by Stanford Institute for Human-Centered Artificial Intelligence: "Triangulating Intelligence: Melding Neuroscience, Psychology, and AI". (Some of the great perks of Covid-19, enjoying world class conferences from your own living room…!) And then over breakfast, we'd reflect what does this mean for our education system, our youth, and work life, our personal careers, and us as human beings,…

I want to also thank many incredible men, all who have been patient enough to explain me technical details and fix the bugs while trying the algorithms hands-on, or otherwise trying to make sense of AI and/or ML and their potential impacts as an innovation. My original love for technology derives from the innovative spirit, incredible talent, and hard-working patience to explain the technical details and put them (and a lot of other things in life) into perspective as part of the big picture from my Yoda, Naseer Ahmad. Another inspirational and impactful encounter has been with the AI giant of a human being, the unfortunately now deceased AI researcher and professor Dr. Timo Honkela, whose book ‘The Peace Machine’ tells a lot about his ambitious thinking about the fundamental human-centered aspects and value potential of AI.

On a more practical note, I would not even have applied to the Turku School of Economics, had it not been for my best girlfriend and sister, Lilli Lehtonen and her attending the doctoral defense of Suvi Satama. Her connecting me with my first supervisor Dr. Satu Teerikangas is probably the happiest encounter with the biggest impact over my following years. I would not be here today had it not been for her believing in me and her courage to be open for me studying something that was out of her comfort zone.

To having got this work started in practice, I thank my second supervisor Dr. Tomi Dahlberg, who pushed me to be a reviewer in information system science conference HICCS already after six months from the start of my studies and to submit a first paper based on the early empirical data findings a year after. For the drive to write papers, and the learnings how to write them, I am forever grateful. Not to mention, that I would not have my empirical interview data, had you not helped me when I lacked the patience to plan and sit with the theory to build a solid research foundation to my semi-structured interview questions. Tomi got me started and guided me though the technical half of this doctoral dissertation journey, and Satu took me to this day, to the finish line and patiently guided me when I wondered and got lost in the dark forests of management and organization theory, or quite frankly, in the lack of my theoretical knowledge about it.

To conclude, I want to thank and acknowledge the influence of my family. Thank you, dad, for trying to make me go to Business school after high school. I rebelled then, but after years of consideration, I finally took your advice. And mom, who became an IT teacher and let me try the first Apple computers and draw with them at her school: you are my first inspiration and connection to the world of computers. A solid proof of that must be the drawings we found in the family album, where you had written that the very futuristic designs of me as a two-year-old were “grandma’s computer” and “Raimo’s computer”. And thank you mom, dad, and Arto for bearing with me and supporting me through the storms. And Ville and Veera. You know what I am talking about. I love you all.

14.7.2023
Kaisa Kukkonen

P.S. The last year of editing this thesis taught me what diamonds must feel like…;) So good luck to all my lovely PhD student colleagues: if I could do it, you can do it!

KAISA “THE LADYAI” KUKKONEN

A ONE LADY MULTI-DISCIPLINARY TEAM: A JOURNALIST AND AN ECONOMIST, WHO FOUND HER PROFESSIONAL HOME IN INTERNATIONAL INNOVATION AND TECHNOLOGY MANAGEMENT AND IT. AN AI ACTIVIST AND INDUSTRY EXPERT, WORKING FOR SUPERHUMAN WORK PERFORMANCE AND SUSTAINABLE LIFE QUALITY WITH THE COLLABORATION OF HUMANS AND ARTIFICIAL INTELLIGENCE. RESEARCHER, TEACHER, ENTREPRENEUR.

Declaration of Conflicting Interests

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this doctoral dissertation.

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1 Why artificial intelligence?

“A very dangerous question to humankind is, what do you want? That is a decision humankind needs to decide, when there exists an extremely powerful technology with which we could suddenly get what we want.” (Interviewee 30, CEO, empirical interviews 2019)

“What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity.” (Tim Cook, CEO of Apple, Byrnes, 2017)

“The rise of powerful AI will either be the best or the worst thing ever to happen to humanity. We do not yet know which.” (Stephen Hawking, theoretical physicist, University of Cambridge, 2016)

The effects of artificial intelligence (AI), and digital transformation as a whole (Leonardi & Treem, 2020; Warner & Wäger, 2019), are not only of growing interest but also a growing concern to practitioners and multi-disciplinary scholars as part of shaping the future (Glikson & Woolley, 2020). AI is expected to have disruptive, complex, and/or paradoxical (Leonardi, 2020, Gregory et al., 2021, Raisch, Krakowski, 2021) impacts on individuals, organizations and the society at large. Thus, also the engagement of management and organization scholars has been called for to realize the benefits of AI while mitigating its negative side effects (Raisch & Krakowski, 2021).

Organizations already increasingly use AI for tasks such as selecting suitable applicants for organizational positions, advising clients on financial products, performing financial transactions, giving insurance to clients, scheduling complex logistics, diagnosing patients and suggesting therapies, forecasting technological development, and tracking down criminal activity (von Krogh, 2018). What is significant about these tasks is that *“(s)uch tasks are anything but simple—they make great demands on complex search, analysis, and reasoning traditionally confined to the realm of human intelligence” (*von Krogh, 2018, p 404). Thus, what makes the potential effects of AI-based innovations different from other machines and manually step-by-step programmed information technology (IT) solution algorithms is that with the help of AI and data, machines start to have an increasing amount of human collegial capabilities as *”machines can now learn how to recognize objects, understand human language, speak, make accurate predictions, solve problems, and interact with the world with increasing dexterity and mobility”* (Brynjolfsson et al., 2017, p 34).

Changes are expected as to the way firms organize work and jobs, because of not only the growing ability to collect but also interpret data by using different technologies (Schafheitle et al., 2020). This may be used to predict or even shape employee behavior (Leonardi, 2021). Yet, it is humans, who shape the machine’s behavior: they define the objectives, set the constraints, generate and choose the algorithm training data and provide feedback for the machine (Raisch & Krakowski, 2021).

In this doctoral dissertation, I am curious to explore the practical experiences of those individuals who sit on the driver’s seat of this potentially disruptive change; those individuals, who are giving an increased amount of agency to machines (Larson & DeChurch, 2020; Murray, Rhymer, & Sirmon, 2021; Raisch & Krakowski, 2021). They enable machines to conduct an increasing amount of non-routine thinking or cognitive work (Larson & DeChurch, 2020; Nauhaus, Luger, & Raisch, 2021). These individuals are the industry’s technical and business AI solution developers.

To which tasks and to what extent the AI developers give machines agency is critical because we know from previous research that in some cases the performance of AI already exceeds that of humans. This has happened mostly in the realm of games (Bard et al., 2020; Brown & Sandholm, 2019; Fortunato et al., 2017; Schrittwieser et al., 2020; Tian et al., 2019), but the superhuman performance of AI has also been achieved in laboratory pipetting and flexible liquid handling by robots (Knobbe, Zwirnmann, Eckhoff, & Haddadin, 2022). Interest in AI and its potentially superhuman performance is increasing also elsewhere, as in the examples of the autonomous scientific discovery of materials (Gomes, Selman, & Gregoire, 2019), the improved efficiency, diagnosis and prognosis of medical tasks such as cardiovascular imaging (Siegersma et al., 2019), or as regards simulations for optimized and automated greenhouse control for cherry tomatoes (Zhicheng et al., 2021).

However, the problem with the superhuman performance that AI models achieve is that they are task specific as they *“often fail to adapt to even slight task alterations”* (Lampinen & McClelland, 2021, p. 32970). Thus, in the recent years, it has become increasingly popular to combine the capabilities of both a human and AI in the form of hybrid intelligence (Dellermann, Ebel, Söllner, & Leimeister, 2019), or hybrid-augmented intelligence (Pan, 2016), to augment rather than replace humans (Davenport, Guha, Grewal, & Bressgott, 2020). Together they achieve a task level performance that neither the human nor the machine could achieve without the other. This is because they both not only complement each other but, over time, also learn from each other. This may lead to the improvement of both the human and the machine, both as a whole and as single components of the socio-technological system that they form together (Dellermann et al., 2019).

Against this background, AI seems to open interesting avenues for research as a managerial and organizational phenomenon. This leads me to next introduce the foci of this doctoral dissertation in greater detail.

1.1 Research problem

This research project started in 2018, when AI had just reached the top of the Gartner hype cycle (Gartner, 2018, 2019), and before the Covid-19 pandemic.

By 2020, the total global corporate investment in AI had reached 67 854 million US dollars with a 530 percent growth from 2015 (Zhang et al., 2021). The venture capitalist (VC) investments on AI start-ups had reached 21 percent of all global VC investments in 2020, up from just 3 percent in 2012 (Tricot, 2021). In 2021, the private investment in AI more than doubled from 2020, and totalled around $93.5 billion US dollars (Zhang et al., 2022). Yet, the AI investment concentration had started to intensify, as the number of funded AI companies dropped from 1051 companies in 2019, and 762 companies in 2020, to 746 companies in 2021 (Zhang et al., 2022).

The global consulting company PwC estimates that AI could contribute up to 15.7 trillion US dollars to the global economy in 2030 (Rao & Verweij, 2017). Out of this PwC expects $6.6 trillion to come from increased productivity and $9.1 trillion to come from consumption-side effects (Rao & Verweij, 2017). However, despite the expectations and potential, AI is considered to embody a productivity paradox (Brynjolfsson, Rock, & Syverson, 2019).

Earlier research has identified four principal candidates for similar situations with technological optimism and poor productivity performance: 1) false hopes, 2) mismeasurement, 3) concentrated distribution and rent dissipation, and 4) implementation and restructuring lags (Brynjolfsson, 1993; Brynjolfsson et al., 2017). One other potential explanation for AI's productivity paradox might be that AI, or more specifically machine learning (ML), has been compared to other disruptive general purpose technologies (GPT) such as electricity and the combustion engine (Brynjolfsson & Mitchell, 2017, p 1534).

This can make AI both interesting and challenging from the value creation perspective because GPTs require *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1). These complementary innovations need to be developed and implemented by multiple people to realize the full effects of AI in machines, business organizations, and the broader economy (Brynjolfsson & Mitchell, 2017).

All this combined, the great expectations, fears, performance, and global investments in AI, make AI a particularly rich and controversial subject of study. AI as a phenomenon seems to capture something especially fascinating and complex from the socio-technical (Manz & Stewart, 1997; Pasmore, 1995) management and organization as well as value creation perspectives (see more in chapter 5.3.5). Thus, as my main research problem in this doctoral dissertation, I am curious to explore AI further in multiple industry settings, and I ask:

MRP: What makes artificial intelligence -based value creation challenging from the management and organization perspective?

I approach this main research problem through five sub-research questions in this doctoral dissertation. Both the main research problem and the sub-research questions have been finalized toward the end of this grounded theory -based and phenomenon-driven research project.

The first sub-research question emerged from the confusion both in the industry and within the literature as to how AI should be defined: *How is artificial intelligence defined in the management and organization literature and in multiple-industry settings?*

Table 1. Overview of the positioning and research design and scope of this doctoral dissertation.

Literature	Artificial intelligence and/or machine learning in premium general management and organizational studies literature				
Identified AI use phases	1 AI use antecedents	2 Use of artificial intelligence	3 AI use (empirical) impacts	4 Expected (cumulative) AI impacts	5 AI related paradigm shift
Research problem	What makes artificial intelligence -based value creation challenging from the management and organization perspective?				Discussed
Research design	Phenomenon-driven, qualitative, and grounded theory -based research design				AI ≠ method
Empirical data	34 artificial intelligence -based solution developers from 18 different industries in Finland and North America				Out of scope

The second through fifth sub-research questions have been finalized via a continuous, iterative abductive back-and-forth analysis reverting between empirical findings and theory. Based on the previous literature on AI and ML in premium outlets on general management and organizational studies, five phases in relation to the use of AI were identified (see chapter 2): 1) antecedents preceding AI use, 2) the actual use of AI, 3) (empirical) impacts of using AI, 4) expected (cumulative) impacts of using AI, and finally 5) AI-related paradigm shift in management and organization research methods and theoretical contributions. The four remaining sub-research questions cover the four first AI use phases (see table 1).

To explore the antecedent phase before AI is used, as my second sub-research question I ask: *How are the managerial decisions formed on whether to invest in AI-based technology development?*

To explore the actual use of AI, as my third sub-research question I ask: *Why might the actual and wanted use of AI differ?*

To explore the empirical impacts of AI use, as my fourth sub-research question I ask: *How are the impacts of AI-based technology development investments measured?*

And finally, to explore the expected cumulative impacts of using AI, as my fifth and final sub-research question I ask: *When approaching time as an organizational resource, which temporal dimensions are expected to be influenced by AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation?*

The fifth AI use phase, AI-related paradigm shift in management and organization research is out of the (direct) empirical scope of this doctoral dissertation, because it would have required the use of AI as the research method (see chapter 2.4.5). The reasoning for these sub-research questions is further elaborated in the method section in chapter 3.2.4.

In the next sub-section, I elaborate further the reasoning for this decision, and introduce other limits set to the scope of this study.

1.2 Scope of the dissertation

The scope of this dissertation is on AI as an organizational and managerial phenomenon, not in AI as a research method. Consequently, as previously noted, the AI related paradigm shift (as the fifth AI use phase) is out the empirical study scope of this dissertation. This is because in ‘AI related paradigm shift’ AI is used as a method to study AI as the subject of study. (See table 1, and chapter 2.)

The empirical interviews have been limited to AI solution developers with both technical and business experience in developing AI solutions (see chapter 3.2.21). Thus, the direct individual user perspective is excluded from this dissertation except for the double-role of those AI solution developers that both develop and use AI solutions. These AI solutions may either be developed by themselves or by someone else for the organization that the interviewee works for.

Another noteworthy and proactive exclusion in this thesis are the representatives from organizations that have adopted a so-called reactive or passive AI strategy (see chapters 3.2.3.4 and 4.2.1). This refers to the use of AI without proactively and strategically managing AI in the organization. As this dissertation focuses on practical industry effects, also purely academic representatives were excluded from the interviewee sample.

The focus of this dissertation is in studying AI as an organizational and managerial phenomenon. I study the potential effects of AI on management and organizing through the experiences of 34 AI solution developers from 18 different industries.

In this study, AI is theoretically closest to the definition of machine learning as a general purpose technology, equivalent to those of electricity and the combustion engine (Brynjolfsson & Mitchell, 2017), whose value creation and value capture require *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1). Based on the empirical findings, in the multiple-industry settings, AI is understood and explained to 1) consist of a combination of many different technologies and fields that 2) may or may not enable the performance level of artificial narrow, general or superintelligence; and/or from the non-technical experts' point-of-view 3) the use of AI may seem to have an increasing amount of human colleague features (see chapter 4.1).

I next briefly introduce the research design and contributions of this dissertation.

1.3 Research design

This doctoral dissertation is phenomenon-driven. The research started free of any theoretical straightjacket (Schwarz & Stensaker, 2014), and it was to be grounded (Glaser & Strauss, 1967) on the pre-study phase observations in multiple-industry settings. This was to enable theoretical discoveries during the analysis phase. Were such discoveries to be made inductively or abductively, they would have the potential to "*offer something empirically 'new,' without necessarily understanding all the theoretical mechanisms behind it"* (Christianson & Whiteman, 2018, p 397). In hindsight, this is a scary but rewarding research strategy to adopt, because theoretically it is not framed into a single theoretical foundation rather it requires an extensive reading and adoption of a wide variety of theoretical discussions in our field (Glaser, 1992; Glaser & Strauss, 1967).

I started this phenomenon-driven research journey with an engaged scholarship approach (Van de Ven, 2007) within my pre-study phase to guide my empirical data collection. Engaged scholarship is defined as *"a participative form of research for obtaining the different perspectives of key stakeholders (researchers, users, clients, sponsors, and practitioners) in studying complex problems. By involving others and* *leveraging their different kinds of knowledge, engaged scholarship can produce knowledge that is more penetrating and insightful than when scholars or practitioners work on the problems alone."* (Van de Ven, 2007, p 9). In practice, I spent a year in the field in 2018-2019 consulting industry experts on AI. Moreover, I organized machine learning (ML) excursions with different industry data scientists. Additionally, I attended AI/ML meetups, conferences, summer schools, and seminars in Finland, Sweden, Estonia, Belgium, and Australia to better understand AI as a phenomenon.

This pre-study phase, and the initial challenge to find AI-related literature within the field of management and organization, guided me to a phenomenon-driven (Schwarz & Stensaker, 2014) or phenomenon-based (von Krogh, Rossi-Lamastra, & Haefliger, 2012) approach for down-the-road theorizing (Christianson & Whiteman, 2018; Krogh, 2020) about AI as a managerial and organizational phenomenon. Down-the-road theorizing and phenomenon-based discoveries may pave the way for future research *"to provide empirical information and new ideas about managerial phenomena that can be used to stimulate subsequent theory building papers and hypothesis-testing"*. As such, they may serve as pre-theory on poorly understood phenomena. (Van de Ven, 2015, p 2).

As the management and organization literature on AI remains rather immature, I adopted an explorative qualitative research strategy in this dissertation. In this dissertation, I explore the practical use and management of AI in contemporary organizations across industries via five qualitative studies. The engaged scholarship pre-study phase laid the semi-structured foundation for the 33 empirical interviews from 18 different industries.

Methodologically, I conducted most of the analysis via grounded theory (Glaser & Strauss, 1967) based Gioia methodology (Corley & Gioia, 2011; Gioia, Corley, & Hamilton, 2013) building theory from the empirical interview answers. Additionally, in three out of five empirical studies, I used casing (Ragin, 1992) as an analytical tool (Eisenhardt, 1989). Through casing, these studies were to yield more accurate and generalizable theoretical insights and constructs (Eisenhardt, 1991; Yin, 2014), because they enable triangulating the findings within case and between cases.

Theoretically, the relevant analytical lens has varied in each empirical study depending on its results. The synthesis of this doctoral dissertation is theoretically framed under the literature review on AI in premium outlets on general management and organizational studies (see chapter 2).

All in all, the foundations of this phenomenon-driven research is problem-oriented, where rigor relies on capturing, documenting, and conceptualizing the observed phenomenon, and contributions facilitate new knowledge creation and theory advancement (Schwarz & Stensaker, 2015; Van de Ven, 2016a). By exploring AI holistically as a managerial and organizational phenomenon both empirically and theoretically, I pave the way for management and organization scholars to better position their studies among the AI literature. With this, I hope other scholars to be able to make more specific contributions in future studies to the management and organization literature on AI as a managerial and organizational phenomenon.

In the next sub-chapter, I give a brief overview of the proposed main contributions of this study. (See further methodological details in chapter 3.)

1.4 Contributions

In this phenomenon-driven doctoral dissertation, my work has been heavily influenced by the editorials of Academy of Management Discoveries (AMD). It is dedicated to publishing *"phenomenon-driven empirical research that theories of management and organizations neither adequately predict nor explain"* (Bamberger, 2018, p 1).

The aim of this abductive research has been to surface various unexplored aspects of AI as a managerial and organizational phenomenon. The contributions work toward proposing *"robust and parsimonious 'first suggestions'"* (Bamberger, 2018, p 1) for why AI-based value creation might be challenging from the management and organization perspective. To do this I have aimed to explore *"the nature, antecedents, and consequences of such phenomena, as well as the new or transformed theoretical frameworks required to make sense of them"* (Bamberger, 2018, p 1), to the best of my ability.

Theoretically, the synthesis of this doctoral dissertation builds on the insights and contributions gained from the literature review (see chapter 2). It is based on AI as a phenomenon in premium outlets on general management and organizational studies. The primary contributions of this doctoral dissertation can be divided into ten parts based on both the literature review and the empirical studies (see chapter 5.1 and its sub-chapters for details).

The first two contributions build on the literature review and its findings. Firstly, I identified three different research approaches adopted to AI by premium management and organization scholars. Secondly, I identified five different AI use phases based on the literature. They also served as the theoretical framing for the empirical studies in the synthesis phase of this dissertation (see chapter 5.1.1).

The third contribution answers the first sub-research question. It explores the definition of AI both in the literature and in multiple-industry settings (see chapter 5.1.2).

The fourth contribution emerged from the empirical interviews during the analysis phase: these are the five types of identified AI strategies. They emerged through casing the interviewees based on the different AI strategies that the organizations that they represented had adopted (see chapter 5.1.3).

The fifth though ninth contributions build primarily on the empirical findings and answer the sub-research questions two to five (see chapters 5.1.4-5.1.8). As the fifth contribution, I propose technical and socially constructed criteria that may impact managerial decision-making on whether to invest in AI solution development or not. As the sixth contribution, I propose six types of AI use types that should be explored further from the AI agent portfolio management perspective in future studies.

As the seventh contribution, I propose that there may be differences in the kind of measurable results and meters between organizations adopting different AI strategies. During the analysis phase, however, two interesting observations were made. Firstly, I noted that the measures might be categorized with similar terms and measure similar things. Secondly, I observed that these measures seem to imply different stages in AI solution development maturity. Building on this second observation, as my eighth contribution, I propose a temporal process development framework for measuring AI.

With the ninth contribution, I answer the fifth and final sub-research question of this study. I propose 13 AI-related temporal dimensions that may have already started to influence the time resource allocation needs in organizations on three aggregate dimension levels. They are related to the 1) organization time; 2) organization and individual time; and 3) human-centric time.

Finally, as the tenth and final primary contribution, I answer the main research problem, in so doing intending to tie together all the learnings from the five sub-research questions (see chapter 5.1.9). This leads me to propose an initial process model that starts to partly explain why AI-based value creation might be challenging from the management and organization perspectives.

As noted throughout this chapter, this thesis builds on the foundations of phenomenon-driven research, which is problem-oriented and where rigor relies on capturing, documenting, and conceptualizing the observed phenomenon, and contributions facilitate new knowledge creation and theory advancement (Schwarz & Stensaker, 2015; Van de Ven, 2016a).

In the next, and final, sub-section of this introduction, I provide an overview of the structure of this thesis.

1.5 Structure of the thesis

The remainder of this dissertation is structured as follows. In the next chapter, I start by introducing the literature on artificial intelligence (AI) and/or machine learning (ML) and explain why these terms are used interchangeably in this dissertation (see chapter 2.1). This theory section also includes an overview of the different research approaches that management and organization scholars have adopted regarding AI-related research (see chapters 2.2-2.3.3), theories that have been contributed to with AI-related papers, and the identification of different AI use phases within the literature (see chapters 2.4-2.4.5). Finally, I summarize the avenues for future research that have been suggested in the contemporary AI literature in premium outlets on general management and organizational studies (see chapters 2.5-2.5.5).

The method section (see chapter 3) has been structured in the form of a timeline of how I conducted this phenomenon-driven and grounded study. It explains more in detail the how and the why of the research method and design adopted in this doctoral dissertation. The method-section is followed by the empirical findings of each of the five sub-research questions (see chapter 4).

Finally, in the discussion and conclusion chapter (chapter 5), I have set the focus on *"raising questions, introducing new phenomena, and speaking perhaps more intently and vividly about context"* (Rockmann et al., 2021, p 428). With the AI literature in management and organization only emerging, alongside the proposed contributions, I discuss and suggest avenues for future research to both open new avenues for research and to resolve the limitations of this study. Bearing an industry background myself, I have considered drawing managerial implications to be an additional heavy focus area to be discussed. As typical to phenomenon-driven research, the main theoretical conversation is at the end of the thesis, *"where only plausible explanations are given for the empirical 'discoveries'*" (Rockmann et al., 2021, p 428).

As this whole dissertation journey has aimed to answer 'what is this a case of', it was only with the help of the pre-examiner statements that I could reflect on the whole dissertation one more time and crystallize to myself and to the audience the connection between the title and my study, and the theoretical discussions it might be best suited to contribute to in the future. Thus, as final concluding remarks I added the final subsection 5.4 that ties together this whole work. There I discuss my work in relation to the previous literature and adopted understanding of 1) strategic management, 2) value creation, 3) productivity paradox, and 4) artificial intelligence as a general purpose technology. Thus, finally, I can say that this dissertation is a grounded case of the strategic management of value creation and productivity paradox of AI as a general purpose technology. In this work, this framing is the end, but for the future work it will be the beginning.

2 Artificial intelligence in management and organization

In this theory section, I analyze the literature related to artificial intelligence (AI) in premium journals on general management and organizational studies. By searching two databases, Scopus and Web of Science, for the journals with the ranking 4 or 4* in Academic Journal Guide 2021 (Chartered Association of Business Schools, 2021), a total of 9 outlets in general management and 5 outlets in organizational studies were searched for with search terms *"artificial intelligence"* or *"AI"* or "*machine learning*" or "*ML*" included in title, abstract or key words of the article. When relevant empirical articles, literature reviews, conceptual papers and editorials were included, a total of 42 articles were found and analyzed for this sample (see table 2, articles included up until fall 2021, see chapter 5.2 for limitations).

Table 2. Relevant articles found related to artificial intelligence and/or machine learning in premium journals on general management or organizational studies.

Journal title (4 or 4*)	AI/ML article amount
British Journal of Management	8
Organizational Research Methods	8
Leadership Quarterly	7
Organization Science	4
Academy of Management Review	3
Journal of Management Studies	3
Academy of Management Perspectives	2
Journal of Management	2
Organization Studies	2
Academy of Management Annals	1
Administrative Science Quarterly	1
Human Relations	1
Total	**42**

The reasoning for searching for articles with both the terms artificial intelligence (AI) and machine learning (ML) is explained in the next section. It is followed by the analysis of the articles related to the chosen research approaches to AI, theories contributed to with AI-related articles, identified types of AI use phases in the included literature, and finally, the suggested avenues for future research related to AI in the general management and organizational studies literature.

2.1 Defining artificial intelligence

In this section, I introduce the key terms artificial intelligence (AI) and machine learning (ML). In addition, I give an overview of the relationship and reasoning behind the intertwined use of these key terms as part of this dissertation.

What makes AI different from other preceding technologies, is that with the help of ML *"machines can now learn how to recognize objects, understand human language, speak, make accurate predictions, solve problems, and interact with the world with increasing dexterity and mobility"* (Brynjolfsson, Rock & Syverson, 2019, p 34). Machines are already used to solve real-life problems related to designing, planning, searching, sorting, and structuring: *"AI can be used to design lightweight building components, assemble financial portfolios that fit client needs, have simple conversations with patients, and recommend rerouting cargo in a clogged railway transportation system"* (von Krogh, 2018 p 406).

When deployed to organizations, these technologies start to have an increased *"capacity to exercise intentionality over protocol development or action selection in the practice of organizational routines, thereby affecting organizations in new and distinct ways"* (Murray, Rhymer, & Sirmon, 2021, p 552). What is novel and interesting about AI and ML is the increased agency (Larson & DeChurch, 2020; Murray et al., 2021; Raisch & Krakowski, 2021) that they now seem to enable for machines.

From the technical point of view, AI consists of a *"broad collection of computer-assisted systems for task performance, including but not limited to machine learning, automated reasoning, knowledge repositories, image recognition, and natural language processing"* (von Krogh, 2018, p 405). These systems can handle but also require ML algorithm training data input in a wide variety of forms such as sound**,** text, images, and numbers (von Krogh, 2018).

After the data is collected, it is used to train the models or algorithms to produce a task output that may include, but may not be limited to, sound**,** text, images, and numbers. When humans have defined and enabled the machine to do so, it may even execute an action such as change a price (Davenport et al., 2020), examine a patent application (Choudhury, Starr, & Agarwal, 2020), or steer autonomous vehicles in (nearly) real time (Tofangchi, Hanelt, Marz, & Kolbe, 2021).

The level of human involvement varies in different phases of the AI use. In the algorithm training phase, human involvement depends on what types of ML algorithms are used. ML algorithms can be classified e.g. to supervised, unsupervised and reinforcement learning (De Spiegeleire, Maas, & Sweijs, 2017), where supervised learning requires the most and reinforcement learning the least human involvement in the algorithm training process.

Based on the premium literature in the fields of general management and organizational studies, we can observe that scholars in our field often use the terms AI and ML interchangeably (Brynjolfsson & Mitchell, 2017; Ding, Zhang, & Duygun, 2019; Fleming, 2019; Leonardi, 2021; Leonardi & Treem, 2020; Masuch & LaPotin, 1989; Pandey & Pandey, 2017; Pantano, Dennis, & Alamanos, 2021), or ML is considered as part of the larger whole of AI (Glikson & Woolley, 2020; Gregory, Henfridsson, Kaganer, & Kyriakou, 2021; Larson & DeChurch, 2020; Raisch & Krakowski, 2021; Sheng, Amankwah-Amoah, Khan, & Wang, 2021; Shrestha, He, Puranam, & von Krogh, 2021; Truninger, Ruderman, Clerkin, Fernandez, & Cancro, 2021). (See table 3.)

However, some articles consistently use only the term AI (Johnson, Bauer, & Niederman, 2021; Nguyen & Malik, 2021; Phan, Wright, & Lee, 2017), or ML (Akhtar, Frynas, Mellahi, & Ullah, 2019; Bhatia, Olivola, Bhatia, & Ameen, 2021; Doornenbal, Spisak, & van der Laken, 2021; Kaibel & Biemann, 2019; A. Lee, Inceoglu, Hauser, & Greene, 2020; Mayo, van Knippenberg, Guillén, & Firfiray, 2016; Murray et al., 2021; Nauhaus et al., 2021; Pachidi, Berends, Faraj, & Huysman, 2021; Putka, Beatty, & Reeder, 2017; Speer, 2020; Tonidandel, King, & Cortina, 2018). Some articles apply or study a specific ML algorithm or model in their paper (Akstinaite, Garrard, & Sadler-Smith, 2021; Antons, Breidbach, Joshi, & Salge, 2021; Furman & Teodoridis, 2020; Kobayashi, Mol, Berkers, Kismihók, & Den Hartog, 2018; Schulz, Valizade, & Charlwood, 2021; Spisak, van der Laken, & Doornenbal, 2019; H. Zhao & Li, 2019).

Some use another term, where either AI or ML is used as an embedded part of another term in the paper. Such embedded terms are used e.g. in computational literature reviews that are augmented by ML (Antons et al., 2021). Another term, automated scientist, is used when researchers' tasks are automated with the help of AI (Johnson et al., 2021). Digital technologies and digital age is said to be enabled by hardware, software, internet and mobile communications, as well as AI (Menz et al., 2021). Digital collaboration platforms integrate data analytics, social networking, and AI (Wu & Kane, 2021).

The application of heuristics, which is one of the most central topics of AI, is studied to imitate powerful human heuristics to find solutions in large complex problem spaces (Bettis, 2017). One more commonly used embedded term in the literature is expert systems (Lawler & Elliot, 1996; McDonald & Wilson, 1990;

Shadbolt & Milton, 1999) that refer to AI applications that have shown great promise as decision aids. 'Expert systems' is a term that was commonly used in the context of applied use of AI in the earlier literature.

In this dissertation the term AI is used to cover both the terms AI and ML. Before collecting the empirical data, the closest theoretical definition to match the engaged scholarship pre-study phase observations was that by Brynjolfsson and Mitchell, (2017), where AI is defined to include ML, and ML is defined as a general purpose technology (GPT), similar to those of electricity and combustion engine. As was the case e.g. with electrification and computerisation (Brynjolfsson & McAfee, 2014), GPTs require *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1) to realize its full effects in machines, business organizations, and in the broader economy (Brynjolfsson & Mitchell, 2017).

Thus, I moved away from the more known technological aspects of AI and approached AI more from the human perspective as a multiple-industry managerial and organizational phenomenon in this explorative doctoral dissertation.

In the next section, I move on from the definition of AI to analyzing the different approaches that management and organization scholars have adopted regarding AI in premium literature on general management and organizational studies.

Table 3. AI and/or ML definitions in general management or organizational studies journals.

First author, year	Artificial intelligence	Machine learning	Embedded term	Impact
Akstinaite, 2021		text analysis, advanced computational techniques for predictions		
Antons, 2021		text analysis	computational literature reviews augmented by ML	augment
Bhatia, 2021		automated method relies on ML and 'big data'		
Doornenbal, 2021		learn patterns & make predictions		
Gregory, 2021	advanced technologies in functional domains: combination, recursiveness, and phenomena	ML as part of AI, offers novel value and dramatically improved performance-price ratio		
Johnson, 2021	expected impact: automate researchers' tasks with AI		"automated scientists"	
Kaibel, 2021		randomization, statistics, computer science, technical requirements		
Leonardi, 2021	patterns, data turned into predictions			
Menz, 2021	digital age enabled by HW, SW, internet and mobile communications and AI		Digital technologies and digital age	
Murray, 2021		structured ML algorithm = augmenting technology, unstructured ML=automation	Related term: conjoined agency between humans and technology	
Nauhaus, 2021		Text and sentiment analysis, supervised ML algorithms or classifiers		

First author, year	Artificial intelligence	Machine learning	Embedded term	Impact
Nguyen, 2021	advanced technology features: skill, characteristic, and benefit examples		Related term: AI acceptance	
Pachidi, 2021		algorithmic technologies, such as data analytics, deep learning, and robotics		almost every process and ways of working and organizing
Pantano, 2021	AI & ML suitable for understanding and predicting emergent trends	emotional responses collected from customers in real time with ML	bridge gap between use of AI and big data analytics	
Raisch, 2021	AI-based solutions to automate routine and non-routine tasks	ML techniques allow tasks for AI-based solutions		augments human abilities and experiences
Schulz, 2021		Random forest analysis, a class of ML		
Sheng, 2021	AI often appears together with the underlying ML algorithms, key for success is human–computer collaboration	Underlie AI, predictive analytics technique category	Big data analytics	
Shrestha, 2021	ML is a subdomain within the field of AI	Explaining the fundamentals of ML		
Speer, 2021		Natural language processing, ML create estimates of performance standing based on text		
Truninger, 2021	AI-informed voice-analytic technology to assess vocal delivery	a patented voice-analytic software uses ML to compute predictions		
Wu, 2021	integrate data analytics, social networking, and AI		digital collaboration platforms	
Furman, 2020		Text analysis for predictions, identify similarities within text without predefined assumptions		

First author, year	Artificial intelligence	Machine learning	Embedded term	Impact
Glikson, 2020	highly capable and complex technology that aims to simulate human intelligence	ML as one commonly used component of AI		
Larson, 2020	ML examples of AI, AI has limits & ethical concerns, performs tasks normally requiring human intelligence	ML can detect patterns, learn, predict, recommend		With AI technologies to teams as autonomous team members
Lee, 2020		subfield of computer science, algorithms with ability to learn from patterns in data to make predictions of outcomes without constant supervision and reprogramming by a human	Related term: big data analytics	
Leonardi, 2020	algorithmic processing with expected impacts		Related terms: digitization, digitalization, and datafication	
Spisak, 2020		ML methods such as random forests with named ideally suited situations		
Akhtar, 2019		Big data-savvy teams depend on multi-disciplinary skills including ML	big data analytics	
Ding, 2019	big data and AI technologies are capable of analyzing high-frequency data			
Fleming, 2019	Highly advanced computer algorithms mimic human capabilities and display person-like reflectivity			AI absorbs manual work, cognitive and non-routine jobs
Pandey, 2019	Synonymous use of AI and ML, AI algorithms can identify language components, natural language processing capabilities are AI techniques for textual analysis	Examples and technical requirements for use mentioned	Related terms: computerized textual analysis	

First author, year	Artificial intelligence	Machine learning	Embedded term	Impact
Zhao, 2019		Software uses topic modelling	software tools automatically code a large volume of research	
Kobayashi, 2018		text mining facilitate the automatic assignment of text strings to categories, making classification expedient, fast, and reliable		
Putka, 2018		Caution: advances in ML, computer science, and statistics may be valuable but only, if clear translations provided between mathematically laden treatments of these advances and the problems faced within a specific discipline	Prediction analyses involving Big Data	
Tonidandel, 2018		modern data analytic methods, and where they are ideally suited, complementary research approach	Related term: big data	can be integrated in an iterative process to improve scientific techniques
Bettis, 2017	Heuristics as one of the most central topics of AI, AI researchers seek to imitate powerful human heuristics to find solutions in large complex problem spaces		Heuristics	
Phan, 2017	AI starting to be included into everything			Expected impact: no longer productivity enhancement but reordering of value creation and appropria-tion by human effort and the nature of work itself

First author, year	Artificial intelligence	Machine learning	Embedded term	Impact
Mayo, 2016		ML system creates entire classification structure represented in a rule decision tree in which each attribute is associated with a number representing the amount of information that that particular attribute provides to the entire system		
Shadbolt, 1998	has a relatively long history in dealing with knowledge from both a theoretical and practical perspective with influences from multiple disciplines		Expert system is a machine that does intelligent things (has commonly been used as a synonym for AI in the earlier literature)	
Lawler, 1996	Expert systems are AI applications that have shown great promise as decision aids across several functional areas of management		Expert system	
McDonald, 1990	Possibility of computerized assistance for strategic marketing planning, explaining the history of expert systems		Expert system	
Masuch, 1989	Explain experiences with AI compared to traditional programming techniques, primarily an inductive, trial-and-error-driven endeavor, AI has produced along the way the tools for a new generation of computer models	(Synonymous use of AI to modern use of ML)		

2.2 Research approaches to artificial intelligence

When examining the research approaches that the management and organization scholars have taken to AI, the literature can be divided into three categories (see table 4): 1) the studies, where AI is of interest as a novel research method that enables new kinds of contributions, 2) the studies where the research focus is set on AI as the subject of study with traditional research methods, and 3) the studies that use AI as a method to study AI as the subject of study.

Within the extant premium literature, the most popular research approach to AI has been set to using AI as a novel research method in the fields of management and organization (21 papers). The second most common approach to AI has been to study AI as the subject of study with traditional research methods, or to develop conceptual papers about the expected impacts of AI (15 papers). The emerging third approach combines AI use as a research method to study AI-related phenomena as the subject of study (6 papers, see table 5).

Table 4. Positioning the role of AI in this dissertation.

Research approach to AI:	This dissertation's approach:
AI as a research method	
AI as the subject of study	x
AI as a method and the subject of study	

In this dissertation, I have adopted the second approach and study AI as a phenomenon with qualitative research methods to explore the practical experiences of AI solution developers in multiple industries about AI use and their views on how AI is, or should be, managed (see table 4).

In the next section, the extant and emerging contemporary literature on AI is analyzed further with the emphasis on theories contributed to and their chosen units of analysis. Additionally, these findings are cross positioned based on their adopted research approach to AI.

Table 5. Overview of the adopted research approaches, theories contributed to, units of analysis and AI use phases in general management or organizational studies journals.

Approach	Journal	1st Author	Theories	Analysis	AI phases
method	Administrative Science Quarterly	Masuch, 1989	organizational decision making, garbage can model, tools from artificial intelligence	building an AI-based model of organizational decision making & reiterating computer simulation as a technique of theorizing	Use
method	British Journal of Management	Akstinaite, 2021	hubristic and other forms of destructive leadership, theory of natural language use, use of lexical choices	explore the potential of ML for recognizing and analysing linguistic markers of hubris in CEO speech	Use
method	British Journal of Management	Sheng, 2021	big data analytics, methods in use, predictive and prescriptive analytics, future of work, changes in consumer behaviour and new marketing practices, product/service development and innovation, operations and e-supply networks, global value chains and future resilience, challenges in sustainability, governance and public policy	review the methodological innovations in studying big data analytics and how they can be utilized to examine contemporary organizational and management issues arising from the global pandemic caused by COVID-19	Antecedents
method	British Journal of Management	Ding, 2019	risk management strategies when dealing with fluctuating commoduity prices, GARCH estimator	how AI techniques can be used to model the volatility of commodity prices	Use
method	Human Relations	Schulz, 2021	intra-organizational pay inequality research, inequality and trust, perception of fairness, employee collective voice	multi-level effects of intra-workplace pay inequality on employee trust in managers	Use
method	Journal of Management	Bettis, 2017	theory of organizational intractability, intractable decision problems, heuristics, finance and strategic management concept of organizational intractability intended to make it possible to identify important decision probelms that managers and organizations need to "decide" despite being intractable for organizations, secondly heuristics are appropriate for organizationally intractable decision problems.	organizational decision making based on a metaphor provided by the theory of computational intractability in computer science	Use

Approach	Journal	1st Author	Theories	Analysis	AI phases
method	Leadership Quarterly	Bhatia, 2021	computational methods, implicit leadership theories	predicting leadership effectiveness judgments, computational method for predicting, and identifying the correlates of, leadership perceptions for prominent individuals, predicting leadership perceptions for individuals, and with regard to traits	Use & paradigm shift?
method	Leadership Quarterly	Doornenbal, 2021	algorithmic machine learning techniques, leader trait paradigm	how ML can be used to model leadership as an outcome of complex patterns in traits, and predict leadership role occupancy	Use & paradigm shift
method	Leadership Quarterly	Truninger, 2021	the ascription–actuality trait theory of leadership	vocal delivery analysis of managers with the help of voice-analytic cloud-based software (that uses AI &ML) to study leader competency, leader emergence and effectiveness	Use
method	Leadership Quarterly	Lee, 2020	Big Data, predictive models in leadership research, leadership research, leadership effects	how ML can be used to advance leadership research from theoretical, methodological and practical perspectives and consider limitations	Antecedents & paradigm shift?
method	Leadership Quarterly	Spisak, 2019	leader trait paradigm, ML methods for predicting leader effectiveness	predicting leadership effectiveness of managers with high-dimensional data, added value of newer ML methods for predicting leader effectiveness versus conventional regression methods commonly utilized in leadership research, mechanisms driving leader emergence versus leader effectiveness	Use & paradigm shift?

Approach	Journal	1st Author	Theories	Analysis	AI phases
method	Leadership Quarterly	Zhao, 2019	computerized approach, leadership research, science mapping, computational literature reviews	a computerized technique to generate visual representations of academic research from bibliometric data, mapping the topics/authors network, topic development over time	Use & expected Impacts
method	Organization Science	Shrestha, 2021	ML techniques in theory construction, induction, abductive reasoning, algorithm-supported induction	prediction model as path to theory development from data followed by theory testing in a mutually complementary manner	Antecedent, use & expected impacts
method	Organizational Research Methods	Antons, 2021	systematic literature reviews	how to design, conduct, and document such computationally augmented literature reviews	Antecedents
method	Organizational Research Methods	Kaibel, 2021	randomised and ML allocation algorithms for experiments	subject allocation in experiments, efficiency and ethical comparisons through the use of simulations	Antecedents & expected impacts
method	Organizational Research Methods	Speer, 2021	methods in organizational research, natural language processing, performance evaluation,	detailing development of NLP scoring for performance narratives and investigating validity of derived scores in upward and downward judgements of managers and employees	Antecedents, use & impacts
method	Organizational Research Methods	Pandey, 2019	natural language processing (NLP), computer-aided content analysis methodology, organizational culture construct context	introduce AI based NLP capabilities into computer-aided content analysis methodology and develop a computer-aided content analysis based measure of organizational culture	Antecedents & use
method	Organizational Research Methods	Kobayashi, 2018	text classification, text mining	familiarize with text mining techniques from ML and statistics, describe the text classification process	Antecedents

Approach	Journal	1st Author	Theories	Analysis	AI phases
method	Organizational Research Methods	Putka, 2018	predictive modeling methods	introduce several modern prediction methods and compare them against traditional prediction methods	Antecedents
method	Organizational Research Methods	Tonidandel, 2018	big data methods	overview the big data phenomenon and its potential for impacting organizational science in both positive and negative ways	Antecedents
method	Organizational Research Methods	Mayo, 2016	team diversity, leadership, measuring categorization salience, ID3 algorithm	propose a technique to capture the salience of different social categorizations in teams that does not prime the salience of these categories	Antecedent, use & expected impacts
subject	Academy of Management Annals	Glikson, 2020	human trust, AI	factors influencing cognitive and emotional trust in robotic, virtual & embedded AI in organizations	Antecedents
subject	Academy of Management Perspectives	Johnson, 2021	automation, management and business science	research tasks that can be automated in the short and long term	Antecedent, use & expected impacts
subject	Academy of Management Perspectives	Phan, 2017	robots, AI, work and jobs	big leaps necessary for theorizing rapid phenomena & types of conversation difficult to have in science journals	Expected impacts
subject	Academy of Management Review	Murray, 2021	organizational routines, technology and organizing	types of human–nonhuman ensembles that exist in contemporary organizations, and their impacts on routines	Expected impacts
subject	Academy of Management Review	Raisch, 2021	automation, augmentation, paradox theory	emergent use of AI-based applications in organizations to automate and augment managerial tasks	Use & expected Impacts
subject	British Journal of Management	Shadbolt, 1998	Knowledge management, knowledge engineering,	identifying three antecedent problems, business process re-engineering tool adaptations, and impact benefits in case studies	Antecedents, use & impacts

Approach	Journal	1st Author	Theories	Analysis	AI phases
subject	British Journal of Management	McDonald, 1990	expert systems in strategic management	empirical testing of expert system prototype development, appropriate technology, problems suitable for expert systems, the role of computer and reviewing the value of applying expert systems to the marketing planning process	Antecedent, use & expected impacts
subject	Journal of Management	Lawler, 1996	behavioral decision theory, expert system, human resource management, problem solving, task complexity	expert system efficacy within an human resource management context	Impacts
subject	Journal of Management Studies	Leonardi, 2021	remote work, digital technologies, first- and second-order effects, digital exhaust, digital footprints, AI	second-order effects of remote work	Antecedent, use & expected impacts
subject	Journal of Management Studies	Menz, 2021	Corporate strategy, theory of the firm, digital age	implications of digital age for three domains of corporate strategy: corporate (competitive) advantage; firm scale, scope, and boundaries; and internal structure and design	Expected impacts
subject	Leadership Quarterly	Larson, 2020	technology and team leadership; technology as context, as sociomaterial, as creation medium, and technology as teammate	team leadership, how technologies affect teams and the needs for team leadership	Expected impacts
subject	Organization Science	Pachidi, 2021	radical technological change, technology and organizing, regime-of-knowing, technology introduction in the workplace, symbolic action	regime-of-knowing perspective on technology-related organizational change in a sales organization	Impacts
subject	Organization Studies	Leonardi, 2020	behavioral visibility, in digitization, digitalization, and datafication context, paradoxical consequences, agency	define various components of behavioral visibility, conditions through which it is commonly produced, and potential consequences of it	Antecedents, use, expected impacts & paradigm shift

Approach	Journal	1st Author	Theories	Analysis	AI phases
subject	Organization Studies	Fleming, 2019	automation, bounded automation, computerization, work, second machine age	socio-economic influences that fundamentally shape the diffusion of digital technologies in certain occupational settings	Expected impacts
subject	The Academy of Management review	Gregory, 2021	data network effects, user value, AI, platform	role of artificial intelligence and data network effects for creating user value	Antecedent, use & expected impacts
both	British Journal of Management	Nguyen, 2021	adoption of AI, AI service quality, AI satisfaction and job satisfaction	AI effects on nature of work and in its relationship with hotel employees and managers	Impacts
both	British Journal of Management	Pantano, 2021	emotions in strategic management, retail management literature with regard to customers' emotions and big data analytics	explore match between the supply of new analytical tools and retail managers' attitudes towards new tools to capture customers' emotions	Antecedents & use
both	British Journal of Management	Akhtar, 2019	resource-based view, extant and emerging literature on big data -savvy teams skills, big data-driven action, and business performance	the links between the use of big data-savvy (BDS) teams' skills, big data-driven (BDD) actions and business performance in global agrifood networks	Antecedents, use & impacts
both	Journal of Management Studies	Nauhaus, 2021	behavioural theory of the firm, decision comprehensiveness theory, strategic decision making in the digital age, literature on sentiments, sentiment analysis, and opinion mining	high risk capital allocation decisions, expert sentiment analysis	Antecedents, use & impacts
both	Organization Science	Wu, 2021	network-biased technical change, information technology, transactive memory systems	technological tool effects to transactive memory systems, types of employees, performance	Use, impacts & expected impacts
both	Organization Science	Furman, 2020	automating technology, knowledge production, automation of motion-sensing research	impact of an automating technology on the rate and type of knowledge production	Use & impacts

2.3 Contributions with artificial intelligence

This chapter builds on the previous chapter by introducing the kind of contributions management and organization scholars have made with the three different research approaches to AI: 1) AI as a research method, 2) AI as the subject of study, and 3) AI as both the method and the subject studied with it.

The most common adopted research approach to AI in the premium general management and organizational studies' literature is AI as a method, and the novelty of AI as a method was used to draw new theoretical contributions. This research approach can be found in 21 papers. In 15 papers, AI is approached as the subject of study with traditional research methods. In 6 papers both approaches have been adopted, when AI is applied as a research method to study AI as the subject of the study (see table 5). Technically AI consists of a wide variety of technologies that are studied in other disciplines such as information system sciences. In management and organization literature, AI seems more a phenomenon rather than a contributing discussion stream to any specific theory. Instead, the diversity of the theoretical discussions within management and organization contributed to via AI is noteworthy.

In the next three sub-sections, I give a short overview of how the management and organization scholars have contributed to literature with these three approaches to AI: 1) AI as a (novel) research method, 2) AI as the subject of study, and 3) AI as both the method and the subject studied with it.

2.3.1 AI as research method

Among the papers, where AI is approached as a *research method* (see table 5), contributions are made to methodology literature (Kaibel & Biemann, 2019; Kobayashi et al., 2018; Putka et al., 2017; Sheng et al., 2021; Shrestha et al., 2021; Speer, 2020; Tonidandel et al., 2018). Some focus specifically to systematic or computerised literature reviews by using AI (Antons et al., 2021; H. Zhao & Li, 2019). By using AI as a method, novel contributions are made to leadership literature (Akstinaite et al., 2021; A. Lee et al., 2020; Mayo et al., 2016; H. Zhao & Li, 2019), or more specifically to the leadership trait theory (Bhatia et al., 2021; Doornenbal et al., 2021; Spisak et al., 2019; Truninger et al., 2021). Some have focused on studying team diversity (Mayo et al., 2016).

With the help of AI as a method, others have contributed to decision making literature (Bettis, 2017; Masuch & LaPotin, 1989), price volatility in risk management (Ding et al., 2019), intra-workplace pay inequality and trust (Schulz et al., 2021), or organizational culture as part of the AI method construct (Pandey & Pandey, 2017).

2.3.2 AI as subject of study

In the context of AI as the subject of study with *traditional research methods* (see table 5), different aspects of work implications (Phan et al., 2017) and automation that have gained scholarly interest. These studies include focus on micro and macro extremes with their different levels of analysis such as task level (Johnson et al., 2021) and societal level (Fleming, 2019). Conceptual work-related contributions have been positioned between automation and augmentation with the help of paradox theory (Raisch & Krakowski, 2021). Leonardi (2021) has approached AI in the context of remote work. He has emphasized not only its primary but secondary effects through the increased data production and data collection. This is because of remote work and the use of AI to analyze the data produced by it at scale, AI can be used to predict and even shape human behaviors through it (Leonardi, 2021).

Glikson and Woolley (2020) have focused on the factors that influence cognitive and emotional trust in the different robot, virtual, and embedded forms of AI in organizations, whereas Murray (et al., 2021) have focused on the organizational routines and the collaboration between humans and AI by identifying different forms of conjoined agency.

In the contemporary literature, AI is already expected to affect team leadership in multiple ways (Larson & DeChurch, 2020). Changes are also expected through technological changes caused by AI and their impacts on organizing (Pachidi et al., 2021). AI is expected to have new data network effects (Gregory et al., 2021), or to question even core theories in the field of management and organization such as the theory of the firm (Menz et al., 2021).

Other theories that have been contributed to when AI has been chosen as the subject of study include behavioural decision theory (Lawler & Elliot, 1996), behavioural visibility (Leonardi & Treem, 2020), knowledge management (Shadbolt & Milton, 1999), and expert systems (Lawler & Elliot, 1996; McDonald & Wilson, 1990).

2.3.3 AI as both the method and the subject of study

Finally, when management and organization scholars have chosen *AI as the method to study AI as a phenomenon* (see table 5), they follow partly along the same lines of theoretical discussions and contributions as above. In these papers, AI-related contributions are deepened through empirical findings, e.g. through studying the empirical work implications of AI service quality in hotels (Nguyen & Malik, 2021).

Other management and organization theories that have been contributed to include automating technology and knowledge production (Furman & Teodoridis, 2020), and behavioural theory of the firm (Nauhaus et al., 2021). Additionally, paradoxical consequences are expected through network-biased technological change (Wu & Kane, 2021). More novel contributions relate to emotions in strategic management (Pantano et al., 2021), but also more traditional theoretical discussions have been touched by AI such as those of resource-based view, skills and data-driven action (Akhtar et al., 2019). (See further details and the units of analysis in table 5.)

In the next section, I will introduce how the premium AI-related literature in the fields of general management and organizational studies can be categorised to five different types of AI-related use phases. Each of the identified five use phase -sub-chapters will also include the cross-analysis from all the three research approaches, when AI is used as a method, when AI is the subject of study, or when AI is used as a method to study AI as the subject of study.

2.4 Use phases of artificial intelligence

Based on literature review in premium outlets of general management and organizational studies, the AI-related literature can be divided into five phases in relation to the use of AI: 1) antecedents preceding AI use, 2) the actual use of AI, 3) (empirical) impacts of using AI, 4) expected (cumulative) impacts of using AI, and finally 5) AI-related paradigm shift in management and organization research methods and theoretical contributions (see table 6).

Many of the contemporary management and organization studies on AI address multiple phases of AI use (see table 6). It is possible that the iterative nature of AI theory development is particularly highlighted at this emergent phase of the AI literature in the premium outlets of general management and organizational studies.

Authors not only focus on teaching other management and organization scholars about the potential benefits and limitations before using AI, but also give practical step-by-step advice for other management and organization scholars on how to use it in future research. They reflect the use and impacts of AI use as the antecedents of AI use in the future (see chapter 2.4.1).

The actual use of AI has been of interest to scholars as a novel method. AI is of interest to scholars also because of the related technological change and other phenomena already taking place in organizations and the society (see chapter 2.4.2).

At this point the biggest gaps seem to be in studying the actual empirical impacts of AI (see chapter 2.4.3). On the other hand, a lot of conceptual work is done on the expected impacts of AI (see chapter 2.4.4). Some papers have even started to address a potential AI-related paradigm shift (see chapter 2.4.5). Even new theories might be emerging. Some scholars question fundaments of multiple existing theories such as the theory of the firm (Phan, Wright & Lee, 2017), bounded rationality (Menz et al., 2021), or paradigms such as agency belonging only to humans (Raisch, Krakowski, 2021). A paradigm shift may be caused also by using AI as a novel research method.

Table 6. Extant literature on AI in premium general management and organizational studies.

	Antecedents	AI use	Impacts	Expected impacts	Paradigm shift
AI as method	Antons, 2021 Ding, 2019 Doornenbal, 2021 Kaibel, 2021 Kobayashi, 2018 Lee, 2020 Mayo, 2016 Pandey, 2019 Putka, 2018 Sheng, 2021 Shrestha, 2021 Speer, 2021 Spisak, 2019 Tonidandel, 2018	Akstinaite, 2021 Bettis, 2017 Bhatia, 2021 Ding, 2019 Doornenbal, 2021 Kaibel, 2021 Masuch, 1989 Mayo, 2016 Pandey, 2019 Schulz, 2021 Shrestha, 2021 Speer, 2021 Spisak, 2019 Truninger, 2021 Zhao, 2019	Speer, 2021	Shrestha, 2021 Tonidandel, 2018	Bettis, 2017 Bhatia, 2021 Doornenbal, 2021
AI as subject of study	Akhtar, 2019 Glikson, 2020 Gregory, 2021 Johnson, 2021 Leonardi, 2021 Leonardi, 2020 McDonald, 1990 Shadbolt, 1998	Akhtar, 2019 Gregory, 2021 Leonardi, 2021 Leonardi, 2020 McDonald, 1990 Shadbolt, 1998	Akhtar, 2019 Lawler, 1996 McDonald, 1990 Pachidi, 2021 Shadbolt, 1998	Fleming, 2019 Gregory, 2021 Johnson, 2021 Larson, 2020 Leonardi, 2021 Leonardi, 2020 McDonald, 1990 Menz, 2021 Murray, 2021 Phan, 2017 Raisch, 2021	Leonardi, 2020
AI as method and subject of study	Nauhaus, 2021 Pantano, 2021	Furman, 2020 Nauhaus, 2021 Pantano, 2021 Wu, 2021	Furman, 2020 Nauhaus, 2021 Nguyen, 2021 Wu, 2021	Wu, 2021	

In the following sub-chapters, each AI use phase is introduced more in detail per AI research approach.

2.4.1 The antecedents of AI use phase

Among the antecedents of AI use phase, AI has been approached as a research method, as the subject of study, or both.

When approaching *AI as a method*, the management and organization scholars have focused on factors that precede AI use in different ways. Some educate other scholars about AI or ML (Antons et al., 2021; Ding et al., 2019; Doornenbal et al., 2021; Kobayashi et al., 2018; A. Lee et al., 2020; Pandey & Pandey, 2017; Putka et al., 2017; Sheng et al., 2021; Shrestha et al., 2021; Spisak et al., 2019; Tonidandel et al., 2018). Some show it can be used to solve a methodological problem that existed before using ML as a research method (Antons et al., 2021; Kaibel & Biemann, 2019; Kobayashi et al., 2018; Mayo et al., 2016). Some have focused their primary contribution around the development of a better performing algorithm application for future studies (Ding et al., 2019; Kaibel & Biemann, 2019; Speer, 2020).

Whereas when the approach to AI has been set as the *subject of study*, the scholarly focus on the factors that precede AI use include both technical and non-technical aspects. Among the technical antecedents are automation of key tasks in the scientific research process (Johnson et al., 2021), the technical antecedents of knowledge (Shadbolt & Milton, 1999), the technical antecedents of expert system development and problems suitable for expert systems (McDonald & Wilson, 1990). Other technical and practical antecedents include creating and collecting required data for ML (Leonardi, 2021), and the user-centric (technical) antecedents of data network effects (Gregory et al., 2021). An important technical antecedent to AI use are also the required AI-related skills (Akhtar et al., 2019).

The non-technical antecedents to AI use, when AI is the subject of study, have included examining the factors that influence workers' trust in AI (Glikson & Woolley, 2020). Also data, AI-related behavioral visibility, and the process of organizing have been explored to understand how AI might change the way people will work (Leonardi & Treem, 2020).

When top publishing management and organization scholars have approached *AI as both the research method and the subject of study*, they have contributed to the practical utility decision-making before implementing AI (Pantano et al., 2021). Others have focused on the development of better performing algorithms as an iterative antecedent for future research (Nauhaus et al., 2021).

In the next section, I overview not the antecedents nor the impacts but the actual use of AI within studies published in premium general management and organizational outlets.

2.4.2 The usage of AI

When approaching *AI as a research method*, the actual use of AI is the other most popular AI use phase in addition to what precedes its use. As AI is still being introduced from other disciplines as a novel research method to the fields of management and organization, this seems understandable.

Best publishing management and organization scholars have introduced AI as a method both directly and indirectly. AI has even been applied as a metaphor for organizational problem solving. One such example is using heuristics and computational intractability from computer science as a model to decide important decisions that are intractable for organizations (Bettis, 2017).

However, most scholars have used AI or big data methods directly. AI has been used as a tool to solve methodological problems by developing applications for research problems such as that of organizational decision making (Masuch & LaPotin, 1989), or studying leadership traits (Akstinaite et al., 2021; Bhatia et al., 2021; Doornenbal et al., 2021; Spisak et al., 2019).

Other problems approached with AI-related methods include modelling future volatility of commodity prices with all the market information included (Ding et al., 2019), or demonstrating a curvilinear relationship between pay inequality and trust (Schulz et al., 2021), or using AI-based technique to measure categorization salience that applies to multiple dimensions of diversity in multiple combinations (Mayo et al., 2016).

AI has also enabled extending research design to new data formats such as the analysis of audio with the help of AI-informed voice-analytic technology (Truninger et al., 2021), or using AI for conducting computerized literature reviews (H. Zhao & Li, 2019). Scholars have even simulated inductive theorizing-pattern detection with the help of AI (Shrestha et al., 2021). Others have simulated an alternative allocation procedure for randomized controlled trials in organizational research (Kaibel & Biemann, 2019). At this stage of AI use maturity as a research method, it has also been important to test ML construct validity (Pandey & Pandey, 2017; Speer, 2020).

When management and organization scholars have approached *AI as the subject of study*, they have been interested in business process re-engineering in case studies (Shadbolt & Milton, 1999), or in developing an expert system for strategic marketing planning (McDonald & Wilson, 1990). The contemporary scholars have been more concerned about the use of ML to turn the digital exhaust of employees' remote work into predictions; and about how these predictions might be shaping employee behavior (Leonardi, 2021). Relatedly, other scholars have become concerned about producing behavioral (hyper-)visibility through self-presentation, aggregate quantification, and algorithmic ordering (Leonardi & Treem, 2020). Yet, some have also focused on the AI opportunities such as how to realize the data-driven learning scale and improvements with AI in the context of data network effects (Gregory et al., 2021).

Finally, the research related to AI usage has also been approached with *AI as both the research method and the subject of study*. This combination has been used to analytically detect emotional responses from customers' static images (Pantano et al., 2021), or to analyze expert sentiment from text at scale regarding high risk capital allocation decisions (Nauhaus et al., 2021). Scholars have studied the enactment of data-driven actions in big data-savvy teams (Akhtar et al., 2019), whereas others have focused on using ML to study the adoption of an expertise search tool per employee type (Wu & Kane, 2021). Also the use of automating motion-sensing research technology with novel measures based on ML techniques has gained scholarly attention to estimate how its use changes the types of knowledge that are produced (Furman & Teodoridis, 2020).

In the next section, the third AI use phase after antecedents and AI use is overviewed more in detail.

2.4.3 The (empirical) impacts of AI use

The research on the impacts of AI are only emerging, yet expected impacts of AI have been speculated not only among information system scientists but also among management and organization scholars since the 1960's (Meinhart, 1966). Yet, the empirical impacts of AI use remain among the bottom two of the least studied AI use phases. This is together with the emerging AI-related paradigm shift phase.

Among the empirical impacts, the research approach mostly focuses on AI as a subject of study, or scholars approach AI as both the subject and the method in their studies. The least amount of research in this AI use phase approaches *AI only as a research method*. However, there is one paper that can be categorized to do so: Speer (2020) has studied the variation in construct validity evidence based on which algorithm is used.

When we look at the studies that focus on the *empirical impacts of AI as the subject of study*, recent findings and contributions have focused on the enhanced business performance measures (Akhtar et al., 2019). Pachidi (et al., 2021) have created a better understanding on how different perspectives to change led to the full implementation of an algorithmic technology in a sales organization.

Older studies have studied the empirical impacts of knowledge engineering to knowledge management (Shadbolt & Milton, 1999), the performance and psychological outcomes of using an expert system as a decision aid in a job evaluation system (Lawler & Elliot, 1996), or the iterative value creation while first identifying suitable problems and then applying expert systems to them in a marketing planning process (McDonald & Wilson, 1990).

When AI has been approached as a *research method to study the empirical impacts of AI*, the contributions have been based on examining hotels where AI has been adopted: what are the effects of this change to AI service quality and hotel employee job satisfaction (Nguyen & Malik, 2021). Other recent studies have focused on the empirical data impacts on firms' allocation of capital decision-making (Nauhaus et al., 2021), on the empirical impacts of adopting an expertise search tool to employee work performance (Wu & Kane, 2021), or on the empirical impacts of a technology that automates research tasks (Furman & Teodoridis, 2020).

2.4.4 The expected (cumulative) impacts of AI use

When we extend the research focus from single impacts of AI to cumulative impacts of AI, large majority of scholarly attention is set on AI as the subject of study in the premium general management and organizational studies.

However, some have also focused on the *expected impacts of AI as a research method*. Based on these papers, ML techniques are expected to help with inductive theorizing-pattern detection (Shrestha et al., 2021). Big data phenomenon has potential to impact organizational science in both positive and negative ways (Tonidandel et al., 2018) already, and even more so when the cumulative use of AI as a research method is expected to increase.

Among the premium general management and organizational studies, only one paper approaches *AI as a method to study AI as the subject of study*. In this paper, the expected impacts of AI include the opportunity that digital collaboration tools may overcome old demographic institutional biases, and create new network-biased technical change (Wu & Kane, 2021).

Majority of the papers that can be categorized under expected (cumulative) effects have approached *AI as the subject of study*. The expected cumulative impacts of AI focus on work and workforce implications. Scholars expect that organizational forces such as pricing of labor, organizational power relations, and the nature of the task itself mold the application of technology and replacement of jobs in the employment sector (Fleming, 2019). Many current technologies are found to be applicable to automate researchers' tasks and they are expected to be able to do so even more in the future as these technologies are continuously being developed further. As a result, the potential dystopian and utopian future scenarios of automated management research are then discussed (Johnson et al., 2021). Work implications are not expected only on a single task level but more holistically, as digital technologies are expected to affect organizing through 12 leadership implications. These leadership implications are expected to be related to technology as context, technology as sociomaterial, technology as creation medium, and technology as teammate (Larson & DeChurch, 2020).

Not only primary, but also the second order effects of AI are expected to shape the trajectory of work for several decades. This is because remote work creates vast amounts of digital exhaust, which is then used to turn employees into data representations. Finally, these representations are used to predict (and shape) employee behavior with the help of AI (Leonardi, 2021).

Other expected *indirect or secondary side effects and/or antecedents of potential AI effects* include the consequences of behavioral visibility. They might come in the form of three tradeoffs and paradoxes related to self-presentation, aggregate quantification, and algorithmic ordering (Leonardi & Treem, 2020). Even a *paradigm shift* is expected, when AI is included in everything, including thinking work: then the conversation is no longer about productivity enhancement but the reordering of value creation and appropriation by human effort and the nature of work itself (Phan et al., 2017). Thus, the interlink between value creation and work seems to be suggested to deserve further research attention in the future.

When focusing on *perceived value of AI,* a positive direct relationship between the AI capability of a platform and the value perceived in the platform by its users is found to be moderated by platform legitimation, data stewardship, and user-centric design (Gregory et al., 2021). The perceived value may consist of a combination of data network effects and direct network effects (Gregory et al., 2021). Focusing not only on value creation, but more so to *competitive advantage,* new realities of the digital age are expected to have implications for corporate strategy related to corporate (competitive) advantage, firm scale, scope, and boundaries, and internal structure and design (Menz et al., 2021).

AI is also expected to impact *organizing* as technologies with capacity to exercise intentionality are affecting organizations in new and distinct ways, thus organizations are suggested to possibly evolve differently based on the type (or types) of conjoined agency on the chosen technology they adopt (Murray et al., 2021). When decisions are made about the approach chosen to AI use in organizations, augmentation and automation are suggested to be interdependent across time and space (Raisch & Krakowski, 2021). By adopting both rather than either automation or augmentation, the paradoxical tension is expected to be possible to be solved, and through that be able to benefit business and society (Raisch & Krakowski, 2021).

When moving away from the contemporary contributions to older ones, expert systems were expected to help structure, validate and disseminate marketing knowledge (McDonald & Wilson, 1990). At a theoretical level they were expected to challenge the expert system creators to understand and critically evaluate the elements of marketing knowledge and their inter-relationships (McDonald & Wilson, 1990). However, instead of verifying these expectations, more recent premium papers still seem to focus on the expected rather than empirical impacts of AI on marketing (Davenport et al., 2020).

In the fifth and final AI use phase, the emerging changes in research paradigms due to AI are introduced.

2.4.5 The AI-related paradigm shift

Even among the contemporary literature on general management and organizational studies, few papers already seem to contribute to an AI-related paradigm shift.

When approaching *AI as a research method*, a potential paradigm shift relates to contributions already starting to focus on *making predictions*: one paper has used ML as a research method to be able to both predict leadership perceptions and uncover the psychological cues for the specific correlates of leadership perception (Bhatia et al., 2021). Another paper has used ML to predict leadership role occupancy (Doornenbal et al., 2021).

When *applying ML as a method indirectly*, in one paper, AI methods have been applied as a metaphor to propose new organizational theory based on and inspired by AI heuristics (Bettis, 2017).

One more paradigm shift related to potentially new theory and results from studying AI use antecedents as *the subject of study*. These contributions propose new phenomenon-based theory on behavioral visibility (Leonardi & Treem, 2020).

In the next section, I move from the AI-related contributions to overview what the management and organization scholars have suggested as future avenues for AI-related research.

2.5 Suggested avenues for AI-related research

General management and organizational studies' scholars address one or several AI use phases both in the extant literature and among their suggestions for future research related to AI (see tables 6 and 7). This applies to all three research approaches: 1) AI as a method, 2) AI as subject of study, and 3) AI as a method to study AI as the subject of study.

Table 7. Artificial intelligence use phases and management and organization approaches to AI-related research, future research directions.

	AI use antecedents	AI use	AI use impacts	Expected AI Impacts	AI related paradigm shift
AI as method	Akhtar, 2019			Akhtar, 2019	
	Akstinaite, 2021	Akstinaite, 2021			
	Antons, 2021	Antons, 2021			Antons, 2021
	Doornenbal, 2021	Bhatia, 2021	Bhatia, 2021	Bhatia, 2021	Bhatia, 2021
	Glikson, 2020	Ding, 2019			
	Johnson, 2021			Johnson, 2021	
	Kaibel, 2021	Kaibel, 2021		Kaibel, 2021	Kaibel, 2021
	Kobayashi, 2018	Leonardi, 2020		Lawler, 1996	Sheng, 2021
	Lee, 2020		Lee, 2020		
	Masuch, 1989		Leonardi, 2020		
	Mayo, 2016	Mayo, 2016			
		Menz, 2021			
	Nguyen, 2021	Nguyen, 2021			
	Pandey, 2019	Pandey, 2019			
	Pantano, 2021	Pantano, 2021			
	Putka, 2018	Putka, 2018	Putka, 2018	Putka, 2018	
	Shadbolt, 1998	Schulz, 2021			
	Shrestha, 2021	Shrestha, 2021	Shrestha, 2021	Shrestha 2021	
	Speer, 2021				
	Spisak, 2019	Spisak, 2019		Spisak, 2019	
	Tonidandel, 2018	Truninger, 2021			
	Zhao, 2019	Zhao, 2019			
AI as subject		Bettis, 2017		Akhtar, 2019	Fleming, 2019
				Furman, 2020	
				Glikson, 2020	Glikson, 2020
				Gregory, 2021	
			Larson, 2020	Larson, 2020	Johnson, 2021
	Lee, 2020	Lawler, 1996	Lee, 2020	Lee, 2020	
	McDonald, 1990		McDonald, 1990	Leonardi, 2020	Leonardi, 2020
			Menz, 2021	Leonardi, 2021	Menz, 2021
			Murray, 2021	Murray, 2021	Pachidi, 2021
	Nguyen, 2021		Nguyen, 2021	Nauhaus, 2021	Phan, 2017
	Pantano, 2021	Pantano, 2021	Pantano, 2021	Raisch, 2021	Raisch, 2021
			Shadbolt, 1998		Sheng, 2021
			Wu, 2021	Wu, 2021	

	AI use antecedents	AI use	AI use impacts	Expected AI Impacts	AI related paradigm shift
AI as method and subject				Gregory, 2021 Leonardi, 2020 Raisch, 2021 Shadbolt, 1998	Leonardi, 2020 Sheng, 2021

This section is organized in the opposite AI use phase order than the previous section on extant contemporary literature. I start from AI-related paradigm shift and end in the AI use antecedents despite most future research suggestions being related to antecedents and use of AI as a method. I want to start with the paradigm shift because it seems the most interesting (Davis, 1971) in relation to the chosen research focus of AI as a multiple-industry managerial and organizational phenomenon.

2.5.1 Future research and AI-related paradigm shift

The AI-related paradigm shifts may fundamentally change the way a part of management and organization research is conducted in the future. With AI, the underlying paradigms in extant theories may be fundamentally questioned, or new theories are being proposed. Additionally, in the future with AI-related paradigm shifts, the borders between using AI as a method or approaching AI-related phenomena as the subject of study may get blurrier. Research may call for both the use of AI as a method to understand the changes caused by AI to capture the potential changes in theoretical paradigms:

> "*At minimum, such a paradigm shift entails a recognition that assumptions that people and organizations cultivate and direct their behaviors toward specific strategically crafted audiences misses the new reality that most of our behaviors become visible due, in tremendous measure, to digital connectivity, not to the audiences we intend them to. Instead, they are often seen by third parties who are voyeurs or eavesdroppers of our behaviors. And because of the increasingly complex and efficient large-scale data quantification practices and algorithmic ordering via artificial intelligence, those third parties have ample opportunities to make inferences about the contexts, motives, and causes of our behaviors and may act in ways that affect our behaviors in a performative manner. Thus, to effectively study behavioral visibility in this age of digital connectivity will require not only a focus on third parties, but a detailed understanding of the working of algorithms and data presentation and how such sociomaterial infrastructures are implicated in the emerging visibility of our behavior.*" (Leonardi & Treem, 2020, p 1621).

There is also another example where AI is used as a method to enable studying changes caused by AI, but to explain it, I will first explain the paradigm shifts in research methods enabled by AI.

When AI is used as a research method, the paradigm shift refers to the emergence of AI-enabled methods for predictive analysis (Bhatia et al., 2021; Sheng et al., 2021). AI may enable individualized practices and personalized recommendations

(Kaibel & Biemann, 2019), or be used for analysis in (nearly) real time (Antons et al., 2021; Bhatia et al., 2021).

Using AI as a method may also lead researchers to interesting new subjects of study. E.g. changes in the market may be identified first through continuous real time data collection, and then by using data mining and descriptive analytics for the data analysis, to meet the evolving needs of consumers (Sheng et al., 2021). In the longer run, scholars can then use the insights to develop marketing resilience, or to study whether these technologies can enhance customer experiences (Sheng et al., 2021). Thus, the border between the use of AI either as a method or approaching AI-related phenomena as the subject of study might get blurrier in the future.

The paradigm shift in relation to AI as a predictive and prescriptive method is mentioned to be required to help bridge the gap between research and practice in turbulent times (Sheng et al., 2021). Also, other scholars focused on AI as a subject of study either encourage other management and organization scholars to *"join the emerging multidisciplinary discussion that may determine the way organizations will integrate and use AI in the future"* (Glikson & Woolley, 2020, p 651), or already do so themselves through their own work (Fleming, 2019).

Not only that, but scholars are starting to question existing theories as fundamental as the theory of the firm (Phan et al., 2017), bounded rationality (Menz et al., 2021), or paradigms such as agency belonging only to humans (Raisch & Krakowski, 2021). Others propose solutions for the challenges and radical changes addressed by other scholars in previous literature (Pachidi et al., 2021). Even the underlying philosophies of science may be questioned as suggested by Johnson (et al., 2021, p 306):

> "*The automation of science would effectively result in a paradigm shift (Kuhn, 1970) in the philosophy of science. The business disciplines will have to reexamine what it means to know, what it means to be known, how knowledge changes when exchanged by humans and machines, and by what means we can test what we think we know to ascertain its truth and its value… Addressing these and doubtless many more questions will demand cross-disciplinary research ranging from philosophy to management research to computer science, and many fields in between*."

Thus, AI-related paradigm shift starts to call for either multi-disciplinary research collaboration or an increased understanding of algorithms even among management and organization scholars both when studying AI as a phenomenon and when using it as a method.

In the next sub-section, I continue from AI-related paradigm shift to the suggested future directions related to the expected AI impacts.

2.5.2 Future research on expected AI impacts

Alike with the AI-related paradigm shift, most of the suggested future research on expected AI impacts focus on AI as the subject of study. Yet, scholars have identified future research topics also for the expected (cumulative) impacts of using AI as a method alone or in combination with studying AI as the subject of study.

Scholars expect AI to have the potential to become a valuable new research tool (Kaibel & Biemann, 2019), and/or an additional or complementary research method among the traditional quantitative and qualitative methods (Putka et al., 2017; Shrestha et al., 2021). Some expect fundamental methodological changes because of the new ability to combine highly dimensional data with ML for discoveries (Spisak et al., 2019). Continuous technological advancement of AI-related methods is expected (Akhtar et al., 2019; Johnson et al., 2021; Lawler & Elliot, 1996), and authors encourage other scholars to build outperforming models compared to the models that they have introduced in their own work (Bhatia et al., 2021).

Few avenues for future research also focus on expected (cumulative) AI impacts when using AI as a method to study AI as the subject of study. AI is expected to impact finding inductive patterns and changes over time related to behavioral visibility (Leonardi & Treem, 2020), exploring linkages between data network effects and competitive advantage (Gregory et al., 2021), and using technology to capture knowledge about knowledge management and organizational effectiveness (Shadbolt & Milton, 1999). Some simply argue on a more general level that *"the ways in which scientific research on AI is currently conducted need to change to accurately capture and analyze its organizational and societal implications for managerial practice"* (Raisch & Krakowski, 2021, p 203).

When looking at the expected impacts of AI as the subject of study, a vast amount of future research is suggested. The suggested future avenues for research related to AI as the subject of study range from automation impacts (Furman & Teodoridis, 2020; Johnson et al., 2021) to leadership (Glikson & Woolley, 2020; Larson & DeChurch, 2020). More research is also needed about new organizing practices (Leonardi & Treem, 2020), sociomateriality and agency (Leonardi & Treem, 2020), or conjoined agency (Murray et al., 2021).

Other suggested future directions are advised on trust in human-AI co-operation (Glikson & Woolley, 2020), or on work augmentation through the complementary interaction between humans and machines (Nauhaus et al., 2021; Raisch & Krakowski, 2021). Some guide future research toward decision-making processes (Nauhaus et al., 2021), whereas others are concerned about the unexpected effects and implications of increasing primary and secondary data usage (Leonardi & Treem, 2020), or big data quality and cybersecurity issues (Akhtar et al., 2019).

In the context of AI as the subject of study there seems to be an increasing call for management and organization scholars to participate in the human-related discussion and questions related to the paradoxical positive and negative (Gregory et al., 2021; Leonardi & Treem, 2020; Raisch & Krakowski, 2021) or unexpected (Wu & Kane, 2021) impacts on how AI is to shape our future.

In the next sub-section, I continue from the suggested future directions related to expected AI impacts to the suggested future directions on empirical AI impacts.

2.5.3 Future research on AI impacts

Quite interestingly, no suggestions for future research are made that at least directly suggest using AI as a method to study AI-related phenomena.

When the suggested future directions focus only on the impacts of using AI as a method, management and organization scholars highlight that this will enable to better replicate and extend studies (Bhatia et al., 2021) in the future. However, scholars also note a shift in demanded skills when AI is used as a research method (A. Lee et al., 2020; Leonardi & Treem, 2020), because the AI-related research methods differ in the degree to which their results may be easily explained (Putka et al., 2017). The use of AI can also magnify the biases present in the training data and *"such biases may constitute a more serious problem in ML than in traditional statistics because many ML models remain difficult to interpret and thus may have difficult-to-spot potential biases"* (Shrestha et al., 2021, p 870).

Suggested future research on the impacts of AI as a subject of study include AI impacts on different levels of team leadership (Larson & DeChurch, 2020), augmentation (Larson & DeChurch, 2020), or conjoined agency effects in organizations (Murray et al., 2021). On the firm-level, additional research needs were identified on the effects of digitalization on the external boundary or internal arrangement of the firm, on transaction costs, on valuable corporate resources, and on different elements of performance (Menz et al., 2021). More research was also called for on the potential AI-adoption disparity and changes in power imbalance in increasingly digital organizational environments (Wu & Kane, 2021).

There seems to also be an interesting inter-relation between the suggested AI impacts and antecedents as the subject of study. These inter-relations include legal and ethical concerns related to the impacts of sensitive data use in leadership research (A. Lee et al., 2020), or collecting private data (Pantano et al., 2021). Less dramatic issues include the role of user interface design in delivering AI-related benefits (McDonald & Wilson, 1990). On algorithm level, new moderators are suggested to further understand AI and its impact in the workplace (Nguyen & Malik, 2021).

In the final two sub-section, I will briefly overview the suggested avenues for future research related to AI use and its antecedents.

2.5.4 Future research on AI use

A large majority of the suggested avenues for future research related to the use of AI focus on its use as a research method.

When using AI as method, future directions were suggested for the model component development (Akstinaite, Garrard & Sadler‐Smith, 2021, Bhatia et al., 2021, Nguyen, Malik, 2021, Truninger et al., 2021), and/or by addressing the limitations or concerns related to the use of AI as a method (Bhatia et al., 2021, Ding, Zhang & Duygun, 2019, Kaibel, Biemann, 2021, Nguyen, Malik, 2021, Pandey, Pandey, 2019, Spisak, van der Laken, Paul A & Doornenbal, 2019, Truninger et al., 2021). Some authors simply explained what novel things big data methods enable for conducting future research (Antons et al., 2021, Bhatia et al., 2021, Kaibel, Biemann, 2021, Leonardi, Treem, 2020, Mayo et al., 2016, Menz et al., 2021, Nguyen, Malik, 2021, Pantano, Dennis & Alamanos, 2021, Putka, Beatty & Reeder, 2018, Schulz, Valizade & Charlwood, 2021, Shrestha et al., 2021, Truninger et al., 2021, Zhao, Li, 2019).

A few avenues for future studies on AI use as a subject of study were mentioned. They included studying system adoption willingness depending on a specific subsector (Pantano, Dennis & Alamanos, 2021), different aspects of the use of heuristics in decision making (Bettis, 2017), or different contexts and processes of expert system use (Lawler, Elliot, 1996).

No suggestions for approaching AI as both the method and the subject of study in the actual AI use phase were identified.

In the final sub-section of the suggested avenues for future research on AI, I give a brief overview of the suggestions on future research related to the AI use antecedents.

2.5.5 Future research on AI use antecedents

Other than the above-mentioned inter-relation between AI impacts and antecedents as the subject of study (see chapter 2.5.3), all the other suggestions related to the antecedents of using AI in the future studies focus on AI as a research method.

Some give advice to those organization scholar readers who are thinking of using AI as a method in their own future research. They remind the article readers and other scholars about AI's research-related fundaments, or concerns related to them (Akhtar et al., 2019, Akstinaite, Garrard & Sadler-Smith, 2021, Glikson, Woolley, 2020, Lee et al., 2020, Masuch, LaPotin, 1989, Nguyen, Malik, 2021, Pandey, Pandey, 2019, Pantano, Dennis & Alamanos, 2021, Shrestha et al., 2021, Speer, 2021, Spisak, van der Laken, Paul A & Doornenbal, 2019).

Many also otherwise increase the method understanding before the other scholars are advised to take AI into use (Antons et al., 2021, Doornenbal, Spisak &

van der Laken, Paul A, 2021, Kobayashi et al., 2018, Lee et al., 2020, Mayo et al., 2016, Putka, Beatty & Reeder, 2018, Shadbolt, Milton, 1999, Shrestha et al., 2021, Speer, 2021, Tonidandel, King & Cortina, 2018, Zhao, Li, 2019).

Some authors educate other management and organization scholars and give practical guidance or mention valuable resources for learning how to use AI as a method in future research (Antons et al., 2021, Doornenbal, Spisak & van der Laken, Paul A, 2021, Johnson, Bauer & Niederman, 2021, Kaibel, Biemann, 2021, Kobayashi et al., 2018, Lee et al., 2020, Putka, Beatty & Reeder, 2018, Speer, 2021, Spisak, van der Laken, Paul A & Doornenbal, 2019, Tonidandel, King & Cortina, 2018).

Before moving on to the method section of this dissertation, I shortly summarize how this study is positioned in relation to the previous literature on AI as a phenomenon in the management and organization literature.

2.6 This study in relation to previous AI literature

In this doctoral dissertation artificial intelligence (AI) is understood to cover machine learning (ML) that is defined as a general purpose technology (Brynjolfsson & Mitchell, 2017) similar to those of electricity and combustion engine. However, in this phenomenon-driven study I have moved away from the more known technological aspects of AI and approached AI more from the human perspective as a multiple-industry managerial and organizational phenomenon. This is to explore the human rather than technical aspects of AI as a potentially disruptive innovation.

In previous literature on AI as a phenomenon in premium general management and organization outlets, AI has been used for new contributions either through using it as 1) a novel research method, or 2) AI has been studied as the subject of study with traditional methods, or 3) AI has been used as a method to study AI as the subject of study. In this dissertation, AI as a multiple-industry managerial and organizational phenomenon is explored as the subject of study.

Finally, the literature review on AI as a phenomenon in premium general management and organization studies outlets can be divided into five phases: 1) antecedents preceding AI use, 2) the actual use of AI, 3) (empirical) impacts of using AI, 4) expected (cumulative) impacts of using AI, and finally 5) AI-related paradigm shift. In this dissertation AI is approached as a multiple-industry managerial and organizational phenomenon. The scope of this dissertation is on the first four AI phases with AI as the subject of study: 1) antecedents preceding AI use, 2) the actual use of AI, 3) (empirical) impacts of using AI, and 4) expected (cumulative) impacts of using AI. The fifth AI use phase, 5) the AI related paradigm shift, is out of the empirical study scope of this dissertation, because its inclusion would have required the use of AI as a research method to study AI as the subject of study. (See chapters 1.2, 2.4.5 and 2.5.1.)

The next chapter focuses on the qualitative research strategy and methodology of this dissertation.

3 Research method and design

In this method section, I explain my methodological journey that started with a phenomenon-driven engaged scholarship pre-study phase. This pre-study phase guided my data collection. The analysis phase builds on grounded theory, more specifically the Gioia methodology. The Gioia methodology enabled rigor for the analysis of snapshots of the non-longitudinal empirical interview data as pre-theoretical insights and pre-study for future studies on the emerging processes.

As this study is partly bi-disciplinary, my first focus was to understand the technical foundation of AI in the field of information system sciences and to validate my understanding in their conferences. This was especially relevant, as this study started at the top of the Gartner hype cycle (Gartner, 2018, 2019), but with only few papers on AI within the field of management and organization at the time.

Thus, my explorative study journey on AI as a managerial and organizational phenomenon continued by authoring conference papers adopting various metatheoretical framings such as resource-based view, relational agency, performance management, and temporality. The reviewers' feedback on these conference papers provided me with valuable feedback and guidance on AI, and finally in fall 2021 there were enough AI papers published in premium general management and organization studies' outlets to enable conducting a literature review on AI as a managerial and organizational phenomenon.

Through the abductive interplay between the empirical conference papers and the literature review, I could finally finalize the research questions and contributions for this study.

In this chapter, I provide a more detailed overview of my research journey: of the pre-study phase, of the grounds for the chosen research strategy and design, and of the analysis phase. I also evaluate the research quality, reliability, and validity of this research at the end of this chapter.

3.1 Pre-study phase

This research project started in 2018, when AI had just reached the top of the Gartner hype cycle (Gartner, 2018, 2019), and before the Covid-19 pandemic. Because of this hype, consulting companies such as Gartner predicted rapid changes in workforce in the short term ("TechRepublic 1," 2017; "TechRepublic 2," 2017). Others, such as McKinsey, gave global numerical estimates about the longer term (Manyika et al., 2017). Researchers have been more cautious with estimating numbers or timelines, though they too have expected changes or effects on workforce (Brynjolfsson & McAfee, 2012; Brynjolfsson & Mitchell, 2017; Ernst, Merola, & Samaan, 2019; Fleming, 2019; Forum, 2018; Frey & Osborne, 2017; Furman & Teodoridis, 2020; Johnson et al., 2021; Lundvall, 2017; Phan et al., 2017; Raisch & Krakowski, 2021; Susskind & Susskind, 2015; Wu & Kane, 2021).

One of the factors potentially driving these expected significant changes in the workforce were based on the number of investments in AI. By 2020, total global corporate investment in AI had reached 67 854 million US dollars with a 530 percent growth from 2015 (Zhang et al., 2021). The venture capitalist (VC) investments on AI start-ups had reached 21 percent of all global VC investments in 2020, up from just 3 percent in 2012 (Tricot, 2021).

Throughout this study, the global investments in AI have continued rapid growth (Tricot, 2021; Zhang et al., 2021). Thus, as a young scholar I wondered what is done in practice in the industry with all these major AI investments, and what implications might these investments have toward the way we manage and organize.

As then, even the definition of AI remained unclear, owing to the multiple variations in understanding or defining AI (see chapter 2.1). In some papers, the definition of AI is even an object of debate and controversy (Cohen, 2005; French, 2000; Hayes, Hayes, & Ford, 1995; Turing, 1950; Whitby, 1996). Therefore, as a young scholar I could not help wondering - what are people spending money on when they talk about AI?

Haunted by this initial observation that surprised me in the engaged scholarship pre-study phase, it turned into my initial pre-study question.

3.1.1 Engaged scholarship

Puzzled both by the theory and the media on what is artificial intelligence, I needed to engage with both academics and industry experts. To understand AI both as a term and a as a phenomenon, I was inspired by engaged scholarship (Van de Ven, 2007) in the pre-study and pre-data collection phase. Engaged scholarship is defined as *"a participative form of research for obtaining the different perspectives of key stakeholders (researchers, users, clients, sponsors, and practitioners) in studying complex problems. By involving others and leveraging their different kinds of knowledge, engaged scholarship can produce knowledge that is more penetrating and insightful than when scholars or practitioners work on the problems alone."* (Van de Ven, 2007, p 9).

In practice, I first spent a year in the field in 2018-2019 to consult both multi-disciplinary academic and industry experts on AI in Finland, Sweden, Estonia, Belgium, Greece, and Australia. During this time, I organized 13 machine learning (ML) excursions for a female programmer community in Finland. This helped me to gain hands-on understanding on what AI consists of both as a technology and as a phenomenon in contemporary industry settings. Additionally, I attended AI/ML meetups, conferences, summer schools and seminars in Finland, Sweden, Estonia, Belgium, Greece, and Australia to understand AI as a technology in different industries and world leading expert organizations on applying AI.

In hindsight, the interactions in these events built the foundation for my semi-structured interviews to follow. In the above-mentioned events, I met professionals from various industries. They had varying disciplinary backgrounds, and they worked both in- and outside academia in multiple-industry settings at the time. At first, I was just curious about what these different experts were working on, and why, and how.

Later, I also found it an essential foundation for my study to better understand AI as I was not an AI expert when I started. Yet, it was these unofficial conversations, keynotes, workshops, and interviews that drove the empirical interviews rather than any specific theory or theoretical discussion stream. At the same time, my early research was influenced by many theories and theoretical discussions.

These interactions and continuous dialogue jumping from academia to industry and back to academia unveiled pain points and points of friction between theory and practice that ultimately caught my academic interest in AI as a phenomenon in relation to humans rather than having the focus only on the technological aspects of AI.

This human-centric focus on AI was also heavily influenced by factors such as policy makers and scholars starting to address a growing concern towards the ethical aspects related to the use of AI and its impacts on humans. In May 2018, the European Union had started to apply the European Data Protection Regulation in all member states to harmonize data privacy laws across Europe ("General Data Protection Regulation GDPR," 2019). Simultaneously scholars in the United States of America started to *"advance AI research, education, policy and practice to improve the human condition"* by founding a new institute committed to studying, guiding and developing human-centered artificial intelligence technologies and applications (A. Adams, 2019). This Institute of Human-Centered AI (HAI) guides and builds the future of AI in the Stanford University.

All this combined with the expected disruptive changes of AI toward work and workforce predicted by both scholars and consultants led me to focus my empirical data collection on the human-centered aspects of AI. More specifically, I was interested in investments in AI solution development across multiple industries to better understand AI as a human-centred managerial and organizational phenomenon, as opposed to AI just as a technology.

In the next sub-chapter, I provide an overview of the first literature review in the field of management and organization.

3.1.2 First literature review

My first literature reviews on AI in the field of management and organization returned only few articles. Thus, I was puzzled, and I wondered whether I had used the accurate search terms. Based on the literature from information system sciences I searched Scopus and 15 leading journals in management and organization with search terms "artificial intelligence" OR " AI " OR "augmented intelligence" OR "intelligence augmentation" OR "machine learning". This search resulted in only five fairly old papers that focused on AI as their main object of study (Holloway, 1983; Lawler & Elliot, 1996; Masuch & LaPotin, 1989; Meinhart, 1966; Orsini, 1986). The lack of prior research led me to adopt an inductive research strategy. Inductive research is particularly suitable for *"developing theoretical insights when research focuses on areas that extant theory does not address well"* (Ozcan & Eisenhardt, 2009, p. 249).

Even with the recent surge in AI-related literature in the fields of general management and organizational studies, AI still continues to reveal *"qualities of being a new but poorly understood phenomenon"* (von Krogh, 2018, p 408). This is despite the long multi-disciplinary research history on developing AI as a technology that dates back to the 1950's (Mccarthy, Minsky, Rochester, & Shannon, 1955; Turing, 1950).

Additionally, the empirical impacts on humans, management and organizations seemed to be missing to a large extent in the literature. Thus, my semi-structured interviews were to be free of theoretical straightjacket (Schwarz & Stensaker, 2014) though grounded (Glaser & Strauss, 1967) on the pre-study phase observations to enable theoretical discoveries during the analysis. Were such discoveries to be made inductively or abductively, they would have the potential to "*offer something empirically 'new,' without necessarily understanding all the theoretical mechanisms behind it"* (Christianson & Whiteman, 2018, p 397).

3.2 Phenomenon-driven research strategy

The paucity of prior empirical research on AI as a managerial and organizational phenomenon laid a foundation toward a phenomenon-driven (Schwarz & Stensaker, 2014) research strategy. Phenomenon-driven research enables freedom from the theoretical straight-jacket, and it methodologically helps to conceptualize the observed phenomenon toward potentially novel knowledge creation (Schwarz & Stensaker, 2014; Van de Ven, 2016). With this, I was able to learn from fields such as information system sciences and robotics, but not be tied to them only, nor to the neglected previous research on AI as a managerial and organizational phenomenon. I was able to test different literature streams as metatheories in the context of AI, but I was also able to maintain a holistic and curious exploration towards AI as a phenomenon.

What about the rigor? What would make my phenomenon-based research rigorous? Scholars von Krogh, Rossi-Lamastra, and Haefliger (2012, p 277) have defined that *"(r)igorous phenomenon-based research tackles problems that are relevant to management practice and fall outside the scope of available theories. Phenomenon-based research also bridges epistemological and disciplinary divides because it unites diverse scholars around their shared interest in the phenomenon and their joint engagement in the research activities: identification, exploration, design, theorising and synthesis."*

In phenomenon-driven practice of science, an important first element is to establish the phenomenon *(Merton, 1987, see* Van de Ven, 2015, p 2). The established phenomenon needs to have enough importance or regularity to require explanation in the context of that phenomenon, because *"(i)n this way pseudo facts that induce pseudo problems are avoided"* (Van de Ven, 2015, p 2).

In this dissertation I have explored AI as a managerial and organizational phenomenon, but that was not self-evident from the start. Rather, I started with the technical foundations and definition to understand, what is AI. Yet I soon discovered that even the definition of AI was heavily debated both in the literature and in the industry. Thus, rather than choosing a pre-defined definition for AI for this study, I decided to ask the interviewees in the basic information survey, how the interviewees themselves define AI.

This way, I started my study free from the theoretical straight-jacket of even defining AI. The only thing I knew was that I was curious to explore AI in a human-centric (A. Adams, 2019) way in the work context as that was a discussion stream that had started emerging in multiple fields (Brynjolfsson & McAfee, 2012; Brynjolfsson & Mitchell, 2017; Ernst, Merola, & Samaan, 2019; Fleming, 2019; Forum, 2018; Frey & Osborne, 2017; Lundvall, 2017; Phan et al., 2017).

I was advised to focus on a specific technology under the umbrella of AI, such as chatbots that were gaining popularity in information system sciences and in the industry at the time of the data collection. However, based on my pre-study phase, I knew I was looking at a bigger phenomenon. I did not quite know what it was, but there was something about AI that made it relevant across industries. Additionally, the expected impacts of AI on workforce and society had started to become a growing concern among researchers across disciplines (Brynjolfsson & McAfee, 2012; Brynjolfsson & Mitchell, 2017; Ernst et al., 2019; Fleming, 2019; Forum, 2018; Frey & Osborne, 2017; Furman & Teodoridis, 2020; Johnson et al., 2021; Lundvall, 2017; Phan et al., 2017; Raisch & Krakowski, 2021; Susskind & Susskind, 2015; Wu & Kane, 2021).

Thus, I wanted my empirical data to not only focus on a specific industry but to cross industry boundaries. Nor did I want to focus on a specific technology, rather I wanted to cover as wide a variety of technologies under the umbrella of AI as the AI expert interviewees saw fit.

Later, based on how the AI expert interviewees defined and explained AI in their work context, the definition that best captured what I had been witnessing during my engaged scholarship pre-study phase was that by Brynjolfsson and Mitchell (2017): they define AI to include machine learning (ML), which they define to be a general purpose technology (GPT), similar to electricity or the combustion engine. Yet, in the context of organizations, an interesting early finding was how the AI experts felt the need to *explain* AI to managers, employees, or clients in practice. They did this rather than using a specific definition for AI. The AI experts seemed to find it challenging but necessary to try to translate what AI *means* in the context of human work in each organization, rather than to tell what AI is, or how it works. It was noteworthy that no two definitions for AI were a hundred percent alike.

Maybe part of what makes AI hard to understand can be explained by the nature of GPTs. They are complex as innovations or technologies, because they require *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1) to realize their full effects in machines, business organizations, and in the broader economy (Brynjolfsson & Mitchell, 2017). Maybe partly because of this, AI is also found to embody a productivity paradox (Brynjolfsson et al., 2017). All this combined to the massive investments in AI (Tricot, 2021; Zhang et al., 2022, 2021) in the industry, AI as a phenomenon seemed to capture something especially interesting from the management and organization perspective.

Later during the analysis phase and while presenting my first empirical findings, I was searching for an answer to a question posed by multiple senior scholars: what is the whole phenomenon of AI a case of from the management and organization theory perspective? The more I read, the clearer it became that AI seems to have qualities that can be studied from multiple perspectives in the field of management and organization. Thus, there was no one theory or framework that seemed to fit, *capture and explain* the whole phenomenon of AI in management and organization theorizing, except that of AI as a phenomenon. Thus, the synthesis of this doctoral dissertation is first and foremost also theoretically framed under the identified AI use phases and among the identified research approaches to AI (see chapter 2). Only secondarily, *parts* of this dissertation, could be theoretically framed additionally under specific management and organization theories and be turned into conference papers. At the same time, this literature review on AI in the premium literature on general management and organizational studies contribute to the understanding of AI as general purpose technology, and its impacts as an innovation, as the contributions of the elite scholars in our field have not only contributed to different streams of literature in our field by approaching AI as the subject of study but also as a novel research method. These insights and findings start to reveal the potential scope and versatility of the phenomenon we might be dealing with not only academically but in the society at large.

I submitted papers to conferences both in the fields of information system sciences and management and organization. In these conference papers, I framed my contributions to different management and organization metatheories such as resource-based view (see chapter 5.3.1), relational agency (see chapter 4.3), performance management (see chapters 5.1.2, 5.1.4 and 5.1.6) and temporality (see chapter 4.5) based on the emerging grounded findings. These efforts were a valuable step on my research path and in turn also gave insights to better understand and make sense of the previous literature on AI during the literature review phase to follow. By fall 2021 there were enough AI related articles in premium general management and organization studies' outlets that I was able to conduct a literature review. This literature review focused on AI as managerial and organizational phenomenon. This had been my original research plan from the start.

The literature review seemed to confirm my early empirical findings: also other management and organization scholars were starting to contribute to a wide variety of theoretical discussion streams with the help of or through the study of AI.

Finally, after a rigorous interplay between the empirical findings and literature review, I finally got the theoretical framing that I had been searching for.

Firstly, AI as a managerial and organizational phenomenon could be broken down to three research approaches that helped in positioning my study (see chapter 2.3). The three research approaches that I found to be used were: 1) AI as a method, 2) AI as a subject of study, and 3) AI as a method to study AI as the subject of study. Additionally, AI as managerial and organizational phenomenon could be divided into five AI use phases (see chapter 2.4): 1) AI use antecedents, 2) AI use, 3) empirical impact(s) of AI, 4) expected (cumulative) impacts of AI, and 5) AI-related paradigm shift(s).

Within this proposed theoretical frame of AI as a managerial and organizational phenomenon, the established and phenomenon-based discoveries of future research have the potential *"to provide empirical information and new ideas about managerial phenomena that can be used to stimulate subsequent theory building papers and hypothesis-testing"*. As such, they may serve as pre-theory on poorly understood phenomena (Van de Ven, 2015, p 2).

The foundations of phenomenon-driven research is in problem-orientation, where rigor relies on capturing, documenting, and conceptualizing the observed phenomenon, and contributions facilitate new knowledge creation and theory advancement (Schwarz & Stensaker, 2015; Van de Ven, 2016a). By exploring AI holistically as a managerial and organizational phenomenon both empirically and theoretically, I aim to pave the way for management and organization scholars to better position their studies among the AI literature. With this, I hope other scholars to be able to make more specific contributions in future studies to the management and organization literature on AI as a managerial and organizational phenomenon.

In the following sub-sections, I introduce the empirical data collection and analysis more in detail.

3.2.1 Qualitative research design

Given the paucity of prior empirical research on AI from the perspective of management and organization, I adopted a phenomenon driven (Schwarz & Stensaker, 2014) qualitative research design (Glaser & Strauss, 1967).

"Qualitative research is particularly relevant when prior insights about a phenomenon under scrutiny are modest, implying that qualitative research tends to be exploratory and flexible because of 'unstructured' problems (due to modest insights)" (Eriksson, 2008, p 6). Thus, it was qualitative rather than quantitative research that enabled me to focus on the complexity of AI as a phenomenon and to aim to start understanding and interpreting it holistically in the context of management and organization. I was particularly interested in understanding the practical AI developers' industry experiences on AI-based incremental innovation development and in identifying issues from their perspective, to understand the meanings and interpretations that they give to AI related issues in their work context, and for this qualitative research design was particularly suitable. *"Qualitative research is most suitable for addressing 'why' questions to explain or understand issues or 'how' questions that describe processes or behaviour"* (Hennink, 2011, p. 10).

Even though my main research question is neither 'why' nor a 'how' question directly, it still aims to start identifying factors that would help to start understanding the reasons why AI-based value creation and productivity might be challenging from the management and organization perspective in four use phases of AI identified in the literature review (see chapters 2.4 and 2.5). When combined, the identified AI use phases form a process that includes the decision-making before AI is taken into use, understanding the complexity of AI portfolio management while an organization is starting to take an increasing amount of AI solutions or agents into use, and measuring the empirical impacts of AI after it has been taken into use. I even try to predict how the cumulative adoption of AI might already be changing the work reorganising needs from the perspective of time and speed.

To interpret and explain AI as a GPT and as a managerial and organizational phenomenon, I focus on the 'how' in the sub-research questions to start to understand how AI is defined (SRQ1), how the decision-making behind AI investments are formed (SRQ2), how and why might the actual and wanted use of AI differ (SRQ3), how are the impacts of AI-based technology development investments measured (SRQ4), and finally what are the expected changes of AI to time and speed in an organization and how might these expected changes need to be taken into account in future work re-organizing and work time allocation (SRQ5, see chapter 3.2.1 for all the research questions). Also the questions asked from the AI developers in the semi-structured interviews that were included as part of the data analysis mostly consisted of 'how' and 'why' questions, either directly or indirectly by trying to identify what might the different factors be that might help to interpret and understand the 'why' or the 'how' of the main and sub-research questions (see chapter 3.2.3.1). Yet as the data collection was not done with a process perspective in mind, the Gioia method seemed a more rigorous research method to identify the explaining factors as part of the whole process to be studied in future research with process methods in mind already at the time of the data collection.

In the following chapter, I focus on the empirical data collection and analysis more in detail.

3.2.2 Empirical data collection

When I started this research, I thought I was conducting an inductive rather than an abductive study. I was first guided by the inductive works of Eisenhardt (Eisenhardt, 1989; Eisenhardt, Graebner, & Sonenshein, 2016), where a specific theory did not guide my data collection. As guided by grounded theory, I had only pre-defined the area of my study (Glaser & Strauss, 1967) to focus on the human-centered aspects of AI in the work context before the empirical data collection started.

I first drafted the semi-structured interview questions based on my pre-study observations through engaged scholarship. Together with my second supervisor from information system sciences, we then divided the questions into a basic information pre-survey and into the semi-structured interview questions (see appendices 1 and 2).

Additionally, we partly modified the questions that I had formed based on the engaged scholarship phase (see chapter 3.1.1). Initial contribution potential to information system sciences was identified to theories such as diffusion of innovation theory (Rogers, 2003), technology acceptance model (Fishbein & Ajzen, 1975), and unified theory of acceptance and use of technology (Venkatesh, Thong,

& Xu, 2012). Upfront, other applicable theories seemed to be continued use of information systems theory (Bhattacherjee, 2001), the resource-based view (J. Barney, 1991; J. Barney, Wright, & Ketchen, 2001; Helfat & Peteraf, 2003; Wernerfelt, 1984, 1995), and value creation (Lepak, Smith, & Taylor, 2007; Priem, 2007).

A wide variety of questions were warranted for this phenomenon-driven research where, unlike deductive or positivist scholars, I was not sure in advance what was it that I was looking for. The basic information survey questions and semi-structured interview questions are listed in appendices 1 and 2.

3.2.2.1 Informant selection

Before collecting the empirical data, the closest match of the engaged scholarship pre-study phase observations of AI was that by Brynjolfsson and Mitchell, (2017). They define AI to include ML and ML as a general purpose technology (GPT), similar to those of electricity or the combustion engine. GPTs require *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1) to realize their full effects in machines, business organizations, and in the broader economy (Brynjolfsson & Mitchell, 2017). Because of this premise set to AI as a GPT in this study, the interviewees were chosen to be those who develop these *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1) in different industries.

I chose AI solution developers as my informants, because of their high potential to not only represent either innovators or early adopters (Rogers, 2003) of AI but also them being the individuals who develop necessary complementary innovations (Erik Brynjolfsson et al., 2017) on top of AI in the industry. Such complementary innovations are required for others such as early majority, late majority or laggards (Rogers, 2003) to be able to adopt the technology in the form or AI-based products or services.

To find relevant interviewees for this study, all the interviewees were to have both technical and business experience on implementing AI-based solutions in the industry. These prerequisites were to ensure gathering reliable and valid interview data, and to minimize AI bias that might be caused by the hype around AI: *"…management scholarship can also make an effort to help practitioners see through all the 'hype' and adopt an informed, prudent, and realistic approach to AI."* (von Krogh, 2018, p 408). Additionally, the set prerequisites for the informants led to the exclusion of purely academic interviewees and set my empirical data collection focus to AI solution developers.

The interviewees were found in one of the following three ways: firstly, from a prescreened AI company landscape listing provided by the Technology industries of

Finland (Poikola, 2018). Secondly, interviewees were found either directly or indirectly through personal networks created during the engaged scholarship pre-study year in 2018-2019 (see chapter 3.1). I either directly contacted AI experts that were known to fill the predefined interviewee criteria and/or found additional interviewees through the recommendations of these international networks. In practice, I used social media platforms such as LinkedIn to ask who should be interviewed for this study with my pre-defined interviewee criteria and with the focus on the human-centered aspects of AI. Third way to find additional interviewees was through snowballing at the end of the interviews when I asked the interviewees, who else should be interviewed.

In total, the empirical data collection included 34 AI solution developer interviewees and 33 interviews. One of the interviews was a pair interview, as requested by the organization representatives in advance of the interview. Nine out of thirty-four interviewees were female, twenty-five were male.

3.2.2.2 Basic information survey

A few days in advance of each interview, I sent a background information survey to the interviewees. If the interviewee was not able to fill in the survey in advance, the survey was completed before starting the semi-structured interview. One of the basic information surveys was filled in and returned after the interview. Only one of the two pair interviewees answered the basic information survey on behalf of the organization that both the pair interviewees represented. Thus 33 basic information survey answers were collected.

In total, the interviewees represented 18 different industries (see table 8). However, 11 out of the 33 interviewees represented consulting companies that provide technical AI solutions to their clients in multiple different industries. On the one hand, they may skew the balance between different industry views represented in the interviews. On the other hand, the clients of the consultants represent an even wider variety of industries.

As all the interviewees develop AI solutions either to their own organizations or to the organizations of their clients, the interviewees may have a pro innovation bias towards AI. Because of their practical experiences in developing AI solutions in a wide variety of different industry contexts, many of the interviewees considered the critical views, limitations, and challenges to be overcome while AI solutions are being developed across industries. This served particularly the general purpose technology (Brynjolfsson & Mitchell, 2017) view of the potential impacts of AI to humans, management, and organizations.

Table 8. All background information of the interviews and interviewees, and ones excluded in empirical analysis for sub-research questions 2-4.

Years of AI experience	Industry	AI user/developer/supplier	Organization	Operations in	Country	Expert role	Supervisor	Senior Manager	Interviewed	Interview duration (min)	Interview language	Casing
35	Consultancy	Developer	Startup	Finland	Finland			x	Online	98	Finnish	Product
26	Automation	Developer	Startup	Finland	Finland			x	Live	102	Finnish	Product
20	Entertainment	User & developer	Corporation	Globally	USA	x	x		Online	116	Finnish	Product
20	Robotics	User & supplier	Startup	Europe, Asia	Finland			x	Live	75	Finnish	Robotics
20	Healthcare	Developer, applier, user	City	Finland	Finland	x			Live, Pair interview	58	Finnish	Key part
17	SAAS	User, developer, supplier	Startup	Europe	Finland			x	Live	93	Finnish	Product
15	Robotics	User, developer, supplier	Startup	Europe, North-America	Finland	x	x	x	Live	117	English	Robotics
15	Industrial maintenance	User, developer, supplier	Corporation	Europe	Finland	x			Live	104	Finnish	Key part
13	Legaltech	User, developer, supplier	Startup	Finland	Finland	x		x	Live	127	Finnish	Product
12	Consultancy	Developer	Startup	Nordics	Finland	x	x		Live	125	Finnish	Consultancy
12	Maritime	Developer, business and productization	Corporation	Globally	Finland			x	Live	129	Finnish	Key part
11	Consultancy	User, developer, supplier	Startup	Europe, Asia	Finland	x			Live	141	Finnish	Ingredient
10	Sales	User & developer	Startup	Europe, North-America	Finland			x	Live	102	Finnish	Product
10	SAAS	Supplier	Startup	Europe	Finland			x	Live	93	Finnish	Product
9	Consultancy	User & developer	Startup	Finland	Finland	x	x	x	Live	84	English	Consultancy
7	Consultancy	User & supplier	Corporation	Globally	Finland			x	Live	100	Finnish	Consultancy
6	Consultancy	User, developer, supplier	Corporation	Europe, North-America	Canada	x	x		Online	89	English	Consultancy
5	Manufacturing	User & developer	Corporation	Europe, North-America	Finland		x	x	Live	106	Finnish	Product
5	Banking	Developer	Corporation	Finland	Finland		x	x	Live	106	Finnish	Ingredient
5	Media	Strategist, change agent	Corporation	Finland	Finland	x		x	Live	125	Finnish	Ingredient
4	Healthtech	Developer and supplier	Startup	Finland	Finland	x		x	Live	109	Finnish	Product
4	Consultancy	User, developer, supplier	Startup	Europe	Finland	x			Live	119	Finnish	Consultancy
4	SAAS	Enabler for data scientists	Startup	Europe, North-America	Finland			x	Live	114	Finnish	Product
4	Automotive software	strategy	Corporation	Europe, North-America	Finland		x	x	Live	110	Finnish	Key part
3	Maritime	User, developer, supplier	Corporation	Globally	Finland		x	x	Live	107	Finnish	Robotics
2	Healthcare	User, developer, supplier	City	Finland	Finland	x			Live	97	Finnish	Ingredient
2	Logistics	User & developer	Corporation	Globally	Finland			x	Live	113	Finnish	Ingredient
2	Consultancy	User & developer	Startup	Europe	Finland	x			Live	113	English	Consultancy
1	Customs	Specification, testing, evaluation, find use cases	State	Finland	Finland	x			Live	72	Finnish	Ingredient
Included in analysis for sub-research questions 1 & 5, Excluded from the sub-research questions 2-4										TOTAL: 50h 44min		
40	(Non-tecnical) consultancy	Management consultant	Entrepreneur	Finland	Finland	x			Online	128	Finnish	Excluded
7	(Non-tecnical) consultancy	Management consultant	Entrepreneur	Europe	Finland	x			Live	74	Finnish	Excluded
3	(Non-tecnical) consultancy	Management consultant	Entrepreneur	Finland	Finland	x			Online	89	Finnish	Excluded
2	(Non-tecnical) consultancy/ Matchmaking	Use case identification	Corporation/ Startup	Europe, North-America	Finland			x	Live	92	Finnish	Excluded
										GRAND TOTAL: 57h 7min		

In the basic information surveys, the interviewees were asked about their current job description. One third of the interviewees were in multiple roles. When asked about their personal relation to AI, 28 out of 33 considered themselves to have multiple roles in relation to AI. The most common combination included roles as both the user of AI and the developer and/or supplier of AI solutions. Some also defined their role toward AI with more business focused roles such as a strategist, management consultant, idea level developer, or expert in productization of AI. Some focused also on guiding policymakers regarding regulatory questions of AI.

As part of the basic information survey, the 34 interviewees were asked to define artificial intelligence before the actual interview took place. Seven of them defined AI during the interview and, additionally, one filled in the definition during the interview.

When asked about the duration of personal history with AI, fifteen out of the thirty-three interviewees had ten or more years of experience with AI. However, some of the interviewees problematized this question because of the vagueness of the term AI (see chapters 2.1 and 4.1). Typical to the Finnish culture, many of the interviewees were cautious in overestimating their experience. Some interviewees were quite literal with this question despite the years of related experience preceding work with their work title or work description specifically addressing the term 'AI'. One example of this is illustrated by interviewee 3: *"Well that depends specifically on how it (AI) is defined. AI as a term has come into my life maybe in 2015, but I have worked on the same concepts and elements since the beginning of my studies in 2006."*

Some background information questions were asked also about the organization that the interviewee worked for at the time of the interviews: what AI solutions had already been developed and what sort of an AI strategy had been adopted in his/her organization? This information was used for casing the interview data based on the adopted AI strategies. The AI solutions developed by the organization that each interviewee worked for also served as additional background information to some semi-structured interview answers in the analysis phase.

At the time of the interviews, thirty-one of the interviewees were based in Finland, one was based in the United States of America, and one in Canada. All the interviewees had some connection to Finland. The interviewees were of Finnish nationality either in Finland or abroad, or the expert might have been of foreign nationality but the company s/he worked for had Finnish owners or was situated in Finland. Thus, the cultural context of the interview answers is set in the North European and Nordic country cultural context. While this may be a limitation, it may also complement the previous literature of AI by offering a different perspective e.g. in comparison to the US-based AI giants and market-leading platforms, such as Google, Amazon and Facebook, that all use machine learning and with that have been accused of gaining unfair competitive advantage (Rietveld & Schilling, 2021).

A summary of the basic background information of the interviewees is summarized in table 8. Note that 4 interviewees were excluded from the per AI strategy analysis conducted in studies related to sub-research questions two to four (for reasoning, see chapter on casing 3.2.3.4). They are marked separately in the table as excluded from these studies. All the basic information survey questions are found in appendix 1.

3.2.2.3 Semi-structured interviews

Based on the pre-study phase (see chapter 3.1) inspired by engaged scholarship, I formed semi-structured interview questions for the empirical interviews.

All the semi-structured interviews were conducted in spring 2019 and lasted from 1 to 2,5 hours depending on the interviewee's time resource available for the interview (see table 8). In total, the collected empirical interview data consists of over 57 hours of interview recordings. Out of the interviews, 32 were individual interviews and all the interviewees represented different organizations. One interview was a pair interview as wished in advance by the interviewees, and they both represented the same organization. Five out of the 33 interviews were interviewed using online-conferencing services, the rest were interviewed face-to-face. Four of the thirty-three interviews were in English, the rest were in Finnish, and thus needed to be translated into English in the analysis phase.

During the interview, I both asked the questions aloud and showed the semi-structured questions to the interviewee. I also typed the answers so that the answers stayed visible to the AI developer. This was to enable correcting potential misunderstandings already during the interview.

I recorded all the interviews with the interviewees' consent. To further reinforce correcting potential misunderstandings, I sent a narrative of all the interview questions and answers to the interviewees. During this data validation phase, one of the interviewees deleted some answers not wanted to be included in the research, and one interviewee clarified industry specific information as background to the AI solution answers.

The semi-structured interview questions are listed in appendix 2. In the next section, I try to explain the analysis process as transparently and clearly as possible.

3.2.3 Grounded analysis as a process

It is hard to define where and when the analysis phase of this study started. This is because analysis has been needed from the start of the study, already when choosing the research design. Moreover, early analysis was needed in the engaged scholarship pre-study phase, based on which I formed my initial research questions and the semi-structured interview questions.

One of the most fundamental decisions was how to define AI and making a phenomenon-driven choice to not define AI on behalf of the informants. Rather, I let them define AI as they have experienced it in the industry.

In a basic information survey associated to the semi-structured interviews of this study, 34 AI solution developers from 18 different industries were asked to define, how they themselves understand the term AI. Some of them wanted to specifically emphasize how they *explain* AI to the non-AI experts in their organizations or for their clients. This heavily guided the direction to which the whole study was later going to go.

The original grounded theory approach (Glaser & Strauss, 1967) enabled the flexibility toward what is being analyzed, and how, without forcing the data into a predefined template (Glaser, 1992). With scant previous literature on AI in management and organization studies at the start of this study in 2018, the only thing I knew was that the focus of my study was at the human-centric aspects of AI in the work context.

Based on the pre-study phase, the developers of AI seemed to have started to call for better managerial and organization-wide understanding of AI for it to create value. This also seemed relevant and interesting from research point-of-view because of the hype and massive investments into AI in the industry (Tricot, 2021; Zhang et al., 2022, 2021). So initially, I was not sure what was it that I was looking for.

During and after the interviews, my analysis started to focus on the actual problems (Glaser & Strauss, 1967; Teerikangas, 2006) that the interviewed AI developers had faced while they developed different AI solutions either for inhouse use or for the use of their external clients.

While conducting the semi-structured interviews, I also noted initial observations and new questions that derived from the previous interviews. I then tested these observations in the following interviews to either verify or reject their relevance as part of the whole study, and to increase my own understanding of AI as both a technology and as a phenomenon.

I also wrote a narrative of the whole interview transcript for the interviewee to verify my understanding as soon after conducting each interview as possible. Thus, I was simultaneously looking back at previous interviews (while writing the narratives for the interviewees to proof-read) and collecting new interview data. This parallel dialogue between different informants led to extensive memoing on different initial observations, and constant comparison of these observations against new and previous interview answers (Glaser & Strauss, 1967). These initial observations were to later guide the more detailed and systematic analysis based on the chosen theoretical sample questions and coding incident by incident (Glaser & Strauss, 1967; Teerikangas, 2006), to which I applied the Gioia methodology (Gioia et al., 2013).

In my analysis, I needed the structure provided by the Gioia methodology. This is because the initial observations seemed true based on the data, but I found it challenging to rigorously and transparently demonstrate where exactly the observations derived from.

I realized it was impossible to fit all the required data into the same analysis at an early stage. Thus, the initial observations needed to be transformed into a well-defined main research problem. And that main research problem then needed to be broken down to sub-research questions that could be analyzed based on specific interview question answers. Then I needed to trust the process, that maybe the sum of their parts would lead me a rigorous step closer to capturing the early observations of the whole phenomenon of AI in the management and work organization context.

Thus, I started my analysis from what seemed like the most fundamental level of any topic to be studied, the definition. I asked the literature and the empirical basic information survey answers, how is artificial intelligence defined? Based on the empirical interviews' early observations and the first empirical analysis on the definition of AI no two empirical definitions given for AI were alike (Kukkonen, 2019). An interesting complexity to AI as a phenomenon had started to emerge.

As grounded theory enables research problems to emerge from the data (Glaser, 1992; Glaser & Strauss, 1967; Teerikangas, 2006), I was to follow these early findings. As an attempt to capture this complexity of AI as a phenomenon and the potential impacts of AI as an innovation (Rogers, 2003), I first chose to explore and analyze the data at different levels of analysis. I started from the task level (Kukkonen, 2021b), moving on to a person level (paper submitted to but rejected from the ICIS 2021 conference), the organization level (Kukkonen, 2021c), and finally one step closer to society level by studying the answers on the operating environment level of organizations (Kukkonen, 2021a).

With a literature stream that was only about to emerge in management and organization, the only option to me as a young scholar seemed to be the use of metatheories as the theories to be contributed to. Only in fall 2021, I was able to conduct a literature review on AI as a managerial and organizational phenomenon.

As grounded theory is flexible toward what is being analyzed, whether the focus of analysis is in existing literature or empirical data, I used the similar Gioia methodology analysis logic both to empirical data and the literature: first separately and then together. As a result, I could finally return to my original research strategy of AI as a phenomenon and position my study in relation to the AI literature in management and organization both when approaching AI as the subject of study and regarding the phases of AI use reaching from the antecedents of AI use to the expected (cumulative) impacts of AI (see chapter 2.6).

In the next sections, I relate more in detail about the data selection as well as the usage of the Gioia methodology to analyze the empirical data. I explain how I compared the findings through AI-strategy casing, mapped the findings against metatheories, and how I conducted the second literature review on AI as a managerial and organizational phenomenon. I conclude this sub-chapter on phenomenon-driven research by detailing how all this finally led to finalizing my research questions.

3.2.3.1 Empirical data selection

As the first step of the analysis, I first needed to define which parts of the empirical interviews were the most relevant to answer each sub-research question. Additionally, to ensure the reliability and validity of the analysis, additional and critical decision-making was required to choose whose answers should or should not be included in the analysis of each research question Finally, I decided to use two different sets of interviewees' answers (see table 8).

I used all the available 33 basic information survey answers on how the industry experts define AI for the first sub-research question. For the sub-research questions two, three, and four on AI use antecedents, AI use, and empirical impacts of AI use, I included only 29 interviews. This was because of the methodological decision to compare the answers per adopted AI strategy in the organizations that were represented by the interviewees. Finally, in the fifth and final sub-research question, again I used the whole available interview data of the 33 interviews and 34 interviewees. This is because, as with the AI definition in the industry, there the casing was not relevant rather as versatile answers as possible might lead to interesting new findings about the expected (cumulative) impacts of AI as a GPT in the operating environment of organizations.

At the time of the interviews in spring 2019, three of these additional interviewees worked as private entrepreneurs and influencers of AI innovation development towards top management teams, boards of companies, or policy makers. One interviewee worked at a start-up that was still at the ramp up phase on the road to collect enough data so that the planned AI use was to be useful. Thus, their views were considered to bring potentially relevant additional points-of-view on the understanding of how AI is understood or defined in the industry. Additionally, their views seemed relevant in the context of what larger scale cumulative impacts might be expected in the operating environment of an organization, or society level, because of AI. Yet, they were excluded from the analysis per adopted AI strategy in sub-research questions two to four because they did not represent a company that would have already adopted and implemented an

AI strategy technically. (See more elaborate reasoning for exclusion criteria in chapter 3.2.3.4.)

Next, I move from the included informants to the asked questions when collecting the analyzed empirical insights per sub-research question.

For the first sub-research question on defining AI, in the basic information survey I simply asked: How would you define ‘Artificial Intelligence’?

For the second sub-research question on the AI use antecedents, the answers were included from the following semi-structured interview questions: Based on your view, what use cases are applicable for AI? Why? Based on your view, what use cases are NOT applicable for AI? Why?

For the third sub-research question on personal AI use, the answers to two semi-structured interview question pairs were included in the analysis. The first pair of the interview questions asked, “In your own work, what do you use or would want to use AI for?”. This was supplemented by the opposite view of the same question asking “What would you NOT want to use AI for?”. The second question set focused specifically on the work context of personal AI use asking, “How has your own job description changed after having AI as one of your ´colleagues´?”. This question was then also supplemented by another question focusing on the future orientation of personal AI use: “How would your job description change, if you could use AI for what you would want to use it for?”.

For the fourth sub-research question on organization-level measurable empirical impacts of AI use, I asked the interviewees: What kind of measurable results has your company achieved by applying AI? All the basic information survey and semi-structured interview questions are listed in appendices 1 and 2.

During the data analysis of the fourth sub-research question, it seemed that temporal changes because of AI seemed to start emerging from the data. So as with grounded theory (Glaser & Strauss, 1967), I decided to explore the temporal dimensions further. This led me to ask and explore the fifth and final sub-research question on expected (cumulative) impacts of AI.

Originally the temporal aspects were not included in the interview questions, nor were they planned to be a part of the scope or focus of this doctoral dissertation. Yet, different temporal aspects were often mentioned by the interviewees while they answered other human-centric AI questions. Thus, to stay true to the empirical data, the temporal dimensions could not be ignored in the analysis phase. Additionally, previous research in information system sciences and robotics also had seemed to highlight the importance and relevance of machines in relation to time and speed (Beaulac & Larribe, 2017; Konana, Gupta, & Whinston, 2000; Moskowitz, Drnevich, Ersoy, Altinkemer, & Chaturvedi, 2011).

Thus, I decided to explore this potentially important prevailing temporal dimensions as part of the AI phenomenon further. To better enable potential discoveries about social processes related to both AI and changes in temporality, I collected all the interview answers that referred to any temporal aspects.

For the analysis of all the empirical data, I either applied the Gioia methodology (Corley & Gioia, 2011; Gioia et al., 2013) directly, or first divided the data based on the AI strategy casing and then applied the Gioia methodology. For the fourth sub-research question on empirical impacts of AI use, I also applied temporal bracketing (Langley, 1999) after the Gioia analysis. In the following sub-sections, I explain the use of these analysis methods more in detail.

3.2.3.2 Gioia methodology

After the decision on the analytical sampling for each sub-research question, I continued the analysis by using the Gioia methodology (Gioia et al., 2013) which is based on grounded theory. The Gioia methodology has become a popular method for applying grounded theory analysis, and it fit the exploration of different aspects of AI as a managerial and organizational phenomenon at this emergent phase of AI-related theory. The Gioia methodology was particularly suitable for this study because it not only met the analytical requirement to catch the breadth of the emergent findings but also represented a great communication tool for qualitative data analysis transparency.

To analyze specific interview answers of the chosen interviewees, I conducted the analysis by following the Gioia methodology (Gioia et al., 2013). I first formed short explanations from the interviewee quotes. Based on the direct quotes I tested different data-driven 1st-order concepts. These 1st-order concepts were based on the terms used by the informants to ground these concepts into the interview answers. As with grounded theory (Glaser & Strauss, 1967), my aim was to next identify key findings and relationships that emerge in the data and form core categories to account *"for most of the variation in the studied phenomenon"* (Teerikangas, 2006, p 29). Gioia (Corley & Gioia, 2011; Gioia et al., 2013) calls these more researcher-centric core categories "2nd-order themes" that can be further distilled into bigger aggregated dimensions.

However, this is not a linear process, rather a result of a continuous comparative analysis of the empirical data and its dialogue with the learnings and points of view from a broad spectrum of theoretical literature. Based on an iterative dialogue between the emerged 1st-order concepts and different theories in management and organization, I formed more theory driven 2nd-order themes based on the 1st-order concepts. The 2nd-order themes were then further developed into aggregated dimensions. The aggregated dimensions helped to better understand different aspects of the AI phenomenon in the management and work re-organization context. The 2nd-order themes and aggregated dimensions helped to identify contribution potential to existing or new literature streams in relation to AI, because the Gioia methodology can be used to identify potentially new exploratory research findings that may open avenues for new future research.

I next briefly introduce the temporal bracketing that was used in the study for sub-research question four.

3.2.3.3 Temporal bracketing

As this is not a longitudinal study, the fact that the analysis required reverting to methods for a process perspective was unexpected. Yet, the comparative findings of the fourth sub-research question between the different AI strategy cases on empirical impacts of AI use started to surface temporal process features between the different AI strategy cases.

In temporal bracketing, the empirical data may be decomposed to successive *"periods",* but they may not form a predictable sequential process rather units of analysis for replicating the emerging theory (Langley, 1999). When temporal bracketing is used, the identified periods have some continuity within the activities of each period and some discontinuities in their frontiers (Langley, 1999; Langley & Truax, 1994). As Langley (1999, p 704) observes, *"(c)onceptualizations emerging from the process are unlikely to be very simple, although they stand a better chance of dealing with fundamental process drivers than those produced by certain other strategies"*.

However, in my study for the fourth sub-research question I was not analyzing a process nor specific longitudinal cases. Even the frontiers of the *"periods"* did not emerge from the answers on empirical measurable impacts of using AI, rather the casing was originally formed because of my chosen multiple-case study (Eisenhardt, 1989) approach and to compare the findings between different AI strategies.

Yet, during the analysis phase the use of the Gioia methodology produced similar 2nd-order themes (Gioia et al., 2013) between the different AI strategies, but based on the data-driven 1st-order concepts they were somehow similarly labeled measures but from a different development phase. Some were obviously more advanced than others. So, deciding to study the measurable results and impacts of AI in organizations with different AI strategies led to this discovery. Based on the findings I ended up proposing aggregate dimensions that were based on different phases for measuring AI. Ultimately this even led to forming a temporal process development framework for measuring AI based on the proposed aggregate dimensions (see chapters 4.4.1-4.4.1.5, 5.1.6. and 5.1.7).

However, this potential discovery also calls for re-analyzing the data without the casing based on adopted AI strategies. Potentially also visual mapping could help to identify new labels for AI development maturity of organizations or AI projects. This is because visual mapping allows to simultaneously represent a large number of dimensions, and show precedence, parallel processes, and the passage of time (Langley, 1999). With this sort of comparative and parallel visualizations, the heterogeneity of AI development between organizations and AI projects could lead to valuable new insights in the future.

Next, I continue by showing how the casing to AI strategies was formed.

3.2.3.4 AI strategy casing

To analyze the strategic management of AI, and more specifically the differences in adopted AI strategies, I first needed to identify what these different AI strategies might be. As no previous theory on the types of AI strategies was available, I used casing to identify the different types of adopted organizational AI strategies. For this, I triangulated (Yin, 2014) the information from the basic information surveys, the interviews as well as information on the organizations' websites.

In this type of phenomenon-driven research, casing is not predefined: cases cannot be specified beforehand rather they are found as part of the analysis process (Ragin, 1992). This casing was used while studying the sub-research questions two, three and four on AI use antecedents, AI use, and empirical impacts on using AI. I chose a multiple-case study (Eisenhardt, 1989) approach to these studies to yield more accurate and generalizable theoretical insights and constructs (Eisenhardt, 1991; Yin, 2014) through triangulating the findings within case and between cases.

The original empirical interviews included 33 interviews and 34 interviewees. However, during the casing, I excluded four of these interviews for multiple reasons. They either lacked current association to an AI-solution building organization that was key in evaluating the AI strategy adopted by the organization that the interviewee worked for, or they were excluded because their organization had not yet implemented the planned AI strategy. In this case, the interviewee did have a plan how to use AI in business, but the organization had not yet started to implement these AI plans. The last reason for exclusion from analysis was that the interviewee lacked required technical hands-on experience of developing or implementing AI solutions in the current role. Thus, the studies where casing was used consisted of 30 AI expert interviewees, and 29 organizations that they represented due to one pair interview.

After identifying the interviews to be included for the case study analysis, I triangulated (Yin, 2014) the information of the pre-survey, the semi-structured interview data and the public company websites. Through this triangulation, I first tried to identify and then verify similarities and differences between different AI strategies of the organizations that the interviewees worked for. Initially, two types of main AI strategy categories emerged, 1) the organizations that use AI in their core business, and 2) the organizations that do not use AI in their core business or core function.

Table 10. Summary of identified AI strategies adopted.

AI strategy:	**Organizational AI strategy definition:**
Consultancy (6)	AI-consultancies providing tailored AI solutions to their customers
Product (9)	Companies with AI-product or service as their main core business
Robotics (3)	Physical embodiment of an autonomous robot as core business
Key part (5)	AI as part of one or some of the products or services in the product portfolio
Ingredient (6)	AI supports some other non-AI core business or core function

With a more detailed analysis, AI strategy was selected as part of the core business in three kinds of organizations: 1) Consultancies providing tailored AI solutions to their customers (later called as Consultancy), 2) companies with AI-product or service as their main core business (Product), or 3) a separate special sub-group of companies with AI-product or service and physical embodiment of an autonomous robot as their core business (Robotics). Other 4) companies used AI as part of one or some of their products or services but not necessarily as part of all the products or services that the organization offers (Key part). The remaining organizations 5) used AI primarily to support some other non-AI core business or core function (Ingredient). Out of the 29 organizations, nine had adopted the AI strategy of type Product, six Consultancy, six Ingredient, five Key part, and three Robotics. (An overview of the AI-strategies and the associations to the interviewees are presented in tables 8 and 9.)

After the casing to the five different AI-strategies adopted by the different organizations that the interviewees represented, I continued the analysis based on the Gioia methodology (Gioia et al., 2013).

During the analysis of sub-research questions two and three on AI use antecedents and AI use, I first analyzed all the interview answers included in each study. Only after analyzing all the included empirical answers, I additionally divided the answers based on the adopted AI strategy. In these two studies the emphasis was on comparing the findings between cases in the findings. Lesser focus was set on the analysis of findings within case.

In the study on the fourth sub-research question, I used the casing in a different order. I started the analysis per adopted AI strategy on how the AI developers and their organizations had measured the empirical impacts of AI use. Here, the emphasis was put on firstly understanding the findings within case and only secondly comparing the findings between cases.

In the next two sub-chapters, I give an overview of the theoretical choices and background in this doctoral dissertation.

3.2.3.5 Testing findings though metatheories

During the empirical interview data collection in 2019, and at early stages of the analysis following the interviews, the management and organization literature on AI was still to a large extent missing (Kukkonen, 2019). Both because of the scant management and organization AI-related literature and as recommended by grounded theory (Glaser & Strauss, 1967; Glaser, 1992), I read broadly about other management and organization theories and extended my learning also toward other disciplines. In the second year of my PhD studies, I studied extensively industrial robotics and process automation. I also widened my understanding on AI based on the literature found in information system sciences. Finally, in the fall 2021, I was also able to conduct a literature review on the 42 AI- and ML-related articles found in premium outlets on general management and organizational studies. All this was to help *"bridge the developed and prevailing understanding of the phenomenon studied"* (Teerikangas, 2006, p 28) to be able to draw and propose grounded theoretical contributions.

In the next sub-section, I introduce the details of the second literature review on AI as a managerial and organizational phenomenon.

3.2.3.6 Second literature review

In 2021, I searched for Scopus and Web of Science databases for AI-related literature in premium journals in the field of management and organization. The search terms included "artificial intelligence" OR "AI" OR "machine learning" OR "ML". The articles and editorials needed to have been published in top ranking journals on "general management" or "organizational studies" according to the Academic Journal Guide (Chartered Association of Business Schools, 2021).

The first literature review on AI in the field of management and organization that I conducted in 2018 only returned few papers with the research focus set on AI (Kukkonen, 2019). However, in fall 2021, with the attempt to conduct the literature review again, it was finally possible: the search returned 42 AI/ML-papers including editorials, conceptual papers, and empirical studies.

During the literature review's analysis phase, I explored the literature from multiple different perspectives. First, I was curious to explore how was AI defined in the premium management and organization literature. Secondly, I was curious to explore the contributions that the scholars made themselves, and the future directions that they suggested as avenues going forward in AI related research within management and organization.

During the analysis phase, I collected quotes from all the articles on how the authors defined and/or explained AI in their articles. For a separate analysis, I collected quotes from all the articles that identified the research gap or explained the contribution to be made through each paper. Thirdly I collected quotes from each article on the suggested avenues going forward with AI related research in future studies.

During the analysis, I approached all these quotes in a similar manner as I had done with the grounded analysis of the empirical answers. I was not sure upfront what was it that I was looking for, but some sort of phases in relation to AI use seemed to emerge. I tested the 2nd-order theme labels both with the contributions the authors made in their papers as well as with the quotes related to their suggested future research directions in relation to AI. I also tested the phases against the grounded findings of my own empirical studies for this dissertation. Finally, as a result, I identified the proposed five phases related to AI use. Inspired by temporal bracketing, I set the proposed process phases in order based on the potential impacts of AI when the scope of AI impacts might be growing.

During the analysis, different research approaches to AI also emerged in the literature. This was in addition to the identified AI use phases. While making their contributions, the management and organization scholars approached AI in three ways: 1) AI as a novel research method that enabled making novel contributions to existing literature streams, 2) AI as the subject of study with traditional qualitative or quantitative research methods, or 3) AI as a method to study AI as the subject of study (see chapter 2.3).

All these emergent findings finally helped me to position this phenomenon-driven study: to approach AI as the subject of study and making contributions to four AI use phases. They start from AI use antecedents on a task level. The scope of analysis reaches all the way to the fourth phase on the expected (cumulative) impacts of AI in the operating environment of an organization (see chapter 2.4).

This second literature review on AI forms the main theoretical foundation for this phenomenon-driven dissertation on AI as a managerial and organizational phenomenon. Because the literature review on AI could be conducted only after the empirical studies, the sub-research questions were heavily influenced by various metatheories. The main research problem of this study was identified only after conducting the empirical studies as well as the second literature review on AI in premium management and organization outlets. I next introduce the finalized research questions.

3.2.4 Finalizing the research questions

This study started from exploring what AI really was in the middle of increasing technology hype in 2018 and all the massively increasing investments on it. What was this phenomenon that seemed to be caused by AI in society? What should people know and how should people react to AI as individuals, as part of organizations, and as members of society? What was there about AI that we all needed to know or should learn about this potentially disruptive technology? And what is it about AI that might make it become a disruptive innovation? Is it really a silver bullet?

Personally, bearing an industry background and having faced the first layoffs of my life, or rather a wave of layoffs in the technology industry after the fall of Nokia, and seeing how that effects people negatively, any antidote seemed appealing. Was the answer in startups that are bold enough to try something new, and potentially even change the world? Or the way we used to say in Finland, was one of those startups to become the new Nokia of Finland, a cradle of prosperity, jobs, and global scale business success?

Combining all this to the global scale hype around AI, I could not start but wonder: how should a small but technology driven country like Finland prepare itself for the changes in competitiveness and maybe even gain competitive advantage with the help of AI?

As the management and organization literature on AI was still at its infancy at the start of this research project, I had to start from somewhere: I first needed to know what AI is. With the varying definitions for AI among my interviewees and large variety of definitions for AI in the literature, my first sub-research question finally came to be:

SRQ1: *How is artificial intelligence defined in the management and organization literature and in multiple-industry settings?*

I tested this question in my first conference paper (Kukkonen, 2019). Given the scarcity of AI literature in the field of management and organization, I initially turned for help in information system sciences.

Additionally, with the AI hype of the time, I felt the need to create a rigorous understanding on what is AI technically, and what is it that AI with the contemporary technical maturity level can do? With my first conference paper (Kukkonen, 2021b) in information system sciences, I got validation for my technical understanding on AI from their scholarly community to my paper's research question: how organizations with different AI strategies draw the limits for using artificial intelligence as an organizational resource? After the reviews and conference feedback, as well as the literature review on AI in the premium outlets on general management and organization studies, the second sub-research question of this dissertation found its logical place among the AI use antecedents. The focus is set on managing the expected AI-based contextual value before AI is in use:

SRQ2: *How are the managerial decisions formed on whether to invest in AI-based technology development?*

To understand the personal experiences of the actual use of AI, we originally wrote a conference paper studying the relational agency of AI solution developers and AI with a colleague of mine. In that paper, we explored how relational agency is practiced, impacted, and challenged by humans and AI by the interviewed industry experts who are creating and developing AI-based work solutions in different industries.

However, that paper was rejected from a prestigious conference in information system sciences. Yet, the reviewer comments on AI were the most helpful I had ever received. I gracefully thank for the critical and highly valuable feedback and comments of the anonymous reviewers. That was the first time I had the opportunity to properly interact and engage with senior scholars in my core content field and feel the support. Thus, I am extremely grateful for the valuable time of these senior scholars in AI.

After the reviewer comments and after completing the second literature review, I completely re-did this part of the analysis. As this re-analysis was conducted last, it was also influenced by the findings of sub-research question two (see chapter 4.2). I changed the scope of the selected interview answers to include not only the actual use of AI, but also the wanted use of AI. I wanted to explore how might these findings bring depth to the expected value of AI investment decisions. Yet the foundation of the analysis is still impacted by the original paper, and how relational agency is practiced, impacted, and challenged in the daily working lives by both humans and AI when industry experts create and develop AI-based solutions in different industries:

SRQ3: *Why might the actual and wanted use of AI differ?*

Since the beginning of this dissertation work, I had felt the need to form a solid technical understanding of AI in the information system sciences. I also spent a decent time in understanding industrial robotics to build on the learnings and analysis of the existing collaboration between people and big physical machines. With a more confident initial understanding of different technical aspects of AI, I could finally attempt participating to the theoretical discussions among management and organization scholars. With few examples of AI-related papers in our field, as a young scholar, I finally had at least a few recent examples on what is expected of me to join a new conversation.

I submitted and got accepted to present one of my first papers to management and organization scholars in the conference organized by British Academy of Management (Kukkonen, 2021c). In that paper I explored, how five different types of organizations that already use AI have measured the strategic business or core function alignment when they develop their business specific AI-solutions. After the review comments, feedback, and the literature review on AI as a managerial and organizational phenomenon, my fourth sub-research question was set to focus on the empirical impacts of AI use and measuring its value as part of strategic AI-management:

SRQ4: *How are the impacts of AI-based technology development investments measured?*

The fifth and final sub-research question of this doctoral dissertation emerged from the data so strongly that it could not be ignored. In a paper submitted to and accepted to be presented in the conference of European Group for Organizational Studies (Kukkonen, 2021a) I explored the multitude of different temporal aspects that emerged from the experiences of practitioners developing AI solutions in and across different industries. I was also curious to explore what avenues for future research they might open related to the competitive advantage of an organization. Based on the received review comments, feedback, and the literature review on AI as a managerial and organizational phenomenon, my fifth and final sub-research question focused on the expected (cumulative) impacts of AI on temporal dimensions and possible work (time) re-organizing needs:

SRQ5: *When approaching time as an organizational resource, which temporal dimensions are expected to be influenced by AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation?*

When approaching the synthesis of this doctoral dissertation, I was still constantly puzzled by the question posed to me repeatedly along the way of my research journey: what is this a case of?

I had started my journey with a personal interest toward (national) competitiveness and potentially even competitive advantage with the help of AI in a country like ours where hiring people is considered expensive. However, I kept reading more about the high performance (Bard et al., 2020; Brown & Sandholm, 2019; Fortunato et al., 2017; Schrittwieser et al., 2020; Tian et al., 2019) versus productivity paradox of AI (Brynjolfsson et al., 2017). Also, the expected cumulative impacts on work seemed still too far in the future in relation to my empirical interviews, where AI was useful in specific tasks only. Yet, based on the empirical interviews, some of the companies seemed to have had already achieved even competitive advantage with the help of AI based on specific measurements (see chapters 4.4- 4.4.1.5).

After my studies on the five sub-research questions and while writing the synthesis for this dissertation, I kept coming back to the value creation of AI. But value creation for who, from whose perspective? In a recent paper on AI the contributions by management and organization scholars were called for to realize the benefits of AI and but to mitigate its negative side effects (Raisch & Krakowski, 2021). Especially the sub-research-questions two and three problematize value creation, and these impacts are then visible in the measurable impacts as well: the solutions with the ethical concerns sometimes might offer the best bottom line business performance (see findings chapters 4.3-4.4.1.5).

As my chosen empirical scope includes the AI developers, but not the actual end users of these developed AI solutions, maybe this is a case of the organizational and managerial antecedents of AI-based value creation (see more in chapter 5.3.5)? And a small step towards future research in beginning to understand all the managerial and organizational processes and people that need to be in place, to create an AI solution? Maybe this case offers also at least managerial implications of the fundaments or minimum socio-technical (Manz & Stewart, 1997; Pasmore, 1995) processes and work re-organizing requirements that need to be in place to strategically aim for AI-based competitive advantage? While conducting this research, my personal paradigm shift and potentially even abductive future discovery has been that AI is not about the technology, it is about the people - and their collaboration.

Thus, I finally ended up formulating the main research problem of this doctoral dissertation in the following form:

MRP: *What makes artificial intelligence -based value creation challenging from the management and organization perspective?*

3.3 Toward abductive discoveries

In this phenomenon-driven doctoral dissertation, I have defined AI as a general purpose technology (Brynjolfsson et al., 2017), and I wanted to explore what does this mean as a managerial and organizational phenomenon. Thus, the main theoretical foundation of this study is in AI as a phenomenon in premium outlets on general management and organizational studies (see chapter 2). However, the empirical foundation, and main motivation of this study, is based on the engaged scholarship pre-study phase (see chapters 3.1 and 3.1.1).

I was driven by the puzzle of AI hype: the combination of the great expectations, fears, performance, and global investments in AI. Even the definition of AI seemed unclear, so as a young scholar I could not help wondering: what are people spending money on when they talk about AI? Haunted by this initial observation that surprised me, it turned into my initial pre-study question. It was this feeling of *"that's weird"* that triggered the start of a longer investigation (Tucci, Mueller, Christianson, Whiteman, & Bamberger, 2019, p 211) that then led to this whole dissertation.

I first thought I was conducting an inductive study, but I later learned that the analysis in the synthesis phase of this study might resemble more the abductive process of reasoning. The abductive process of reasoning is described with the following three steps in an editorial of the Academic Management of Discoveries (AMD): 1) *"Observe a phenomenon and stumble upon an anomaly, puzzle, breakdown, or problem"*, 2) *"Ground the anomaly with empirical evidence and relevant literature"*, and 3) *"Conceive of a plausible hunch that dissolves anomaly"* (Van de Ven, 2016b, p 223).

So, after stumbling on this puzzle and seeming breakdown between the investments in AI (Tricot, 2021; Zhang et al., 2022, 2021) and in the actual understanding of AI (see chapters 2.1 and 4.1), I conducted my empirical interviews based on my engaged scholarship pre-study phase, and read some more.

I learned that AI had been found to embody a productivity paradox (Brynjolfsson et al., 2017). Earlier research had found four principal candidates for similar situations with technological optimism and poor productivity performance: 1) false hopes, 2) mismeasurement, 3) concentrated distribution and rent dissipation, and 4) implementation and restructuring lags (Brynjolfsson, 1993; Brynjolfsson et al., 2017). I also learned that AI as a general purpose technology requires (Brynjolfsson & Mitchell, 2017) *"waves of complementary innovations"* (Erik Brynjolfsson et al., 2017, p 1). These complementary innovations need to be developed and implemented by multiple people to realize the full effects of AI in machines, business organizations, and in the broader economy (Brynjolfsson & Mitchell, 2017). All this started to make AI an interesting phenomenon to study further not only from the management and organization but also from AI's value creation perspective in multiple-industry settings.

In the analysis phase, I started with the early observations from the engaged scholarship pre-study phase and empirical interviews. However, when trying to verify these observations as a necessary step in discovering grounded theory (Glaser & Strauss, 1967), I was not able to do this rigorously. I even struggled with what parts of the empirical interviews to select into a specific part of this study. Then my supervisor, and other professors in methodology recommended trying the Gioia methodology, as it has become a popular template for grounded analysis -based studies. I applied the Gioia methodology sort of template throughout this study. But I think, the fifth sub-research question on the expected cumulative impacts of AI is the only one that truly starts to capture the essence of the original grounded theory (Glaser & Strauss, 1967) already in the phase of what part of the empirical interviews to include into the analysis.

For me the quote from von Krogh (2020, p 160), and how he captures the relationship between a phenomenon and the process of grounded theory building, helped to understand this relationship. It also guided me toward a deeper methodological understanding from Gioia: *"This relationship between a theory about a phenomenon and empirical facts about it is an important one. For example, Glaser and Strauss' (1967) method of discovering grounded theory starts with* *verified observations. Rather than limiting empirical discovery to completely grounded theorizing, however, empirical discoveries at some point may also involve existing theories about and models of that phenomenon (as a way in which we can reason about novel facts). Whereas novel social facts may reveal surprising aspects about a phenomenon, novel theories discovered in the abstract or by 'abductive reasoning' with the data (Behfar & Okhuysen, 2018; Locke, Golden-Biddle, & Feldman, 2008) may also reveal new features of a phenomenon. Over time, this interplay between emerging theory and novel social facts facilitates learning and a better and more coherent scholarly understanding of phenomena (Bamberger, 2018)."*

However, as a young scholar who started this study phenomenon and grounded data first, the choice of which existing theories to abductively reason with was challenging. It was especially challenging at the start of this doctoral dissertation, when only few examples of senior management and organization scholars guided the way on how to theoretically frame a phenomenon such as AI. When theory on AI did not exist yet, I needed to change my original research strategy, as I could not rely on previous literature on AI as a managerial and organizational phenomenon. In conference papers, I needed to turn to different metatheories, and try to frame my findings and to build my theoretical contributions based on them.

To move from findings towards contributions, Van de Ven (2015, p 1) helped me to better understand how to do so, and argue for the contributions proposed even without a positivist or deductive research strategy. With a phenomenon only emerging in the management and organization literature, I could follow this advice on theorizing: *"As the American pragmatist, Charles Peirce (1955) and the philosopher of science, Norman Hanson (1958) argued, theory building follows an abductive (neither deductive nor inductive) form of reasoning. This form of reasoning begins when data call attention to some surprising anomaly, problem or unexpected phenomenon. This anomaly may originate in the practical world of affairs, a theoretical discipline, or a personal experience. It may be perceived to represent an unsatisfying circumstance, a promising opportunity, a breakdown in expected arrangements, or simply a phenomenon not encountered or adequately addressed before."*

Luckily, towards the end of this doctoral dissertation, I could return to my original research strategy, and build the theoretical foundation and the synthesis of this doctoral dissertation on previous literature on AI. However, I feel grateful for the struggles I had first with the opposing philosophies of science between my supervisors, as well as to the lack of AI literature at the start of my research journey. They have enriched my understanding of management and organization as a field, and how our field might be able to contribute to the multi-disciplinary research on AI as a phenomenon.

After a number of consecutive back-and-forth between my empirically grounded findings and different theories from information system sciences and management and organization, my *"plausible hunch that dissolves anomaly"* (Van de Ven, 2016b, p 223) is that AI, and especially its value creation, is not about the technology, it is about the people - and their collaboration. The anomality being the lack of understanding the productivity paradox of AI (Brynjolfsson et al., 2017) despite the superhuman performance of AI (Bard et al., 2020; Brown & Sandholm, 2019; Fortunato et al., 2017; Schrittwieser et al., 2020; Tian et al., 2019), alone and when combined to the intelligence of humans[1], from the management and organization perspective.

The contributions of this dissertation work toward proposing "*robust and parsimonious 'first suggestions'*" for why AI-based value creation might be challenging from the management and organization perspective. To do this, I have aimed to explore *"the nature, antecedents, and consequences of such phenomena, as well as the new or transformed theoretical frameworks required to make sense of them*" (Bamberger, 2018, p 1), to the best of my ability. Additionally, my contributions in this doctoral dissertation are heavily influenced by the foundations of phenomenon-driven research: that is problem-oriented, where rigor relies on capturing, documenting, and conceptualizing the observed phenomenon, and contributions facilitate new knowledge creation and theory advancement (Schwarz & Stensaker, 2015; Van de Ven, 2016a).

If a *"true discovery"* either challenges existing theory or lays groundwork for new theorizing (Tucci et al., 2019, p 209), I cannot claim to have challenged an existing theory. However, I do hope to offer at least a step toward laying the groundwork for new theorizing, because *"AI has the qualities of being a new but poorly understood phenomenon*" (von Krogh, 2018, p 408). I hope to have surfaced a significant and emerging managerial and organizational phenomenon, and through my research to have been able guide other scholars and practitioners toward better understanding on how to manage AI-based value creation (see more in chapter 5.3.5).

[1] Work augmentation (Raisch & Krakowski, 2021) has been theorized in the workforce implication (Brynjolfsson & Mitchell, 2017) context. Other terms related to the emergent discussion on human and AI collaboration are hybrid intelligence (Dellermann et al., 2019), (hybrid-) augmented intelligence (Pan, 2016; Zheng et al., 2017), intelligence augmentation (H. Jain et al., 2018), and/or conjoined (Murray et al., 2021), interdependent (Raisch & Krakowski, 2021), or intertwined (Leonardi & Treem, 2020) agency.

3.4 Research quality, reliability, and validity

The first and most profound research choice that impacts the quality, reliability, and the validity of this doctoral dissertation in a fundamental way is the definition of AI. As a research choice that was based on the engaged scholarship pre-study phase, I decided not to pre-define AI. Rather, I let the interviewees themselves tell what AI for them is. No two definitions given to AI were a hundred percent match, neither in the literature nor in the definitions given by the AI industry experts (see chapters 2.1. and 4.1).

Choosing this approach can question the reliability and the validity of all the sub-studies within this dissertation, because it could be argued that the answers might not be comparable because of not having a clear and agreed upon definition for what is meant by AI in this research context. On the other hand, I am willing to argue that problematizing the definition itself opened the grounded analysis -based theorizing about AI as a potentially complex managerial and organizational phenomenon.

At the very start and with careful consideration based on my extensive pre-study phase in the field, I proactively decided to avoid the theoretical straightjacket (Schwarz & Stensaker, 2014) of pre-defining AI but rather stay grounded (Glaser & Strauss, 1967), and based on it try to better understand AI as a phenomenon as it was experienced in different industries. I was particularly driven by the curious nature of AI as a general purpose technology (Brynjolfsson & Mitchell, 2017) that seemed to have started to diffuse across industry boundaries.

The strength of this chosen approach was that it served the initially chosen phenomenon-driven freedom from the theoretical straight-jacket; and it methodologically helped to conceptualize AI as a phenomenon for potentially novel knowledge creation (Schwarz & Stensaker, 2014; Van de Ven, 2016).

The biggest challenge of this phenomenon-driven research strategy was to choose and answer the theoretical discussion stream(s) in management and organization to which this study most or best would be contributing to. This has been especially challenging, because of the lack of AI-related literature in our field at the start of this research journey (Kukkonen, 2019). Little guidance was offered to me as a young scholar.

Even though the recent years have showed a surge in AI-related articles in the field of management and organization, a phenomenon driven (Schwarz & Stensaker, 2014) or phenomenon-based (von Krogh et al., 2012) approach was and still is to a large extent warranted for down-the-road theorizing (Christianson & Whiteman, 2018; Krogh, 2020) about AI as a managerial and organizational phenomenon in the work context.

The research journey for the empirical essays and the synthesis of this doctoral dissertation started by exploring AI as a phenomenon at a point in time, when AI was at the top of the Gartner hype cycle of emerging technologies (Gartner, 2018, 2019). Thus, the first challenge for research quality, reliability and validity was technical.

I addressed this challenge by starting with a pre-study phase to first understand the technological foundations of AI. This was to be able to differentiate the contemporary technological development level realities from the hype. The understanding on the technological foundations was continued in the empirical interviews. I deepened my theoretical understanding in information system sciences and focused on additional readings in industry 4.0, internet of things, social and industrial robotics, and production automation. On the second year of my studies in 2019, I even attended an extensive series of courses on industrial robotics and production automation to augment my personal understanding on the physical embodiments of robots with or without AI in the industrial settings.

At the time, the AI-related contributions from management and organization scholars were scant but even more important theoretical guidance for the future direction of my study. Working without the support of a research group in this subject area of AI in management and organization, conference paper reviews from information system sciences guided me to relevant technological and theoretical discussions in relation to AI. This was vital to strengthen the cross-disciplinary foundations of this doctoral dissertation. It was a necessary starting point to enable research quality, reliability and validity and required understanding to critically evaluate, problematize, and start to build a cross-disciplinary bridge from information system sciences to the field of management and organization.

In addition to the lack of theoretical foundations of AI as a managerial and organizational phenomenon, or even of the definition of AI as a technology, I needed to identify the suitable interviewees. Their selection has been another fundamental research choice with impacts on the quality, reliability, and the validity of this doctoral dissertation. Because the interviews were to take place at the top of the Gartner hype cycle of emerging technologies (Gartner, 2018, 2019), I set strict pre-requisites for the interviewees: all of them were to have both technical and business experience in implementing AI-based solutions in the industry.

However, despite the prerequisites set for the interviewees, not all of them fit all the studies in the analysis phase. Thus, interview data selection has varied in studies depending on the different sub-research questions. This decision was made to increase the quality, reliability, and validity of the analysis in a sub-research specific context. I put special emphasis on appropriate interview data source selection for each sub-study.

Another concern related to the interviewee selection has been raised by anonymous reviewers in the conference paper reviews or presentations. Some of the anonymous reviewers have addressed their concern about the expertise of some of the interviewees, because of them having only few years of experience with AI. Even after this critique, I have kept these interviews as part of this doctoral dissertation, because of all of them meeting the pre-defined criteria for the interviewee selection to include both hands-on technical and industry application development experience.

Additional reasoning for considering the interview data from the interviewees who themselves have answered to have only few years of experience with AI are threefold. Firstly, as an important and deliberate methodological choice in this phenomenon-driven study, the definition of AI was not pre-set by the researcher. Thus, the interviewees may have counted different number of years as experience with AI depending on their own definition of AI. Secondly, relatedly, and more specifically, what is counted as AI expertise was not pre-defined by the researcher which also may have impacted the AI experience year count. Thirdly, the Finnish cultural context, in which the interview data was collected, represents the opposite approach that one might find e.g. in the USA. Unlike in many other countries, in the Finnish context it is typical to humbly and modestly estimate or even downgrade one's own merits rather than to inflate them while interacting with other people to not be considered boasting.

Additionally, were this dissertation to study AI as a technology, the years of experience with AI, or some other measures that quantify or in some other objective way measure the skill or experience level and merits of the interviewees, would be more relevant. However, in this study the focus was set on AI as a technology only to validate AI understanding and separate it from the hype. Thus, the technological understanding of the interviewee was secondary to the first and foremost emphasis on the interviewee's understanding of AI as a human-centric phenomenon in industry application settings. This is also why e.g. technically extremely skilled but purely academic interviewees were excluded, as they may have deep experience of AI-related algorithms, but some of them may be using only toy or simulated data e.g. to test the technological performance of their algorithms against other algorithm options typically found in top ranking computer science conferences for AI, ML, and data mining (Research.com, 2021).

In total, the interviewees of this study represent 18 different industries, 11 out of the 34 interviewees represented consulting companies. One the one hand, they may skew the balance between different industry views represented in the interviews. On the other hand, the clients of the consultants represent an even wider variety of industries which serves the wider understanding of the potential impacts of AI as a general purpose technology across industries.

Despite the wide variety of industries, the cultural values of the interviewees were fairly homogeneous as either the individuals or the organizations that each of the interviewees worked for was set in the European and Nordic country context. Some of the interviewees had a North American or other cultural background and professional AI expertise twist that enriched the comparative answers to the Finnish cultural context. The answers might have been different e.g. in primarily other cultural contexts and in AI superpowers such as the USA or China.

Yet, the potential third main concern related to the quality, reliability, and the validity of the empirical part of this doctoral dissertation is the research decision to include only one interviewee per organization to this study. To be able to understand AI as a phenomenon across industry boundaries, I was curious to explore AI in multiple industry settings. The following may be a cause of concern to the quality, reliability, and validity of this doctoral dissertation, because of 1) the heterogeneity of the definitions given to AI, 2) the years of experience with AI per interviewee, and because 3) the organizations that the interviewees worked for were in multiple different industries. However, all the above have been a conscious and deliberate strategical research choice.

These choices have also surfaced a new aspect that I had not taken into consideration in advance: that also the organizations that the interviewees worked for were in different phases of AI development maturity. Had I approached AI purely from the innovation management and diffusion of innovation (Rogers, 2003) perspective from the start, I would have framed the empirical questions and interviewee selection very differently.

In this doctoral dissertation, the focus was originally set on understanding the human and AI collaboration from the AI developer point of view in the work context. Going forward one future research direction could be to focus on exploring the different phases that both each AI solution and the organizations developing or using AI solutions go through in AI maturity. This could include different levels of analysis such as studying an AI solution project from its beginning to launch, or more interestingly to longitudinally study the whole lifecycle of the development of an AI solution, an individual working with AI, a team working with AI, an organization adopting AI into use, or the diffusion of AI as an innovation in a global corporation.

After having gone through different perspectives on empirical data collection, I move on to the analysis phase. A potential cause for concern related to the reliability and the validity of the studies on sub-research questions two to four might be the casing in this doctoral dissertation. The casing is based on AI strategies adopted by the organizations that the interviewees worked for at the time of the interviews in spring 2019. The concerns for reliability and validity are threefold. Firstly, the number of interviewees per AI strategy vary from three to nine people (see chapter 3.2.3.4). Secondly, the answers given by the interviewees were not (pre-)limited to the current organization that the interviewee worked for: they reflected the whole work history that they themselves had with AI both as individuals as well as part of the current work organization, and potentially that of the employee's client organizations. Thirdly, it is likely that casing based on something other than the adopted AI strategy of the employee's organization, or no casing at all, would have impacted the analytical lens in a significant enough way to generate different observations and findings.

However, were it not for the casing, I would not have been able to propose potential types of adopted AI strategies for future research. I would not have found how different organizations might use AI in different ways. With the combination of the heterogeneity in years of experience with AI both among the interviewees as individuals as well as among the organizations that they worked for at the time of the interviews, the differences in AI maturity would not have emerged. So, while all this might challenge the positivistic or quantitative qualifications for the quality, reliability and the validity of this doctoral dissertation, this dissertation still offers potentially valuable insight for down-the-road theorizing, and as the pre-examiner Professor Riitta Katila stated a *"one-stop-shopping for someone who is looking for an overview of the AI in organizations literature, sprinkled with up-to-date, interesting examples"*. I also argue this study to be of good quality: valid and reliable against different qualifications more suited to this kind of phenomenon-driven research. Yet, it goes without saying that further research should test and validate these AI strategy categories and potentially complement them with a more extensive quantitative study in future studies.

So, how should the overall contributions, and their quality, reliability, and validity be evaluated in this dissertation? Because empirical exploration takes place at the frontier of theory, plausible theorizing for qualitative research requires a rich description of the phenomenon, and development of tentative claims or *"first suggestions"* about findings (Christianson & Whiteman, 2018).

In this study, all the empirical findings are introduced with as thick a description as possible, and in the contributions-section, the plausible explanations for these findings are discussed. I have tried to theoretically frame different parts of this study under suitable metatheories when the management and organization theory on AI was still too neglected to be framed into. The whole dissertation was finally possible to be framed into the context of AI-related theory in management and organization, and in the beginning partly even under AI-related theory in information system sciences and economics in relation to the productivity paradox of AI (Brynjolfsson, 1993; Brynjolfsson et al., 2017). Thus, I have tried my best to rule in or rule out plausible theoretical explanations based on AI findings as an empirical phenomenon and to provide as extensive empirical evidence as possible to support the claims (Christianson & Whiteman, 2018). That said, the empirical evidence can always be more extensive in quantity in the same and/or in different geographical and cultural contexts. However, testing the findings and early observations of this dissertation are out of the scope of this dissertation, and remain to be tested and validated, or challenged, in future studies.

What about the rigor of this dissertation? How should the rigor of this study be evaluated? Christianson and Whiteman (2018) comment on the importance and criteria for rigor as follows: *"While aiming to surface a new phenomenon, rigor needs a special emphasis. Deep engagement with the phenomenon and gathering sufficient data is required to rule out other plausible explanations, best practices of chosen methodological approach need to be adopted, increased transparency is required about the research process and methodological innovations to enable a path forward for scholars who want to engage in similar kinds of empirical exploration."*

To ensure the deepest possible engagement with the phenomenon, I put special emphasis on the international and extensive engaged scholarship pre-study phase in the field. This was both among industry experts and academics working with AI in various fields. Not only that, but I also read extensively about AI across disciplinary boundaries in attempt to understand AI as a phenomenon as holistically as possible.

When collecting the empirical data, I have tried to ensure to have sufficiently broad variation in empirical interviews 1) through the variation in industries, 2) in the AI strategies adopted by the organizations that the interviewees worked for at the time of the interviews, as well as 3) in the personal years of experience with AI of each interviewee. I even allowed 4) the maximum variety in the definitions for AI in attempt to examine as wide a range of conceptual possibilities as possible that enabled at least a certain level of *"boldness within plausible theorizing"* and *"innovative conceptual discussions to explain novel empirical findings and to lay out the criteria and groundwork for down-the-road theorizing*" (Christianson & Whiteman, 2018, p 401). All this has guided me in ruling in and ruling out plausible explanations in dialogue with different theoretical discussion streams.

I have tried to follow the best practices of the chosen methodologies. However, I have not been able to follow a single research methodology throughout the study. Instead, I have used different methodologies when they have been applicable in this phenomenon-driven discovery journey on AI as a managerial and organizational phenomenon, with a special focus on the value creation challenges related to it.

Finally, transparency and thick description have been both an essential part of building grounded theory -based research and a final fundamental criterion for rigor in this doctoral dissertation. Thus, I have tried to be as thorough and transparent as possible while explaining the research journey starting from the pre-study phase inspired by engaged scholarship all the way to the proposed theoretical contributions. Yet, the road to discoveries is rarely linear or completely transparent even to the author herself. Also, the time is already different: the people interviewed have potentially moved on to new organizations, and they are likely to have developed their thinking in relation to AI, or they are likely to have developed new (kinds of) solutions based on AI since the interviews took place in spring 2019. Also new technological advancements have been achieved after the empirical interview data collection such as ChatGPT-4 (Bubeck et al., 2023). Thus other scholars can never fully replicate this research journey of mine, but I have intended to document the journey as carefully and rigorously as possible for other scholars to be able to "*engage in similar kinds of empirical exploration*" (Christianson & Whiteman, 2018).

In the next chapter, I move on from the methodology of this doctoral dissertation to introducing the empirical findings of this study.

4 Findings

In this section, I explore the main research problem of this doctoral dissertation through the empirical findings of five sub-research questions. My main research problem for this dissertation is: What makes artificial intelligence -based value creation challenging from the management and organization perspective?

In the first sub-section, I approach this question by complementing the literature with how AI is defined in practise in multiple-industry settings.

In the second sub-section, I approach the main research problem through the empirical findings on the antecedents for AI use. More specifically I asked, based on what criteria are the strategic decisions formed on when to invest or not invest in developing AI as an organizational resource, and as a potential organizational agent.

In the third sub-section, I explore the main research problem through the differences between the wanted and the actual use of AI among the AI developers. In the fourth sub-section, I move from the AI use to its measured empirical impacts. More specifically, I asked how are the impacts of AI-based technology development investments measured?

I finalise this chapter on empirical findings by exploring the expected cumulative impacts of AI on different temporal dimensions that might need to be taken into consideration in future work re-organizing and work time allocation.

4.1 Industry definition of AI

The first sub-research question asks: How is artificial intelligence defined in the management and organization literature and in multiple-industry settings? In the theory section, we could see the versatility of definitions, but there the focus was often set on the relationship between AI and ML (see chapter 2.1). In this findings section, I complement the AI definitions found in the literature with the empirical findings in multiple-industry settings.

As part of the basic information survey (see chapter 3.2.2.2 and appendix 1), the interviewees were asked how they themselves define AI. It is noteworthy that no two definitions were exactly alike. Defining AI was also problematized by many of the interviewees during the semi-structured interviews. Many of the AI definitions

Table 9. Summary of industry AI definitions.

AI term definition in survey	1st-order concept	2nd-order theme	Aggregate dimension
AI is nowadays a term used in exchange for deep learning, which is a sub-field of machine learning which is a subfield of computer science and can be defined as a set of computational methods for learning efficient, hierarchical representations out of raw data. [I1]	Deep learning	Uses a named technology or several technologies	Combination of many different technologies and fields
Not only models but also data and the technologies that enable it. [I5]	Dependent on enablers	Application requires several different fields	
Artificial Intelligence is a wide topic, a branch of science, which is generally a combination of machine learning, robotics, neural networks and several other fields using machines which learn to be intelligent [I22]	Multi-disciplinary	Uses a named technology or several technologies	
Statistical multi-variable methods and computing. [I28]	Statistics based	Application requires several different fields	
I define AI as a collection of Machine Learning algorithms, each trained to perform a specific task within a specific domain, pieced together to perform a larger task previously done by a human. [I19]	Collection of algorithms and actions	Application requires several different fields	
The definition includes machine learning, but also e.g. mathematical optimization and computer programs. [I25]	Based on ML, SW and maths	Application requires several different fields	
I try not to define it, I describe what AI is like in 3 waves. First wave in the 60's was programming logical rules, where the machine does exactly what it is asked to do. Second wave solves the problems of the first wave such as speech detection or image recognition. A human being cannot code their rules, and it does not include flexible intelligence. The first pilots of the third wave are the Star Wars AI, which can learn new things and communicate with people and other AI algorithms. It is humanlike, autonomous, it is capable of independent and team work, and it can explain why it does what it does. [I30]	Definition changes over time	Moving target	Artificial Narrow, General or Super intelligence
AI is a software system created non-biologically. It differs from traditional software by using something more complex than conditional logic or trivial calculations, and thus enables executing tasks that traditionally only biological nervous systems such as human brains has been able to do. [I26]	Narrow vs. strong artificial intelligence	Artificial Narrow or General Intelligence	
I do not use the term AI to describe Artificial General Intelligence (AGI) where a machine can perform any task as well as, or better than a human. [I19]	Narrow vs. strong artificial intelligence	Artificial Narrow or General Intelligence	
Situation where it is hard to identify whether there is a machine or human being in question. [I11]	Turing test	Artificial General Intelligence	
AI is a computer system that can execute the given tasks better than a human by learning from experience. [I23]	Task executed better than human	Artificial General or Super intelligence	
Applying an algortithm or mathematics in a way that appears intelligent from the outside. [I25]	Does something that seems intelligent	Creates an illusion of biological intelligence	AI has limited human colleague features
I use the definition by Russell and Norvig: AI enables machines, devices, software and services to work in a sensible way for the task and situation in question. [I8]	Contextually sensible behavior by machines	Contextually adaptive	
AI is solutions that enable a machine to replace people in task execution. [I17]	Fully automated task execution	Makes task execution easier	
AI is automated problem solving within a well-defined frame. [I5]	Well defined automated problem solving	Makes task execution easier	
AI should be assessed based on its impact. Human centered AI and explainable AI: rather than defining what AI is, people should stop and ask themselves what happens, when AI actually impacts my life. When I wake up, does it have an effect? When I go to work, does it have an effect? And then think, what is the impact that AI actually has in this life? How does it impact my loved ones and the environment? Then we come to what AI actually is. [I9]	AI = the impact its application has	Socially impactful technology	
AI is based on machine learning that is used because the problems to be solved are so complex that a human cannot execute them by programming. A software structure is created to give a direction of what is being tried to do, but the actual problem solving is left for the machine to find by using different options. Modern computers are capable of very fast trial and error process, which are used to try to find a good enough solutions to the problem that is to be solved. [I26]	Finding a good enough solution to a given problem through fast trial and error	Supports people/problem solving	

included multiple different elements. Thus, I duplicated or broke the definition into smaller pieces to catch all the different aspects and factors of the given AI definitions of the industry AI experts and AI solution developers. In total, the definitions formed 70 small data units that I then analyzed using the Gioia methodology (Corley & Gioia, 2011; Gioia et al., 2013).

The emerged aggregated dimensions consist of 1) the description of the enablers or technical and human knowledge requirements of AI termed as a "combination of many different technologies and fields", 2) the classification based on performance to "artificial narrow, general or superintelligence", and finally 3) descriptive features of the use cases and behavior of AI stated as "AI has human colleague features" (see table 10). From these results the following definition for AI could be proposed:

AI consists of combination of many different technologies and fields that may or may not enable artificial narrow, general or superintelligence, and/or the use of AI starts to have an increasing amount of human colleague (seeming) features.

In the following sub-sections, I introduce each of these aggregated dimensions and their findings of the Gioia methodology more in detail.

4.1.1 Combination of different technologies and fields

Combination of many different technologies and fields (see table 10) is the grounded aggregated dimension label that refers to AI as the technical umbrella term: *"Artificial Intelligence is a wide topic, a branch of science, which is generally a combination of machine learning, robotics, neural networks and several other fields using machines which learn to be intelligent."* [Interviewee 28]. The width of the term also gives trouble in the industry: *"The problem with clients is, what is AI in this context. If you talk to a roboticist, that person is all about path planning and mapping and all of that, but if you talk to a Data scientist AI is about optimizing data, and things like that and these are completely different, yet both are AI."* [I22].

Thus, AI applications often require the combination of several different fields such as statistics, mathematics, and computer science. Thus, the enablers of AI are also key: *"In order to work, it (AI) requires enablers such as efficiently working data infrastructure, good quality data, human skills on modelling targets etc."* [I14]. However, there is also a lot of vagueness in the term AI: *"Personally, I do not like the term, because it has so much hype and means a little everything, thus not really anything. I rather talk about data science and machine learning."* [I18]. *"What is AI and what is basic automation, the border is a little vague."* [I29].

4.1.2 Artificial narrow, general or superintelligence

Artificial narrow, general or superintelligence is the grounded aggregated dimension label for AI definitions, where it was described as a moving target over time: *"In the 70's it was Lisp (list processing), graphical user interfaces and machine vision that were talked about. AI was rule based back then."* [I12]. Or: *"AI is about automating* *tasks that in the past have required human effort. By this definition, playing chess used to be AI, navigating on a map used to be AI, and today self-driving cars still feel like AI."* [I3].

AI definitions often also took a stand on the performance level of AI: *"Strong and weak: weak assists, strong does it on its own. And in between these two."* [I24]. AI performance was also often compared against humans: *"I do not use the term AI to describe artificial general intelligence (AGI) where a machine can perform any task as well as, or better than a human."* [I19].

In information system sciences (ISS), the performance level of AI is divided into a three-step scale (Panda & Bhatia, 2018; Pennachin & Goertzel, 2007): artificial narrow intelligence, artificial general intelligence, and artificial super intelligence. With the current sophistication and performance level of AI solutions, and if using the Turing test as the measure of performance (Cohen, 2005; French, 2000; Hayes et al., 1995; Turing, 1950; Whitby, 1996), only weak or artificial narrow intelligence level has been reached, and is a reality in the industry: *"In our use, AI is still far from general artificial intelligence, to which the term is associated by many. That AI is unfortunately still in the future. It cannot fold a shirt or go to the store even though it can discuss with the client in a meaningful way and redirect the issue forward."* [I7]. With artificial narrow intelligence, a machine or intelligent AI agent is able to perform a single task extremely well, but the achieved solution is non-transferrable to other data sets even in the same use purpose (Panda & Bhatia, 2018; Pennachin & Goertzel, 2007).

Yet the comparisons to humans are understandable, as the Turing test and comparing the machine thinking performance to that of (originally) a woman refers to the first definition of a thinking machine that has been considered to set the whole field of artificial Intelligence in motion[2]: *"We have the original AI definition from 1950's."* [I9].

Yet, the performance comparison to humans is blurry depending on the context, and whether machine works alone (automation) or together with a human

[2] The field of artificial Intelligence (AI) is considered to have been set into motion by mathematician Alan Mathison Turing, when he published his article about an imitation game in the journal called the Mind in October 1950. This imitation game later has become to be known as the Turing test, where a human interrogator asks questions from a machine, and the machine tries to fool the interrogator to think that the answer was given by a human being. In the original Turing paper, a human interrogator asked questions through a teletype, and based on the answer to each question, tried to determine was the provider of the answer, A or B, a woman or a machine. With the current sophistication and performance level of AI solutions, and if using the Turing test as the measure of performance against humans, either women or men, (Cohen, 2005; French, 2000; Hayes et al., 1995; Turing, 1950; Whitby, 1996), only weak or artificial narrow intelligence level has been reached.

(augmentation, hybrid intelligence, conjoint agency)[3]: *"Machines, which make intelligent decisions similar to, or better than human beings."* [I22]. *"First and foremost, it is not to replace humans rather do work that people cannot do."* [I13]. Previous literature has proposed that when the heterogeneous intelligences of a human and artificial agents are combined, these socio-technical systems achieve *"a performance in a specific task that none of the involved agents, whether they are human or artificial, could have achieved without the other*" (Dellermann et al., 2019, p. 640).

4.1.3 AI has human colleague features

The aggregated AI definition dimension where AI is labeled to have a limited but increasing amount of human colleague features includes 2nd-order themes such as contextually adaptive. Here the informants both used pre-existing definitions or explained the adaptivity with their own words. *"System ability to process external facts correctly, learn from them and use what it has learned to achieve certain tasks and goals by using flexible adaptation (by Kaplan & Haenlein)."* [I33]. Or: *"Artificial Intelligence is a tool which can learn from experience without explicitly programmed for a task."* [I27].

AI was also mentioned to create an illusion of biological intelligence: *"As a wide concept, AI seems to be emulating human decision making and 'smart' machines."* [I18]. Or in a more detailed way: *"Everything that requires conscious thinking or learning from a person, and can be executed without a human being e.g. by using machines or biologically. Biological intelligence examples from the nature include e.g. the behavior of a shoal of fish is intelligent even though the behavior of a single fish is almost random. When these things are sequenced (if only they could be), we may develop interesting entities."* [I10].

AI is also expected to be a socially impactful technology*: "The first pilots of the third wave are the Star Wars AI, which can learn new things and communicate with people and other AI algorithms. It is humanlike, autonomous, it is capable of independent and teamwork, and it can explain why it does what it does."* [I30].

AI can already support people and/or their problem solving e.g. through its learning abilities: *"At its best AI is when it is combined to human intelligence and it supports people in their work."* [I13]. AI also helps with complex analytics: *"The*

3 In ISS, research on AI can roughly be divided into these two main branches: One of them focuses on aiming to reach human level intelligence with the help of technology alone. This is often referred to with the term artificial general intelligence (S. Adams et al., 2012). The other main branch of research on AI in ISS relates to human-computer interaction (Grudin, 2009) with a special emphasis on the collaboration of humans and the contemporary artificial (narrow) intelligence agents.

most advanced form of using data and analytics, where big data amounts can be analyzed in real time by using machine learning." [I13].

In the next section, I move on from the Ai definitions to the empirical findings of the sub-research question two related to the AI use antecedents.

4.2 AI investment decisions and use antecedents

In this sub-section, I explore the antecedents for AI use. More specifically, the findings focus on what are the criteria for strategic decision-making on when to invest or not invest in developing AI as an organizational resource, and as a potential organizational agent. The findings of this first sub-research question are analyzed on a task specialization[4] (Keon & Carter, 1985) level.

The findings are two-fold and contribute to the antecedent AI use phase (see chapter 2.4.1) from the strategic management decision-making perspective by proposing 1) different types of grounded AI strategies, and 2) offering implications for future research on what technical and socially constructed decision-making criteria may impact the managerial decision-making on whether to invest in developing AI as an organizational resource, and as a potential organizational agent.

4.2.1 Seven AI strategy types implied

Already during the engaged scholarship pre-study phase and during the semi-structured interviews, AI seemed to have had been adopted as part of the organizational strategy in various ways. Thus, in the first phase of analysis, I focused on the casing of the interview answers based on the adopted AI strategies.

First, two core AI strategy types were found: 1) the organizations that use AI in their core business, and 2) the organizations that do not use AI in their core functions. Ultimately, these two main categories were broken down to a total of five distinctive AI-strategy types adopted by the organizations. AI strategy was selected as the core business in three kinds of organizations: 1) Consultancies that provide tailored AI

[4] Based on the literature review on division of labor Keon and Carter (1985, p. 1146) divide the reviewed 87 articles from 1958-1981 to four categories: to those, that 1) use division of labor as a broadly based term, to those, that 2) include its general components such as complexity and/or configuration, and more specifically to 3) specialization and 4) differentiation. Differentiation is divided into structural and functional differentiation. Specialization is divided into three kinds of specialization: task, person and role specialization. The scope of role specialization is organization and "the number of varied roles individuals perform within the organization". The scope of person specialization is an individual, and his or her narrowed interest area that creates a specific area of expertise. The scope of task specialization is the smallest, as it refers to "the narrowing down of a job to smaller routine component parts".

solutions to their customers (Consultancy), 2) companies with AI-product or service as their main core business (Product), or 3) a separate special sub-group of companies with AI-product or service and a physical embodiment of an autonomous robot as their core business (Robotics). Some 4) companies used AI as part of one or some of their products or services but not necessarily as part of all the products or services that the organization offers (Key part). The remaining organizations 5) used AI primarily to support some other non-AI core business or core function (Ingredient). An overview of the AI-strategies as the first finding of this study are presented in table 11 and the more granular breakdown of casing interview source information is shown in table 8 in chapter 3.2.2.2.

Table 10. Summary of organizational AI strategies.

AI strategy	Organizational AI strategy definition
Consultancy	AI-consultancies providing tailored AI solutions to their customers
Product	Companies with AI-product or service as their main core business
Robotics	Physical embodiment of an autonomous robot as core business
Key part	AI as part of one or some of the products or services in the product portfolio
Ingredient	AI primarily supports some other non-AI core business or core function

What is missing from the sample are at least 6) the organizations with no or reactive AI strategy that may offer a potential sixth AI strategy type for future studies. The potential seventh 7) AI-strategy is AI keynote speakers / influencers, who were excluded from this sample.

In the next sub-chapter, I move on to the findings related to AI investment decision-making.

4.2.2 AI investment decision-making criteria

Despite asking the informants directly when AI is or is not applicable, the answers included elements of intertwined comparability and conditionality in the managerial decision-making, when to invest or not invest in AI. This led to proposing a third group of AI investment decisions, here named as ‘conditionally applicable’. These tasks seem to require an additional or more complex managerial consideration and analysis before deciding whether AI is applicable or not for a specific task or in a specific context. Thus, the ‘conditionally applicable’ AI task decision seems to require an extra decision-making step, before deciding on whether AI is applicable or not as illustrated in figure 1.

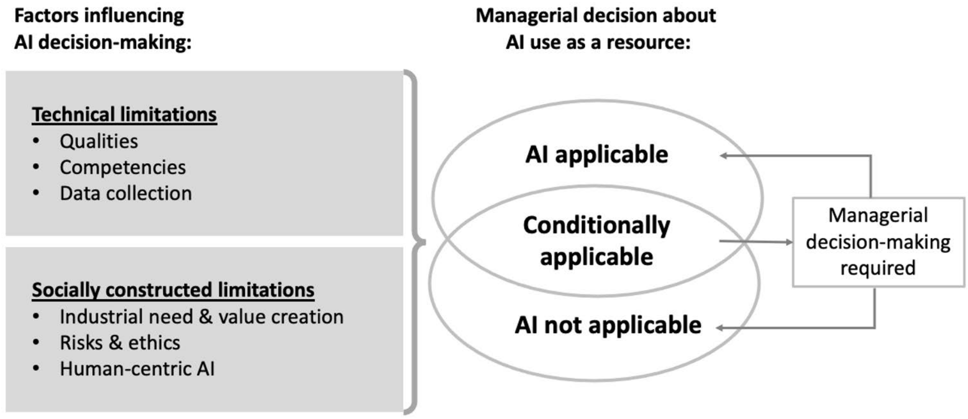

Figure 1. The intertwined technical and socially constructed limits or criteria for investing in developing AI as an organizational resource.

As also illustrated in figure 1, all the three aggregated dimensions on AI task applicability can be broken down to both technical and socially constructed limitations as decision-making themes. The technical and socially constructed decision-making themes consist of three grounded concepts each. All the concepts that form the decision-making themes are introduced more in detail the next sub-sections. I start with introducing the findings on the aggregated dimension when AI is applicable as a resource.

4.2.2.1 AI applicable as a resource

Based on the data, AI is applicable as a resource to a use case if the 1) AI qualities and 2) AI competencies fit the problem or need to be solved with it. The third technical requirement for AI to be applicable as a resource is 3) data. As for meeting the socially constructed requirements for AI, the planned solution needs to meet 4) an industrial need or to create value, 5) take the risks and ethics, as well as its 6) impacts on humans into consideration (see figure 2).

Among the findings, there might be some seeming overlap for the reader between the 1st-order concepts under these six 2nd-order themes. However, this is intentional and explained by the perspective highlighted by the interviewee. For example, under the technical limitations large data amount was categorized under the 2nd-order theme data collection, when the interviewees mentioned it as a requirement for training the ML algorithms.

However, the capability of objective handling of large amounts of data was categorized under AI competence. The use of this capability e.g. for continuous analytics that learns in real time was categorized under the socially constructed industrial need and value creation (see more in chapter 5.3.5). This was because the outcome is expected to create novel value or meet an industrial need of processing data in real time. (A summary of the analysis of the interview quotes is summarized in figure 2.)

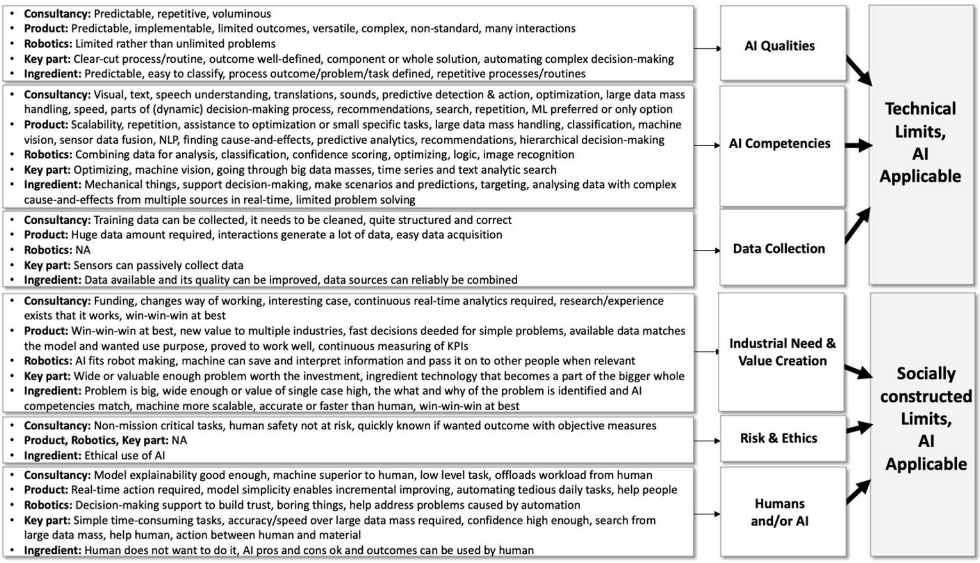

Figure 2. The technical and socially constructed limits for applicable AI use cases.

Technical AI qualities that representatives of all AI-strategy organizations (see table 11 in chapter 4.2.1) mentioned were the use case to be predictable, repetitive, or routine. The case needs to have well-defined outcomes and/or a limited problem to be solved by a machine (Ingredient). This also explains the requirement for volume (Consultancy), or many iterations (Product). The scope of AI already reaches beyond routines-only (Castro Silva & Lima, 2017; Frey & Osborne, 2017): *"Anything predictable, it does not even need to be routine-like"* [I10, Product]. When using AI as a Key part of the products or services, the technical AI qualities can be used either as a component or a whole solution in automating complex decision-making. AI enables versatility, complexity, and non-standard behaviour, but it should also be implementable: *"They are easily implemented to continuous processes. They are continuously useful, and a constant data input with a limited set of simple outputs is available"* [I11, Product].

Technical AI competencies include a large amount of different ML algorithms from detection and recognition to understanding, recommendation systems and optimization. Out of the five AI-strategies Ingredient differs from the other four by the most limited scope of AI competencies mentioned: mechanical things, decision-making support, and limited problem solving. Cause-and-effect relationships are mentioned (Ingredient, Product), and all strategies mention either the ability to handle large data amounts objectively or data handling from multiple different sources.

The unique mentions in Robotics are confidence scoring and logic required in the context of autonomous robots: *"Out of the data, AI can tell the class it has been taught and some probability how confident it thinks to be right. Classic example is AI in games: chess was one of the first AI news… The same way as in chess, the robot calculates through which pixels it would be good to drive to not hit anything."* [I16, Robotics].

Consultants seem to name the biggest number of AI-competencies overall. This seems logical considering the versatility of their projects because of the type of business they are in. AI can be used to handle repeatable things objectively, and sometimes ML is the preferred or the only option: *"Some of them are not possible with any other technique, e.g. image and language processing is possible with AI, that is a unique thing"* [I27, Consultancy].

Technical requirement of data collection was not even mentioned by Robotics, which may be the most striking finding related to data collection. This may be because collecting data from autonomous robot sensors is relatively easy and self-evident: *"In AI, the big disruption is that the messy real world is ok. There is no longer a dependency on the active sensors and data collection. Instead, the machine can passively observe the world, collect data from it and draw conclusions based on it. A microphone or cameras etc. can be attached to a machine, and they passively observe the environment without the environment having to adapt to the machine."* [I31, Key part].

In all other than Robotics AI-strategies it was mentioned that training the machine requires data. Data need to be collected or acquired. In the context of Product AI-strategy it was mentioned that interactions generate a lot of data. Consultants also highlight the need for the data to be cleaned and structured correctly for ML. Processing the data varies. The quality of data should be possible to be improved over time (Ingredient), and data sources need to be combined in a reliable way.

Socially constructed industrial need and value findings are most directly associated to the strategic alignment of IT and business strategies (Park & Mithas, 2020; Peppard & Ward, 2004; Ravichandran, 2018). The industrial need, fit and value creation potential is dependent on whether there is a business case, and budget for AI development. In the best-case scenario, AI creates win-win-win value (Consultancy, Product, Ingredient): *"If logistics is optimized correctly, airport optimization is win-win-win: Client wins when planes leave on time, no need for* *waiting, less flights are cancelled. Airport wins with expenses and society wins with less pollution and reduced complaints to consumer authorities."* [I14, Consultancy].

However, in the different AI-strategies, the business case or value creation potential might depend on previous experience that it works (Consultancy, Product, Robotics). Additionally, the available data needs to match the model and the wanted use purpose (Product, Ingredient).

Better performance is achieved from improved processes (Brynjolfsson & McAfee, 2014) and changed ways of working (Consultancy). AI can bring value when it becomes part of a bigger whole (Key Part), or AI may enable scalability, accuracy, and speed (Ingredient), or time-critical and/or continuous decision-making and action (Consultancy, Product, Robotics).

Socially constructed risks and ethics were mentioned to already play a part in AI-related decision-making (Consultants, Ingredient): *"I am really glad that in Finland and Europe we talk a lot about the ethical side of AI usage"* [I8, Ingredient]. The category itself is highlighting risks, so the applicable cases were in the negative form: *"non-mission critical tasks, where human safety is not at risk."* [I19, Consultancy]. Other clear cases, where AI is applicable are the ones, in which the risk level is reduced through clear and objective measures: *"AI suits interfaces and situations where you know fast whether the outcome was the wanted one"* [I20, Consultancy].

Among the socially constructed impacts on humans the heterogeneity of the answers was the widest. AI task handling level was compared to a human (Consultancy, Key part); or the role of AI was to offload workload (Consultancy) or unwanted tasks from humans (Product, Robotics); or to help and support them (Product, Robotics, Key part): *"What is advisable to do, assisting in surgery and decision-making in the operating room, technical assistance with respect to the course of surgery,…"* [I33, Key part].

The explainability and trustworthiness[5] of AI was highlighted to improve the models over time (Product, Key part), or to build user trust (Consultancy, Robotics): *"(Use AI) first to advisory role, so to support decision-making. That is where building trust starts from."* [I17, Robotics].

AI is also used for real-time action and interaction with users (Key Part, Product), when it is impossible for humans to do so: *"If you need to make decisions really fast, so that you have 100ms. Of course, I can never do that. It is totally impossible for a human to solve. It is actually totally irrelevant how bad the model is. You create domains that have never been possible before."* [I3, Product].

5 See more about explainable AI (e.g. in Barredo Arrieta et al., 2020), or how it might be important to build trust in AI solutions (von Krogh, 2018, p 407).

Next, I introduce the findings of the opposite end of applicability, the clear cases when AI is not applicable as a resource.

4.2.2.2 AI not applicable as a resource

Compared to the applicable AI use cases, the technical limitations of the not applicable ones are to a large extent their opposites (see figure 3). However, asking for the not applicable use cases did complement the socially constructed limits for AI.

In total, there were the least amount of use cases that were mentioned to be directly not applicable. This is mostly because many of these answers ended up being categorized as conditionally applicable rather than not applicable AI use cases. This may be explained by the strong pro-innovation bias among the interviewees, whose job it is to develop new AI applications rather than to resist them. Rather than saying 'not applicable', many interviewees preferred to test the limits of AI before judging for it to not be applicable. Because of the contemporary early adapter phase (Rogers, 2003) of complementary innovations based on AI, it may also be that there is not that much experience on failed AI use cases or that the interviewees rather talk about success stories and opportunities than failures.

Technical AI qualities are to not include totally unpredictable environments (Consultancy) or unclear situations (Ingredient): *"Emergency situations are not clear. Sometimes the information needs to be derived from between the lines, and the received information needs to be interpreted. It is hard to teach to AI."* [I32, Ingredient]. AI cannot be applied, if the problem cannot be formalized to data and calculations (Consultancy), if a lot of conceptual background information is required (Product), or if the question is too wide to find any patterns (Key part, Consultancy): *"If something is totally unpredictable, there is no model or pattern that can be learned."* [I2, Consultancy].

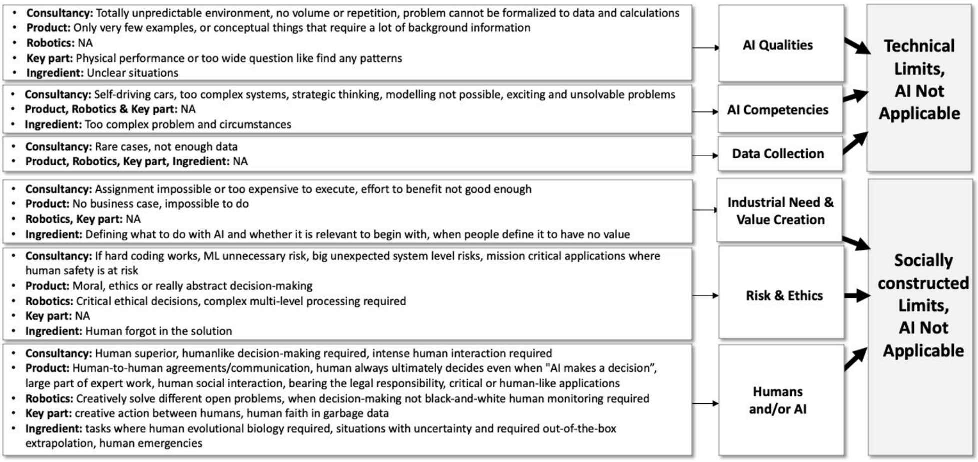

Figure 3. The technical and socially constructed limits when AI is not applicable.

Technical AI competencies that were mentioned to be out of scope of AI were related to the problem complexity. This was mentioned only by interviewees from organizations with Consultancy and Ingredient AI-strategies: *"Too complex problem to be solved. The circumstances generate such combinations that teaching them to the model requires simply too much time with the currently available data"*. [I7, Ingredient]. Also, AI-driven strategic decision-making (Consultancy) was said to possibly work, but as a rule operational decisions are best suited for AI. Interestingly and maybe a bit surprisingly, self-driving cars that are already being built got attacked and classified as not applicable AI use cases: *"E.g. for self-driving cars: even the landscape changes. Saudi Arabia and Helsinki look different, the vehicles, the streets, and everything in the scenery is 100% different in these two geographies. People look different, everything is different between the two landscapes. Same goes for satellite images, where detected roads and buildings look totally different, the datasets and models don't transfer. E.g. computer vision might not be transferrable to another geographical location."* [I19, Consultancy].

Technical requirement of data collection presents the obvious finding specifically addressed and clarified only by consultants. Too rare cases do not generate the needed data for AI. Yet, the same applies to all AI-strategies: *"If there is no data that the machine can learn from. Data need to be able to be retrieved or acquired, cleaned and it needs to be correct."* [I2, Consultancy].

Socially constructed industrial need and value may not be met because of a lacking business case if the effort to benefit is not good enough, or if the solution is too expensive. It may also be that people do not give value for using AI in a particular context; or the solution might still be impossible to do by using AI (Consultancy, Product). E.g. AI cannot define itself what it should and should not be used for: *"It* *is hard to evaluate is the thing where AI is used a good place for AI to begin with. (Evaluating) that requires a completely different kind of a project."* [I25, Ingredient].

Socially constructed risks and ethics were also considered out of scope to be decided by AI: *"Ethical decisions are such where it is good to keep a human as the final decision-maker. In ethical situations, we usually need to decide something extremely critical such as will we collide with a cruise ship and people will die; or will we cause a big natural disaster if we run aground. They are not nice decisions for a human either. For now, ethical decisions have the complexity of the situation, whereas the decision-making and chain of logic of a machine is based on training. It still cannot necessarily take all elements into consideration."* [I17, Robotics]. AI is not capable of handling this sort of complex processing that requires understanding different abstraction levels yet (Robotics, Product).

Humans (Ingredient, Robotics) or human safety should not be forgot while developing the AI solutions (Consultancy). Sometimes AI also presents an unnecessary risk**:** *"If a working model can be achieved by rule hardcoding, then using AI is an overkill and brings an unnecessary risk by it making guesses. E.g. if suspicious payments are wanted to be stopped, it is easier to say that all payments above 10M€ and all payments to these 17 countries need to always be checked."* [I2, Consultancy].

Socially constructed impacts on humans should be limited when human is superior to a machine. These cases still cover most things at this development level of artificial narrow intelligence (ANI). With ANI a machine or intelligent agent is able to perform a single task extremely well, but the achieved solution is non-transferrable to other data sets even in the same use purpose (Panda & Bhatia, 2018; Pennachin & Goertzel, 2007). For the most part, humans still need to make the decisions on behalf of AI while training the algorithms (Product), and always bear the legal responsibility for its actions (Product). Large part of expert work (Product) and solving creative open problems (Robotics, Key part, Ingredient) are also still mostly human territory.

However, humans and AI can collaborate: *"We should proceed to where the strengths of both the machine and human are used, and not try to bring the other to the other's territory where neither even could succeed."* [I20, Consultancy]. Thus, AI should not be used, when human-like decision-making is required (Consultancy, Product, Robotics, Ingredient): in cases such as critical or human-like applications (Product), when decision-making is not black-and-white (Robotics), or in cases of emergency. AI should not be used at all in situations of intense human interaction either (Consultancy, Product): "*AI does not suit hanging out with my friends, kids or wife. Not because the technology is not capable of it, but because you want to do it yourself."* [I30, Product]. Finally, a hard no were the cases where people are overly optimistic about AI and use garbage data to train the machine.

Next, I introduce the findings when it is not clear, whether AI is or is not applicable as a resource, and thus an additional managerial analysis and decision-making step is likely to be required.

4.2.2.3 AI conditionally applicable

From both the theory-building and practical implications perspective, the most interesting finding overall is the emergence of a third type of a technical and socially constructed investment decision type: the conditionally applicable one. When AI was mentioned to be conditionally applicable, the applicability of using AI as a resource is not clear (see figure 4).

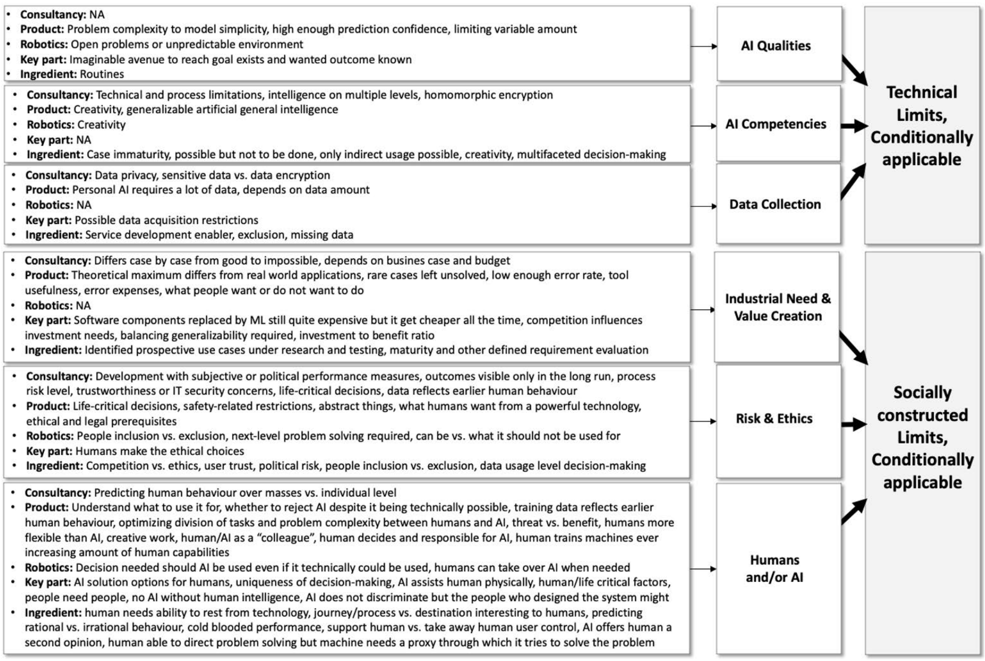

Figure 4. The technical and socially constructed limits when AI use is conditionally applicable.

In this case, the decision is highly context dependent. The decision seems to require a good understanding of both AI as a technology and the organization's business perspectives: what is the strategy, mission and vision of the organization's core function or core business? Both sides seem to be required to be able to evaluate and decide, whether AI is applicable as a resource to a particular use case. These conditionally applicable AI cases also seem to require an extra managerial decision-making step on whether to apply AI or not in a particular context or use case (see figure 1 in chapter 4.2.2).

The technical AI quality limits set between applicable, not applicable, and conditionally applicable decision-making criteria seem logical and coherent both within case of each adopted AI-strategy as well as in comparison to other AI-strategies.

The qualities defined by consultants seem to be more high-level in abstraction compared to the ones mentioned in other AI-strategies. Consultancies focus on event volumes, repetition, and predictability. Consultant AI-strategy case was also the only case which had no conditionally applicable answers. This may be due to being used to simplify AI applicability as a technical resource to a wide range of customers from different industries. The conditionally applicable cases were mentioned and more thoroughly detailed among the other AI strategies.

While deciding, whether to even try to use AI, the outcome needs to be known and there needs to be an imaginable avenue how to reach the wanted goal (Key part). The prediction confidence needs to be high enough, which is often achieved in a closed rather than open problem (Robotics) and by limiting the variable amount (Product): "*The opinions on different cases may vary, but in general a limited set, such as 10 categories leads to a better result than 100 categories, if you want to find the correct classification. You can add more classes, when you teach the machine more and more, but then also the uncertainty increases."* [I16, Robotics].

This explains the AI use case unpredictability in advance and why it is often only after testing that one can decide whether a use case is applicable in a specific context, even if it seems like just a routine: *"But especially in those situations, where the problem is worse defined and it is more complex, we are uncapable of doing so complex models. It leads to having too simple models to too complex problems. People are just overly optimistic about the outcome. In those situations, the things are always much trickier. Sometimes it still works sometimes it doesn't, and you never know what kind of a day it happens to be. This is pretty much the reason why sometimes the model works and sometimes it doesn't."* [I3, Product].

Technical AI competence limits start to show more variance between the applicable, not applicable, and conditionally applicable investment decisions. For all the AI-strategies, the findings on the applicable AI competencies focus on the more specific algorithms and other technologies used in their kind of business or function context. However, the specific algorithm level is not reflected on the not applicable or conditionally applicable reasoning. In them more generic or abstract limits are set to the AI competencies.

Context-dependent ambiguity to the use of AI may be caused by company policies, or technical and process limitations and/or requirements to train the models with encrypted data such as homomorphic encryption (Consultancy): *"The most* *advanced thing that at least I know is: I as a user I own my data and tech would encrypt my data and build ML on top of the encrypted data and then decrypt the data and get the prediction, what is the output. They just see the output for my data for some use case, but the whole data in the middle is encrypted. No one can see it and the model is trained on encrypted data. It is called homomorphic encryption. Maybe that could be the solution?"* [I27, Consultancy].

The degree of AI being able to do something may also be conditionally applicable e.g. in the context of creativity (Product, Robotics, Ingredient): *"I was about to say creative things, though some song has already also been composed by using AI… AI suits creative things in a defined context like browsing through all options, and to generate optimal solutions that you might not have thought to try out yourself."* [I5, Product].

Finally, the last thing mentioned that makes evaluating the AI competencies conditionally applicable is evaluating the levels of intelligence required for solving a problem (Consultancy, Product, Ingredient): *"Many start applying AI to such projects where decision-making is strategic or tactical. It is possible that it succeeds, but the basic ideology is that AI is used for operative functions. It is significantly easier to make e.g. dynamic analysis on what kind of a loan decision should approximately be given to a person rather than thinking should the loan business be given up altogether. AI cannot answer it because it is not able to do the kind of intellectual reasoning that leads to multiple levels and then back."* [I20, Consultant].

Technical data collection of conditionally applicable cases starts to reveal the complexity of AI-related decision-making cases. High level of understanding is required from the people making decisions on whether to use AI as an organizational resource in more knowledge and data privacy intense cases: *"Healthcare can be one example, but it is unique also in the sense that you need to analyze the data, what works and what doesn't. You must work with the data to understand if something is curing and the reasons behind different things. But healthcare is really sensitive with data… It brings the demand that you must find a way to process data without revealing anyone's data who is in the dataset. We must be able to build ML models that are anonymous, and there is no way to trace back from the person just by having the model."* [I27, Consultancy].

Data enables the service development, but if some key data source is missing, or only technical services are available to users, they may start to exclude some users (Ingredient). E.g. in a hospital it may be difficult to acquire health data as oppose to the generated sickness data. Thus, acquiring human-centric data is sensitive to data privacy and other careful considerations, whereas generating data from machines has become increasingly simple as one can attach microphones, cameras and other sensors to almost any machine: *"Then the only question that remains is, does it have* *too much heat, does it have some privacy restrictions, battery life, legal, weight, or size etc. constrains, but they are also sensor restrictions."* [I31, Key part].

Socially constructed industrial need and value need to be defined based on costs to benefits (Key part) and business case (Consultancy). The fit of AI to organization's overall strategy may vary because of a performance level ranging from good to impossible (Consultancy, Ingredient). This is because the theoretical maximum performance of AI differs from real world applications (Product). Rare cases are solved last (Product), which might influence the case-specific costs, error rates and tool usefulness. The decision, whether to use AI as a resource is also influenced by how expensive the potential mistakes might be: *"Even if it worked well technically, it might still not be a good idea. These are really tough business questions for every company to navigate: when it is beneficial to use a machine and when not to."* [I3, Product]. The value of an AI solution may also depend on which tasks people want to do themselves (Product), and/or the industrial need might be influenced by the competitors in the field (Key part).

Socially constructed risks and ethics are becoming increasingly important to evaluate as AI use cases become more common. The strategic management of an organization needs to consider the risk-to-benefit ratios of AI, and related ethical and moral considerations in organizational decision-making on whether to use AI as an organizational resource or not.

Because of the uncertainty associated with the outcomes when AI or ML is used, mission critical tasks and situations where human lives are at risk need to be carefully evaluated both in the short and long term: *"It is currently a really big ethical question, if there is an AI model that can sometimes make mistakes so that someone has a car crash and dies. Then is that still ok, or should it be that it cannot make any mistakes? Statistically some 50 000 people die in car crashes in a year. So, if we can press that e.g. to 10 000, it is a significant improvement despite the model making mistakes. Of course, ethically, it is a really tricky situation."* [I3, Product].

Thus, both legal and ethical prerequisites need to be taken into consideration: to what extent the solution should be tested, what error rate is acceptable, how could risks be mitigated in the whole chain of AI-solution development, who is legally responsible when something goes wrong? AI can never make the ethical choices on behalf of a human. It is always a human who decides the data to be used to train the algorithm. Do the domain experts training the AI, or the people using the AI solution, understand how AI works and what are the outcomes based on? Do the people monitoring the AI solution know what information was used to generate a recommendation? Was there some critical contextual information missing that the human expert has? Answers to all these questions need to be thought of in an organization.

Socially constructed impacts on humans mostly relate to finding suitable roles, interactions, and division of tasks between humans and AI (Product, Robotics, Key part, Ingredient). Now that humans start to train an increasing set of skills to machines, an important decision is how much agency is granted to the machine in the form of decision-making and autonomous action? Does the machine replace or assist a human? Or is it a case where there is no room for a machine, even if it was technically possible? If humans and machines collaborate, how is the interaction designed to fit the human? *"It is not a question of human or a machine. Instead, what is the moral and how things are organized e.g. in healthcare so that the nurses have more time for patient work and that they also actually use the time for it."* [I10, Product].

In which situations the human can or should take over the machine and overwrite its decisions, and how is that done? AI seems to work well for predictions over masses e.g. in recommendations for online-content, but predictions for human behavior on an individual level still seem challenging (Consultancy, Ingredient). Humans are capable of direct problem solving but a machine needs a proxy through which it tries to solve the problem given to it. A lot of both responsibility and power seems to be transferred to the people developing the AI-solutions.

However, also other people who use the solution need to understand that the AI-training data only reflects past behavior (Product), and that there is no AI without human intelligence. This may lead to other managerial considerations. These problems may derive from the fact that AI is not discriminating anyone but the people who designed the system might be: *"A human has designed the systems; it is not the fault of the algorithm if it has been trained to decline e.g. the mortgages of a specific ethic group."* [I28, Key part].

In Ingredient AI-strategy also other implications on humans were mentioned that might have to be considered now or in the future, such as what if we humans need the ability to rest from technology? Is the journey or the destination more interesting and important to humans? *"When a machine scores (in football) for the first time, it is interesting, but if it succeeds every time, it is no longer interesting"* [I9, Ingredient].

In the next sub-chapter, I move from the second sub-research question to explore the findings of the third sub-research question on the differences between the use and wanted use of AI.

4.3 AI use vs. wanted AI use

In this third sub-section, I move on from the antecedents of AI use to its actual use. I build on the findings of the previous section, where the AI developers were asked when AI is or is not applicable as a resource. Yet, managerially the most interesting finding consisted of the conditionally applicable -type AI investment decisions.

In this section, I deepen the analysis of the previous section and ask the AI developers how they themselves use AI in their work, or how would they want to use AI in their own work. These findings seem to widen the spectrum of AI use options from three categories to six categories depending on the different mix on whether AI is used or wanted to be used, and whether AI is applicable, conditionally applicable or not applicable (see table 12).

Table 11. The six types of AI applicability decision options combined to its use or wanted use.

AI applicability	Use AI	Want to use AI
Applicable	Can use & AI in use currently	Want to use AI & already applying / developing AI solution
Conditionally applicable	Can use AI with prerequisites	Want to use AI but something still missing
Not applicable	Cannot use AI	Do not want to use AI even when it is possible

So why did I include also the wanted AI use in the analyzed answers even if AI is not used in those cases (yet)? Already during the interviews, a striking observation was that there seemed to be a heavy contrast between the AI experts developing AI solutions for others, but not necessarily using AI themselves in their own work[6]. Another distinctive observation was related to 1) the role of the interviewees being the developers of AI solutions and 2) to the fact that some of the AI solutions were already in use, some were still in different phases of development for different reasons, and some had already decided to not use AI even if it was technically possible to do so.

6 Cleaver (2007, p. 226) makes a hard self-other division by writing about how agency is *"exercised in a social world in which the structure shapes the opportunities and resources available to individuals"*. Hosking (2011) has developed a softer self-other differentiation, and views people and their worlds as emerging processes that enable the complexity and multiplicity of life (Hosking, 2011; Ryömä & Satama, 2019).

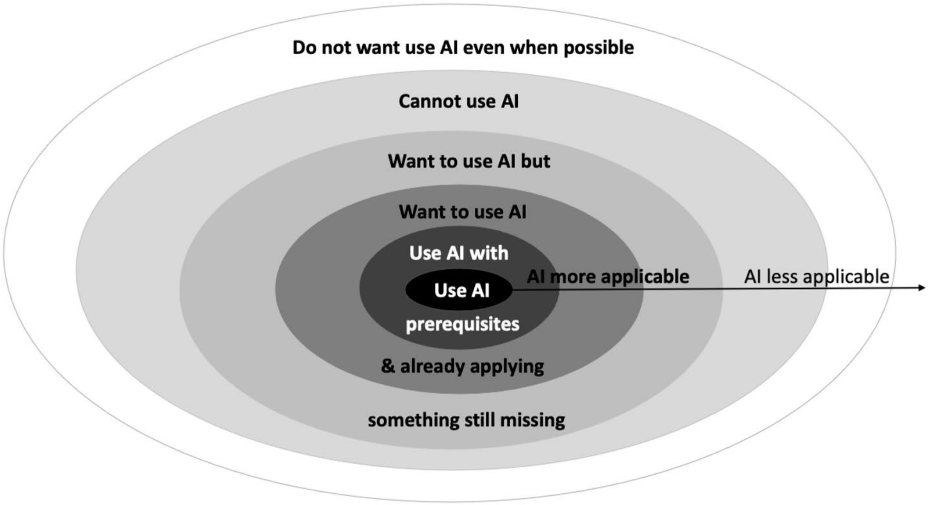

Figure 5. The spectrum of six categories on AI applicabilty and its use or wanted use.

To explore these initial observations of AI use more in detail, it was necessary to include the answers of both when the AI developers use and want to use AI. As a result, a continuum of six types of AI use categories seemed to emerge: 1) AI in use, 2) use AI with prerequisites, 3) want to use AI and already applying it, 4) want to use AI, but something is still missing, 5) cannot use AI, and finally 6) do not want to use AI even when it is possible. In figure 5 these six AI use categories have been organized in order starting from most applicable in the center and moving on toward less applicable use of AI towards the outer edges of the core.

In the following sub-sections, I introduce these six types of AI use categories more in detail.

4.3.1 AI use applicability dimensions

The six aggregated dimensions reach from current AI use to not wanting to use AI even when it was technically and/or otherwise possible. AI is already being used for: a) automation, b) augmentation, and c) as a hidden part of a process or service. When AI is being used, it has already started to impact d) individuals, and e) organizations in practice through the f) different phases and breakthroughs in technical AI development.

When asked about their own use of AI, the developers use AI with prerequisites, if there are g) AI implementation issues, or h) general hybrid intelligence issues. While developing AI solutions, the AI developers want to use AI and they are also already applying it to i) new opportunities, or to j) fix new problems caused by the increasing production of data and use of machines.

When moving toward less applicable use cases of AI, there is a big group of AI use cases to which the AI developers would want to use AI, but to be able to do so, further development of something is still required. So, when the AI developers want to use AI, but there is still something missing that is preventing them to do so, it might be k) a business model problem, or when l) further exploration of AI opportunities are still required. However, the main drivers for wanting to use AI in the (possibly near) future include, but may not be limited to, m) getting rid of non-core work tasks, n) to improve the human-centric approach with AI solutions, or o) to solve complex problems, such that humans alone are not likely to be able to solve without the help of a machine.

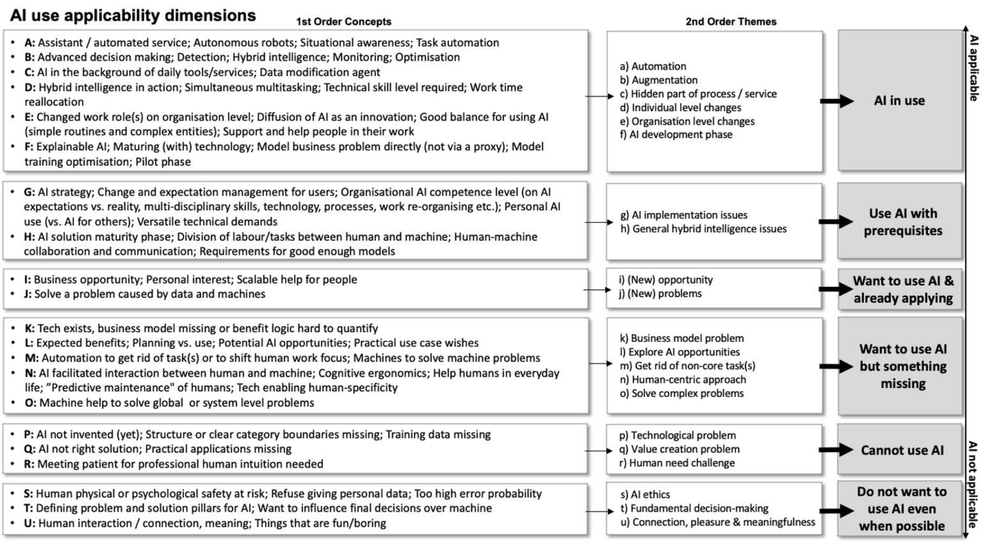

Figure 6. Overview of the six AI use applicability dimensions found.

When asked about AI use in their own work, the AI developers told that they could not use AI due to p) technological problems, q) measurable value creation problems, or r) because there was a human need that would need to be overcome before AI could be fully used.

Finally, the reasoning for the least applicable AI use cases included (but may not be limited to) problems with s) AI ethics, or t) people wanting or needing to do the final or fundamental decision-making. Or AI was not to be used simply because people found that there was no space for AI in things that u) build on human-to-human connection, or give pleasure, or provide meaningfulness for people. Thus, they would rather do it themselves than have a machine do it for them. (See the general overview in figure 6.)

The second order themes are introduced in further detail per AI strategy and with original quotes of the interview data in the following sub-sections.

4.3.1.1 AI already in use

In the context of AI use, automation (Fleming, 2019; Furman & Teodoridis, 2020; Johnson et al., 2021) might replace humans and augmentation (Raisch & Krakowski, 2021) might enable new kind of socio-technical (Manz & Stewart, 1997; Pasmore, 1995) collaboration between humans and artificial agents. However, the findings indicate that AI use may also replace or augment other technologies as a hidden part of a process or a service. Maybe specific to AI developers, one more group of AI use answers refer to the development phase or maturity of AI as a technology in the current AI use. As a separate entity are the impacts of AI, the changes that AI use might have on individuals or on organizations.

I will next briefly present these findings more in detail by comparing different AI strategies adopted. I provide quotes from the interviewees; to which the 1st order concepts, 2nd order themes, and aggregated dimensions are grounded on (see overview in figure 7).

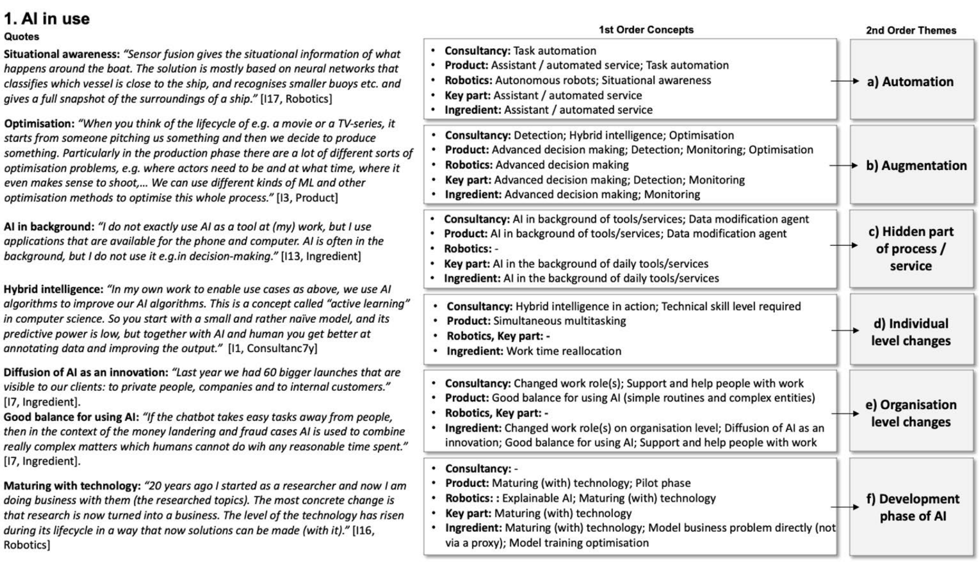

Figure 7. Summary of the Gioia analysis: the aggregated dimension when AI is already in use.

Automation (Fleming, 2019; Furman & Teodoridis, 2020; Johnson et al., 2021) between physical autonomous robots (Robotics) and all the other four AI strategies differs radically: *"In autonomous robots almost every part is somehow AI. They use different logics, traditional optimisation planning algorithms. They are a very integral part of robotics."* [Interviewee 16, Robotics]. Both in Consultancy and Product AI-strategies, AI was used to automate specific tasks such as to optimize video encoding, do the accounting for purchase invoices, or complete specific tasks during the ML algorithm development.

Related might be the use of AI as a technical assistant or while developing some automated service as mentioned in Product, Key part and Ingredient AI strategies. *"We were making a demo video yesterday, and I used a service to get it (the content) scripted: first the speech was needed in a text format and then some native speaker turns it into proper English, and finally AI pushes the text back into a speech format so that it does not sound like 'Rally English'."* [I18, Product].

However, the nature of the services may differ significantly: *"On the other hand we have e.g. a lot of navigation with which we get closer to the target. In that AI could be used as part of it for how the image can be interpreted even further as it is currently being interpreted. Navigation is used to position the surgery to the right location. It can be used in almost all neurosurgeries, because we have precise targets and with that (navigation) you can get to the desired location from a smaller opening."* [I33, Key Part].

Augmentation[7] mostly includes enabling people to do, or helping them with, advanced decision making. It is something, which would be very complex or too time consuming without the help of a machine (Product, Robotics, Key part, Ingredient). An extreme case example of this is advanced autopilot mechanisms: *"We are focusing on using AI to help human operators to benefit from an assisted agent. It has been trained to do some advanced decision making in complicated situations, where people tend to react in wrong possible ways and make wrong possible decisions. We call it advanced autopilot mechanisms. Especially with what has been going on with the Boeing MCAS systems recently, we believe, that an AI with a human would have worked there to take the control from the human and do everything on its own."* [I22, Robotics].

[7] Work augmentation (Raisch & Krakowski, 2021) has been theorized in the context of its workforce implications (Brynjolfsson & Mitchell, 2017). Other terms related to the emergent discussion on human and AI collaboration are hybrid intelligence (Dellermann et al., 2019), (hybrid-) augmented intelligence (Pan, 2016; Zheng et al., 2017), intelligence augmentation (H. Jain et al., 2018), and/or conjoined (Murray et al., 2021), interdependent (Raisch & Krakowski, 2021), or intertwined (Leonardi & Treem, 2020) agency.

Among the other AI strategies, the solutions include finding patterns over large populations (Product), and/or making suggestions (Product), or simulations (Key part) for humans. Often as part of an advanced decision-making process might be detection (Consultancy, Product, Key part) such as automatically detecting cancer cells from a tissue image. AI might do monitoring (Product, Key part, Ingredient) in cases such as machine maintenance, money laundering or fraud attempts. Or AI might help with advanced decision-making related to optimizing (Consultancy, Product): *"Another example is finding new molecular combinations of drugs. There is almost an infinite number of combinations how molecules interact. Then it is very expensive to test it physically. Optimally you want to test the options that will behave as you want. So, you should implement in a lab the real molecules that are more likely to interact. So, it is impossible for humans, because it is extremely time consuming, too expensive to test every combination. So, filtering out what to test and what to actually implement in real life."* [I1, Consultancy].

Yet the most interesting novelty comes when humans and machines actually learn from each other as with hybrid intelligence (Dellermann et al., 2019): *"Before the idea was that we humans have a western art perspective on what works and what does not work e.g. as an image or as a text. We own the creative work. Now a machine interferes with that: a person generates options, and a machine tells what will work for whom. It can work differently as the original bias might have been, and it can be learned from."* [I20, Consultancy].

Hidden part of process or a service was mentioned in all AI strategies except for Robotics. However, within automation it was mentioned that everything in an autonomous robot is somehow AI [Interviewee 16, Robotics], but the hidden nature of AI in autonomous robots was not emphasized as was the case with the other AI strategy interviewees. Yet, also in knowledge work such as sales recommendations *"all our data points are modified by AI at some level"* [I11, Product].

In all the other four AI strategies except for Robotics, AI was mentioned or expected to be in the background of daily tools and/or services such as cell phones, computers, and their applications. *"I probably use it pretty much in a hidden format to structure and analyze things. I use the tools of our own company for development and executing consultancy work. The tools process information, do calculations and statistics. For me AI is like technology in general, you use it without thinking about it too much, in the same way as a calendar assistant."* [I10, Product].

The hidden nature of AI is acknowledged also when the AI-based services have been developed for expert work: *"AI has influenced a large number of employees a little, and an employee might not be interested in how we create recommendations. They only know that now they have something new to support client service that comes from somewhere."* [I7, Ingredient].

The AI developers even problematize, what counts as using AI: *"It depends on the definition, what counts as using AI. There are all sorts of cloud services, and in some part of their optimization something is used that could be described as an AI application. E.g. if it is wanted to be predicted when and based on what kinds of signals one needs to foresee the demand of web services: In this case you need to switch on additional 7 machines at this hour because this is happening there. This is already being done, and in the future, it will be done even on the power grid level. So, you do not directly use it yourself, but you benefit from it roaming within the infrastructure."* [I26, Key Part].

Individual level changes and the organization level changes are the most versatile AI use themes. This is even despite that both include answers only from Consultancy, Product, and Ingredient AI strategies. The most interesting and novel changes relate to hybrid intelligence (Dellermann et al., 2019) in action, where humans and machines cumulatively learn from each other: *"…it provides a dualistic benefit: you automate real-time dynamic pricing and afterwards you can augment the pricing decisions of humans, because you can tell which are the situations in which people are willing to pay more.*" [I20, Consultancy].

However, AI also enables simultaneous multitasking (Product), work time re-allocation (Ingredient), or sets new technical requirements for AI professionals: *"a reinforcement learning project, where we optimize which image should be shown of each series to each person at any given time. Out of (all) the projects, it has been one of the most challenging one, because you have had to create an online system which learns in real time and for the amount of people that are in [the Service name]. It is considerably more challenging than a traditional model where you take the data and re-train the model once a day to make some sort of predictions."* [I20, Consultancy].

Organization level changes are equally diverse as the individual level changes with AI already in use. Diffusion of AI as an innovation (Rogers, 2003) is the theme name used for all the answers related to practical organizational impacts and/or their scope e.g. by percentage of the employees affected by AI: *"AI has impacted almost 100 percent of our personnel. But its impact to their work may also be quite small. It may not play a major part as part of their daily lives."* [I7, Ingredient].

Changed work roles include all the changes to the needs of different multi-disciplinary expert roles, different skills required to the organization for AI development, and even changed work descriptions within a certain expert role in an organization (Consultancy, Ingredient): *"Another customer example: in their factory, we are semi-automating quality control of the output product. What was done before, they tried with trial and error, pressures and temperatures and they had some errors. Now we have sensor data coming from all the factory every minute. With the measures our algorithm is predicting before things are happening. So, for* *the operators, the things are much easier, and they can focus on other things: because now they only have to verify that everything is ok. So not replacing them."* [I1, Consultancy].

In both AI Product and Ingredient strategy organizations, having a good balance for using AI within the organization for routines and complex tasks was mentioned: *"First of all, at our company we are really strict that AI is not used over-optimistically. Rather it is in fact a tool that people use. In a similar way as e.g. Excel. People do not throw a random problem there either and then expect that it gives all the answers. Especially because we are in such a creative industry, and because people are worried e.g. about AI doing and planning everything sooner or later. So that neither actors nor directors or anything else is needed anymore. But in my opinion, [Organization name] has found a good balance in AI being a good tool for doing many types of routine work and to understand complex entities that could be difficult for humans. On the other hand, when these things are done well, it then gives a lot more liberty on the creative front. So, when a director starts to produce something, no machine interferes at all, instead it completely sets the human creativity free. I think that such a balance works really well at the moment."* [I3, Product].

Related to the good balance for the use of AI between routines and complex tasks are its effect on humans. Some organizations have chosen a human-centric approach to AI in a way that AI specifically needs to support and help people in their work: *"while developing AI, we highlight the human work. How we support and help people to better do their job. Better quality information is accessible about the contents, the consumption, and we understand more holistically what we actually do here at [Organization name] through content analysis and machine vision applications."* [I9, Ingredient].

Development phase of AI includes specific algorithms or technical sophistication to solve most complex business problems technically such as explainable AI, where the reasoning behind the decisions made by AI can be justified or explained to another AI or a human (Robotics). Technical sophistication also refers to model training to be technically optimized with minimal resources (Ingredient), or when a business problem can be modelled technically more directly than before. This is because AI usually requires a proxy through which the business problem is approached indirectly: *"I might explore what causes people to feel good: what would be worth investing in to get a certain client experience indicator to rise as efficiently as possible in relation to return on investment. So, to model a business problem directly. We use it as a part of service design and business. And the domain is strongly visible in the focus on such matters that a statistician alone would not know to focus on in a human-centric business."* [I25, Ingredient].

Under the development phase of AI are also the mentions about the business phase of AI commercialization within an AI company, such as the pilot phase (Product). However, potentially the most interesting concept under the development phase of AI theme is the maturing (with) technology. This theme is likely to be specifically highlighted among the chosen interviewees, as they develop AI solutions themselves: they have both a long-lasting personal interest toward AI development and a shared personal history with AI. Maturing with technology includes both the scope of business environment and the human individuals: *"We would not do this whole thing unless AI solution were moving from proof-of-concepts to production. AI is increasingly coming from research labs to real life."* [I18, Product].

An example of personal history and maturing with technology relates to growing together with AI: *"I have been practicing AI since I was 16. So, for me, AI has always been a significant part of what I do, but the way we do AI has changed drastically. There are a lot of new frameworks, new techniques that we could deploy, more support compared to 10 years back,…"* [I22, Robotics].

In the next sub-section, caution for using AI rise a bit, as the AI developers point out when AI can be used but they only use it if certain prerequisites are met.

4.3.1.2 Use AI with prerequisites

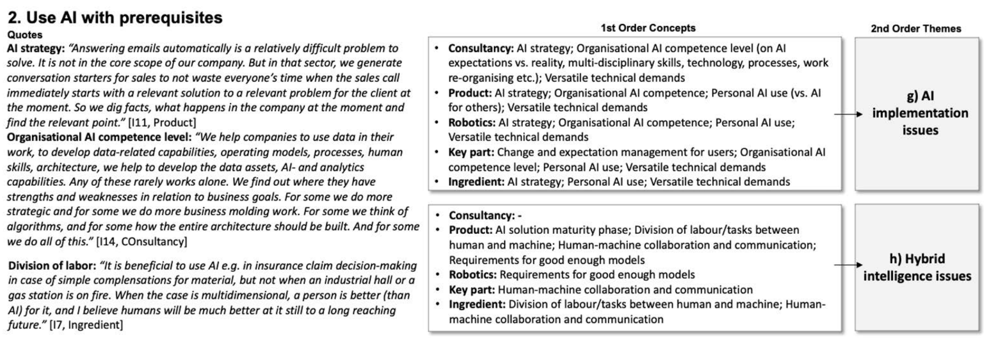

Figure 8. Summary of the Gioia analysis: the aggregated dimension when AI is to be used with prerequisites.

When AI solution developers are cautious about using AI, the problems that make them wary of AI use can be divided into two main types: the implementation issues of AI or issues related to human and AI collaboration.

AI implementation issues relate to practical and strategic implementation of the AI strategy, where AI needs to be contextually suitable for a task or use purpose (Consultancy, Robotics, Ingredient): *"Technology develops so fast. For us that means to stay on the map, what today is possible and what is not. There is quite a* *big difference whether you can get something done 90 or 98 percent, and (AI) may then change from useless into an awesome solution. Understanding this field when thousands of AI solutions come and go; realism of what is possible is important for us."* [I2, Consultancy].

AI development needs to focus on core business or core function of the organization (Product) and be ethically carefully thought through: *"We work a lot with ethics. We are one of the founding members in the Ecpais-network (Ethics Certification Program for Autonomous and Intelligent Systems) under IEEE (Institute of Electrical and Electronics Engineers). There we think of the ethical standards and certifications for AI. We cannot start to use too much AI before such matters are ready. We have tested AI and noticed how powerful it is. But at the same time when it (AI) is straightforward and efficient, it also looks like the one who made it. I do not believe that it can replace the employees of the [organization], instead there always must be a person in the middle."* [I8, Ingredient].

When using AI as Key part, it is essential to take care of change and expectation management for users, because there is always a small gap between the process taken care of by a human versus a machine: *"There is an expectation level, when an AI solution is delivered. Then one key factor in success and implementation is that the users understand what will change and to which direction. It is purely setting the expectations. On average a human does not have a good intuition of what the machine does differently. It is essential to achieve positive results in user satisfaction already during the starting months after the deployment (taking the AI solution into use)."* [I31, Key part].

Organizational AI competence level seems to have variation in the level of people's realistic understanding of AI's potential and requirements to make it work. Thus, a lot of intra-organizational or client expectation management is still required (Product, Robotics), when AI is started to be taken into use in new domains and new industries: *"My job description has not changed because of AI but because of the fact that the use of machine learning models has moved from the traditional customer analytics, fault detection, fraud detection, and insurance things, so from traditional simple models and e.g. from insurance mathematics to the domain where we are at. It is a completely new industry. That has changed my job description because I use an incredibly huge amount of time to make slides and talk with people, and my time coding and making models has reduced significantly."* [I5, Product].

Additionally, the interviewees have experienced that organizational structures need to change (Consultancy). This way they can meet the multi-disciplinary collaboration needs to develop working AI solutions and AI agents for an organization (Product, Key part). For different domain experts such as surgeons the required learning curve with AI may vary depending on what kind of tools they have used in surgery before (Key part), same might start to apply other expert work.

Organizational AI competence level may also depend on multi-disciplinary collaboration ability because the developers need feedback from the AI solution users: *"Now we have crime label prediction in production, so we predict the different crime labels. When we can automate retraining the model e.g. every week, we have a better access to results and can e.g. monitor how much our service team actually uses the prediction, or do they ignore it completely. And whether they use it if I do something to it."* [I5, Product].

In addition to understanding that humans need to adjust to the changes brought by AI, it also actually increases rather than reduces the human work amount: *"The routine-like manual work has reduced with automation, but the work amount has not. The AI-solutions are still very narrow, but all technical development creates the willingness to do something new. The old and the new world live side by side because you need to deal with the remains from the old world, but AI does not have the capabilities to take care of all of them. Something gets automated but the process does not get automated fully. Backlog always remains. At the same time, there is more work in the pipeline, so the work amount has increased because of it. Things change in organizations but not fast enough when you simultaneously construct new and give hospice care to the old."* [I14, Consultancy].

Particularly among these interviewees, it was interesting how common it was that they develop AI solutions for others, but not for themselves or hardly even use AI themselves (Product, Robotics, Key part, Ingredient). For some this sort of AI use with prerequisites may be explained by the versatility of technical demands to develop working AI solutions such as IT or data security concerns (Consultancy, Product, Robotics), critical minimum ML model training data might be missing (Consultancy, Key part, Ingredient), or simply whether one is able to overcome the versatility of all the technical demands: *"The challenge was on the applied machine learning side: how to create the architecture for a system that learns in real time. There are multiple technical factors. You need to think of load balancing and scalability to enable efficient learning when the load is at its peak and to be able to benefit from the learnings at the same time. The machines need to have a shared memory for them to be able to communicate what they have learned. Creating this shared state, in my opinion, is the most complex thing that ML experts run into now-a-days."* [I20, Consultancy].

Hybrid intelligence issues require additional socio-technical learning: 1) humans first develop a machine and then 2) get feedback from the machine and 3) learn to make something better than before with the output of the machine. This cumulative and mutual learning is called hybrid intelligence (Dellermann et al., 2019). This may include but not be limited to learning the limitations of AI in different problems and expanding the scope of solutions where AI can be a part of (Product).

After solving the initial technical problems, the challenges to be overcome include e.g. the interaction between a human and a machine: *"I do not see any specific domain to which AI could not be taken into use in the longer term. Of course, the maturity level of the services is not there yet. E.g. in healthcare you can automate things but things should be done also from the angle of how the other end feels. It is better to automate things only when the experience is good for humans. That includes a lot of big questions. Same goes for autonomous cars. Autonomous vehicles can be made but people are afraid when riding in them when they do not know what will happen next. They are also user interface -related challenges: to tell in advance that now we will turn left so that it does not come as a surprise, or in healthcare services robot lifts or brings something, so how does that interaction happen."* [I18, Product].

Likewise in knowledge work the human-machine collaboration and communication still requires a lot of learning and further development to understand the roles and requirements for both humans and AI agents (Product, Ingredient, Key part): *"A machine does not have the whole context, but it often can analyze the available context significantly better than a human. At the same time the human needs to have the context that the machine had, or did not have, so that the human can bring his/her contribution: additionally I know this."* [I31, Key part].

Thus, the division of labor on task level may change because of AI, but the suitability of AI is context dependent (Product, Ingredient), e.g. because of the requirements for good enough models (Robotics, Product): *"Detection is quite accurately successful. The classification depends on how much data is available. It recognizes basic vessels. We have a database of 3 million images that we have built ourselves, and it grows and gets more specific all the time. The rarer cases, e.g. data on logs in the water we do not have much yet, so the system probably does not recognize yet what it is and still announces it as an unknown object. What makes this challenging is that the navigation signs, signs for fishnet etc. fishing things vary geographically. We collect pictures of them from our collaboration networks in different lighting conditions and with different sensors, at night, during the day, with a radar,…"* [I17, Robotics].

In the next sub-section, the use of AI has already started, as the developers both want to use AI and have already started to apply AI to a specific need. However, these solutions or their further development iterations have not been launched to users yet.

4.3.1.3 Want to use AI and already applying

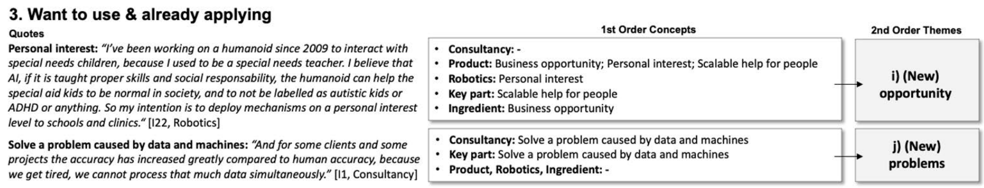

Figure 9. Summary of the Gioia analysis: the aggregated dimension when AI is wanted to be used and applying AI has already started.

When AI developers want to use AI, and they are already applying AI they focus on applying AI solutions that provide new (business) opportunities or solving new problems caused by technology.

(New) opportunities for business are provided by AI (Product, Ingredient), because it enables more nuanced scalability and service in new domains: *"This is a new domain, virtual social media, so the same social norms do not apply there. It is very interesting. That is exactly why I think it is interesting to be here: it is a frame consisting of law, social media, and social psychology. In principle, AI is a robot that can act based on certain rules in this kind of a small box. So, one might think of it as a niche box. It is a very versatile box, but it is still teachable for a machine."* [I5, Product].

Alongside with their work, some of the technical AI experts have their own pet projects like helping children with special needs (Robotics), or other long term personal interests for developing and applying AI in new contexts (Product): *"Then language started to interest me, and how language and learning could be computed based on the rules of chaos theory. I thought that language and learning should also be computable, so I have been on that road since 1997."* [I10, Product].

Some want to use and have already started to apply AI to provide help for people in a scalable way. Examples of this include but are not limited to scalable access to justice by providing automated legal advice (Product), or to help doctors to analyze medical images (Key part). Some even want to free people from all work that does not need to be done by humans and allow people to concentrate on things they themselves find more motivating instead (Product).

(New) problems are caused by the data overload that is too much for humans to handle (Consultancy, Key part), thus machines are needed to solve the problems caused by data and machines: *"On the surgery side, a lot of research is made on the fact that if a patient is e.g. in emergency room, you get so many measurements and variables now. A person is surrounded by machines, and a human eye has trouble interpreting a single variable. In our field a solution is being developed for how to* *make curves and forecasts, because there starts to be so much data that a human cannot make any sense of it when holistic prognosis is made."* [I33, Key part].

In the next sub-section, the developers want to use AI, but they cannot do that yet. This is because there is still something critical missing. Something still needs to be developed, before AI could be taken into use in these cases.

4.3.1.4 Want to use AI, but something missing

When asking the AI experts about their own use of AI in their own work, many wanted to use AI but could not do so for a reason or another. They could see the technical opportunities, but in some solutions the business logic was still to be found to create a sustainably working solution. Almost all interviewees would have wanted AI to take over self-services or non-core work tasks. Not surprisingly, the AI developers were curious to explore new AI opportunities, but they also highlighted the human-centric approach when AI solutions are being developed and implemented. Finally, a wish, that is still in a more distant future but what motivated some of the interviewees, was to use AI to help solve complex system or global level problems in the future.

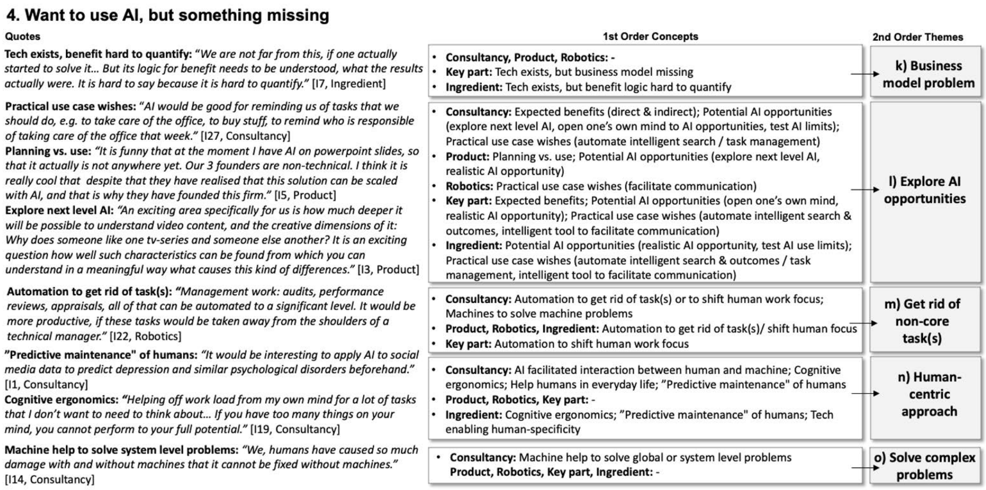

Figure 10. Summary of the Gioia analysis: the aggregated dimension when AI is wanted to be used but something is still missing that prevents the use of AI.

Business model problem refers to the cases, where the technology already exists to a wanted AI solution, but either the benefit logic is hard to quantify, or the business model is still to be discovered to enable personal AI use: *"I would want a lot of things related to the calendar. They are clearly coming, and many parties are trying* *it, but in reality, it does not seem to happen yet. To have something for time management and calendar, to make sense of them, but the technology is not quite there yet. All the necessary technology has been invented already. Now it is only a question of engineer work and business ideation, how to find a business model with which you get enough useful engineering work to make it into a useful product.”* [I31, Key part].

Explore AI opportunities included ideas for wanted AI solutions that would help the AI developers’ own work such as more intelligent and automated search (Key part, Ingredient, Consultancy), or channelling communications in multiple-country teams in a more intelligent way than what is currently possible (Robotics). Others wanted to use AI to gather feedback and be able to influence in an organization with the help of the collected feedback (Key part), or to network and exchange information between people (Ingredient). Some were wishing for a more intelligent predictive AI secretary with co-ordination or management capabilities (Ingredient, Consultancy). Others simply wanted AI outcomes to make things faster or be of better quality (Key part). Some highlighted other direct or indirect benefits that they wished for: *”I wish that the use of AI would show as a nicer user experience for the user: as efficiency of course, as actual quality, even though it is a guess, and hopefully also as an enabler for such things that have not been possible at all before or for which there has not been time for.”* [I2, Consultancy].

Many had identified realistic AI opportunities on an idea level in their own work surroundings, but the ideas had not at least yet been started to be developed further (Product, Key part, Ingredient). Some had also started to open their own minds on how AI might play a part in their own work or change their own work role in the future (Key part, Consultancy): *“The most difficult for AI is to recognise the intuition that doctors have. We meet a patient partly with the kind of intuition that we cannot explain even to ourselves, based on what some of the decisions are made. Thus, it is hard to teach it to a machine. I often feel e.g. when I have seen a bloody protrusion, and I have looked at it on the computer, and I have seen the papers of the patient, so then I already know whether I suggest surgery or not. But then there is a certain limit, if age rises significantly, then I need to see the patient. And then I see already on the doorstep how s/he will recover from surgery and what the resources of the patient are. But even for those cases I have slightly changed my opinion in a way that AI might provide background information. That might help, which do you choose.”* [I33, Key part].

A possible sign of a pro-innovation bias among these respondents might be that some of the AI developers were just curious to test the limits of AI, what it can and cannot do (Ingredient, Consultancy): *“We do not know how AI will develop, and it will develop a lot. I would want to give it almost everything and see what it can do.*

Then in a data-driven way I would then decide whether it makes sense to give it (to AI) in the future." [I14, Consultancy].

Some were more focused and wanted to explore a specific aspect of AI's potential, e.g. to understand why people like specific TV programs (Product), or the ripple effect impacts of AI on creativity (Consultancy): *"But the really interesting aspect about AI is that when we start tackling creativity, and the machine starts to generate options and unique products. What does that do to this global ecosystem that is based on you having a really highly paid designer hero who decides what a good-looking Adidas sneaker looks like. Then you produce a million pairs of them as cheaply as possible. But what would it mean if you instead could produce a million unique pairs? What if you reduced expenses from the creative end and did more flexible production? Is it even possible and how long will it take? Then it is not only the job description that changes but the thought of the whole global supply chain."* [I20, Consultancy].

In some companies AI opportunities have already started to be explored, but then AI has been mostly in PowerPoint slides or in financial round materials to plan what is needed to set up a working AI company, and how much might all that cost. Also, a learning curve, testing and actual implementation is required to make the non-technical expectations meet the technical realities of AI: *"I feel that the service team expects a ready-made AI-component that then magically works. If it works let's say with 89% certainty, it does not mean that it would be usable or that they would know how to use it right away, and that no iterations should be done for it."* [I5, Product].

Get rid of non-core task(s) such as automating management work, reporting, human resources, and financial management are among the dreams of people developing autonomous robots. In general, all sorts of support functions such as the secretary work of the olden days was wished to be fully automated (Product, Ingredient, Consultancy). Planning tasks and writing boiler plate code were also happy to be let go of (Consultancy): *"I would want AI to write some boiler plate code for me. The base structures, it could take care of the mindless stuff like setting up project directories, etc. based on an exact project that you would like to start. Or more intelligent code completion that would be really intuitive. Much like autocorrect, for it to be a helping hand for coding to be more productive, so I can be more focused in the actual task. Even in ML maybe 10-15% is actually designing neural network architectures or doing different configurations, the rest is boilerplate code and designing your training pipeline, and all sorts of trivial software tasks. If I could reduce that and work, let's say 50%, on designing neural networks that would be huge. But that does not quite exist yet."* [I19, Consultancy].

In addition to getting rid of some tasks with the help of AI, some interviewees specified what they would rather spent time on themselves, were AI to take work off their current workload. The interviewed AI developers wanted to focus on work such as research and development (Robotics), developing core things (Product), actual decision-making instead of routines (Key part), value creation, spending time with people, and creative problem solving (Ingredient), or coding (Consultancy). Machines were also wanted to solve machine problems: *“Also a bot for talking to other offices or clients remotely: sometimes we have Internet problems. We spend a lot of time to fix that. Maybe we can use AI to understand the root cause of these issues and fix them or predict the network issues during calls or something. That would be useful.”* [I27, Consultancy].

Human-centric approach refers to different aspects of human well-being. As in factory or production settings, predictive maintenance (M. Jain, Vasdev, Pal, & Sharma, 2022) is started to be wanted also for humans to be able to predict getting sick whether it being a flu or e.g. depression or similar psychological disorders (Consultancy): *“I would want to see AI in work well-being. But I cannot use AI for it because the prerequisites for that are both technical and political. I would be ready to put all sensors in me, if I could predict when a flue is coming, or when some employee is getting a flue, to be able to monitor when it is worth pushing, and when not. But because it is both a technical and a political matter, it can be assumed that the solution will take 10 years.”* [I20, Consultant]. “Predictive maintenance” for humans is also wanted for being there for other people at the right time in a manager or supervisor role: to spot when to be present, help or even offload work burden from team members when necessary (Ingredient).

If predictive maintenance for humans is concerned about the well-being of self and others, cognitive ergonomics (Kalakoski, Henelius, Oikarinen, Ukkonen, & Puolamäki, 2019) is interested in organizing workload in a way that would cause the minimum amount of mental burden: *“At its best, AI trims away irrelevancies: a lot of disturbance is related to work that does not create value. It frees time to creative work. Everything that is away from the state of free association or that interferes with it, AI can clean off. I believe that the human brain capacity is currently way too occupied, and that AI would have a lot of opportunities to help people with this. When the number of stimuli or irritants is heavily reduced, different mechanisms for interaction and ability to be present are born. It would be great, if only we could still reach such a state in work life someday.”* [I9, Ingredient].

AI is also wanted to optimize meetings, for intelligent scheduling, and reminders: *“Optimizing meetings would be really good: when you focus on something, and then you have a meeting, you need to change your concentration. That can be tiring when there are so many meetings, or meetings are not in the right time. It breaks your attention in the middle of the day.”* [I27, Consultancy].

AI was wanted to help in everyday life both in and out of work whether it being life with kids or facilitating work meetings in a way that one would not have to fix the connection for 15 minutes (Consultancy). Related is the wish for AI-facilitated interaction between humans and machines such as user interfaces that work with voice or gestures (Consultancy), or tech enabling human-specificity e.g. when constructing media around each human (Ingredient).

Solve complex problems is a wish for future AI development so that machines could help to solve global or system level problems: *"We have big system level changes: climate change, inequality on different levels, the sinking respect for democracy, and the threat of how to make better decisions as communities,… How can we genuinely take the benefit of the majority into account…? I would want to have the ability to use AI for this. These problems are constructed by humans so I do not think that people-only will be able to untie the knot. Unfortunately, AI is still pretty bad at this, because its complexity. It is not a classic classification problem, or linear regression, or an optimalization problem rather it is a bit of all of these."* [I14, Consultancy].

In the next sub-section, the developers list things to which they cannot use AI for different reasons.

4.3.1.5 Cannot use AI

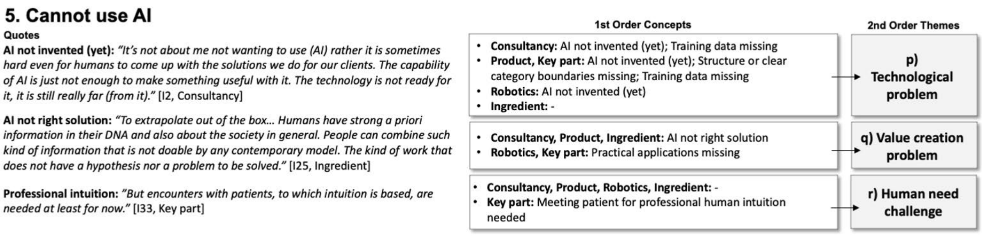

Figure 11. Summary of the Gioia analysis: the aggregated dimension when AI cannot be used.

When the interviewees stated that they simply cannot use AI, the reasons seem to be at least threefold: either there is a technological or value creation problem (see more in chapter 5.3.5) and thus the solution does not exist. However, there are also human and/or humane needs that need to be overcome as part of the potential transition to more AI agents in the work surroundings.

Technological problems that prevent the use of AI include (but may not be limited to) AI not having been developed for a specific use purpose yet (Consultancy, Product, Robotics, Key part). Other more specific technical details include that the needed ML training data (Product, Key part, Consultancy) is missing. Or the lack of required structure, or clear category boundaries prevent the use of AI (Product, Key part).

Training data can be missing because good data exists only for few problems that we would want to solve (Key part), or because in rare or critical decisions a precedent is usually missing. Thus, a machine cannot follow one's own decision-making pattern (Product). Sometimes the data has too many mistakes (Consultancy): *"The use of AI in the form of machine learning can be limited by the existence of data, or its correctness, or the creation of data. Sometimes, it does come as a surprise (to clients) that you cannot teach neither a machine nor automation with historical data that is full of mistakes."* [I2, Consultancy].

Structure or clear categories may be missing if there are no clear and measurable indicators as was the case e.g. with defining what is a liberal state or success (Key part), defining fundamental boundaries (Product), or structures necessary for the machine (Product): *"For my own work that is organizing and prioritising, (using AI is) challenging, because it (AI) requires so much the kind of structure that is rarely found in communications between people."* [I4, Product].

Overall, these tasks might be such that AI does not exist for them yet: *"Everything I would want to give to AI, but my work is pure knowledge work. I insert numbers or sum them etc. very little. As a result, there is very little the kind of things that could be optimized. Every workday is creative problem solving in which you need to handle people. So you need to have a deep understanding of human psychology, motivations, expectations,... and on that level we are definitely not with AI yet."* [I26, Key part]. However, the AI developers emphasize that AI and AI-based solutions are being developed all the time either by themselves or by someone else: *"The work tasks that AI can do are still quite simple. It will first come to automating routines. Maybe someday, but not quite yet, AI will be ready to develop all AI with AI."* [I30, Product].

Value creation problem includes two types of challenges: either AI is not the right solution for a specific need or the practical AI applications are still missing. AI was not considered to give any benefit in communications including meetings and organizing, sharing information, or making plans (Product), solutioning, advising and sales (Consultancy), or to predict the future: *"For example, if you needed to ask what future logistics will look like in 10 years from now. It is not a task for machine learning. Instead, it is some sort of historical study, anthropology, and evaluating the development of technology. It is hard to frame this problem e.g. to a function approximator, because no strong AI exists that could do the same things people do. From big data masses and behavior models you can model what has happened before, but it is hard to draw conclusions from it e.g. for what the society will look like in, let's say, 5 years. Something can influence behavior that cannot be mirrored from there (data) at all, because it does not exist. That is why it makes sense to be extremely cross-disciplinary..."* [I25, Ingredient].

Related is the challenge that practical AI solutions are still missing for most things (Key part, Robotics): *"There has been a lot of talk about AI, but quite little of it is in practical solutions yet. Excel is still used quite a bit."* [I17, Robotics].

Human need challenge in one's own work was brought up by neurosurgeons who are also developing AI solutions to their ward. According to them, intuition is an essential tool for doctors: *"But encounters with patients, to which intuition is based, are needed at least for now."* [I33, Key part]. That is why AI cannot take over all their work at least yet.

In the next and final sub-section for sub-research question three, the developers list things to which they do not want to use AI even if it was already technically possible to do so.

4.3.1.6 Do not want to use even when possible

Even though the technology already allows it, there are certain things that the AI developers refuse to use AI for. Either they have ethical concerns about the AI use, or they do not trust AI with the final decision-making power. If something is purely human-to-human, machines are not wanted, as is the case also with things that the people themselves enjoy doing or that give them meaningfulness.

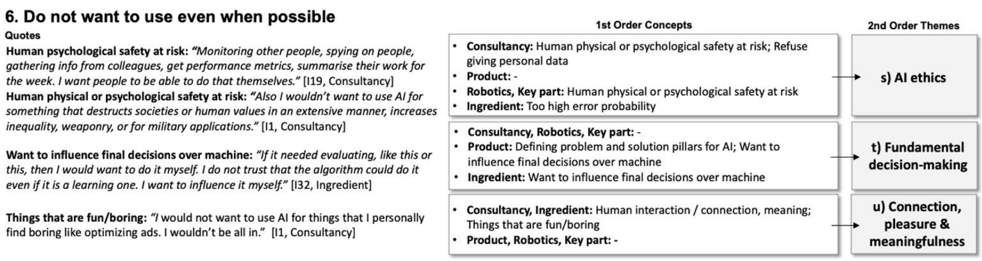

Figure 12. Summary of the Gioia analysis: the aggregated dimension when the AI developers do not want to use AI despite it being technically possible to do so.

AI ethics include situations, where human physical or psychological safety is at risk (Robotics, Key part, Consultancy), when using AI has too high error probability (Ingredient), or when one's data might be used against one's own will (Consultancy): *"I am concerned about too much surveillance, so I would not use AI for recording what I say, or what I do in the office, or like my chats. That data could be useful for some purpose, but don't want to give that data."* [I27, Consultancy].

AI might have too high error probability in various kinds of cases in one's core business such as insurance compensation decisions or in sensitive cases such as dealing with the estate of a diseased person (Ingredient).

AI might also threaten the human psychological or physical safety directly as is the case with military systems: *"Our solutions got interest from the US special forces and went through a field test to detect land mines and save lives, but then came the discussion of unmanned weapon systems. Ethically it was not right so we pulled out of the project. I would stand strongly against weaponized systems, because if a robot crashes against the wall there is a chance that AI can tell what went wrong and we can fix the problem. But if an AI points a weapon and somebody dies there is no use even if AI explains anything. There is too much at risk."* [I22, Robotics].

The use of AI was considered too big of a risk in planes or machine safety in general (Key part). Psychologically AI was considered threatening if it is used for monitoring or spying on people (Consultancy), or even when communicating with subordinates, or giving other people feedback. So in general, AI was not considered to suit situations with a human factor (Key part). There might be also other concerns about outsourcing intelligence to machines[8].

Fundamental decision-making is something that some of the interviewees prefer to do themselves to influence final decisions over a machine (Ingredient, Product): *"To filter information when I search for scientific articles. I want to filter the search myself with algorithms that I know. I do not want the results pre-filtered. Then the tool does not make the decisions on my behalf. AI is a tool, not my boss. It does not make decisions for me."* [I10, Product].

When designing the system design fundaments, their impacts on humans need to be considered. The system design might be possible to be done by a machine with a heavy investment, but humans' work with no AI is also still valuable[9]: *"To define the problem, or to create the pillars for creating the solution. So, such decision-making that could somehow affect people's legal rights or in how the system is designed. It is likely that in the future a machine could go through all options and optimize the best combination from there. It could be more efficient than the framework that we have built on law, social media, and sociopsychology. Its solution forming has been created totally without any AI. Of course, we could have used (AI), but probably not with the current financing."* [I5, Product].

Connection, pleasure, and meaningfulness are at least some of the things people still prefer to do themselves over a machine. Some are simply not interested in some use cases for personal reasons and find them boring (Consultancy), or

8 *"In the long run, outsourcing "intelligence" to machines will neither be useful nor morally right. Although such technologies have many attractive features, they merely emulate cognitive processes and cannot substitute the great flexibility, adaptability, and generativity we associate with human intelligence."* (von Krogh, 2018, p 408).

9 *"Although AI may effectively search out optimal solutions in a pre-defined landscape, people across the organization remain superior in formulating problems worth solving by either humans or systems"* (von Krogh, 2018, p 407).

sometimes the nature of the job or task is such that AI does not fit it very well even in the future: *"AI is not suitable if the nature of the field is absolutely about human interaction and human connections, so I think those fields most likely don't get effected by AI. There can be AI assistants in some sense, but it is difficult to incorporate AI in let's say elementary schoolteacher kind of a job."* [I1, Consultancy].

Especially connection, meaningfulness and the fun of it seem to be dedicated for humans: *"I would not use AI for inter-human communication, or to think what [the organization name] should be: how we create meaning to people's lives. And not for price negotiations, because it is the most beautiful form of business, when you negotiate about the prices."* [I9, Ingredient].

In the next chapter, I move from this third sub-research question on AI use to explore the measurable impacts of implementing AI in organizations with different AI strategies.

4.4 Measuring AI impacts per AI maturity

In this fourth sub-section, I explore the empirical and measurable impacts of AI use. More specifically I asked, *how are the impacts of AI-based technology development investments measured?* For this study I have analyzed the measurable AI-based outcomes per AI strategy. During this analysis, there seems to have started to emerge first signs of different phases in AI solution development maturity, not only per AI project or per AI strategy, but also per organization.

In this sub-chapter, I first introduce how AI development impacts have been measured per AI strategy. Based on these initial observations, I propose a very first draft of potential AI development phases and the temporal process development framework in the discussion and conclusions -chapter (see chapter 5.1.7). Future research is needed to study them more in detail.

4.4.1 Measuring AI impacts per AI strategy

When asked about the measurable results achieved with the help of AI, the AI developers listed a wide variety of measurable impacts. When the Gioia methodology analysis for this sub-research question proceeded, interesting findings started to emerge: the measures would get the same second order theme labels, but they seemed to somehow represent different phases in AI maturity development.

4.4.1.1 AI-strategy: Consultancy

Companies with the Consultancy AI-strategy, who offer technical AI consultancy to their clients, were represented by 6 AI experts in this study (see table 9 in chapter 3.2.3.4). When asked about the measurable results that they have achieved by using AI (see figure 13), the AI-developers mentioned three measurable financial performance measures including savings, increased turnover, and average price for their clients. An example of achieved efficiency in the form of savings is given by interviewee 1: *“One client saves 1 million euros per factory every year with our solution. They were not so efficient when we started.”* [I1].

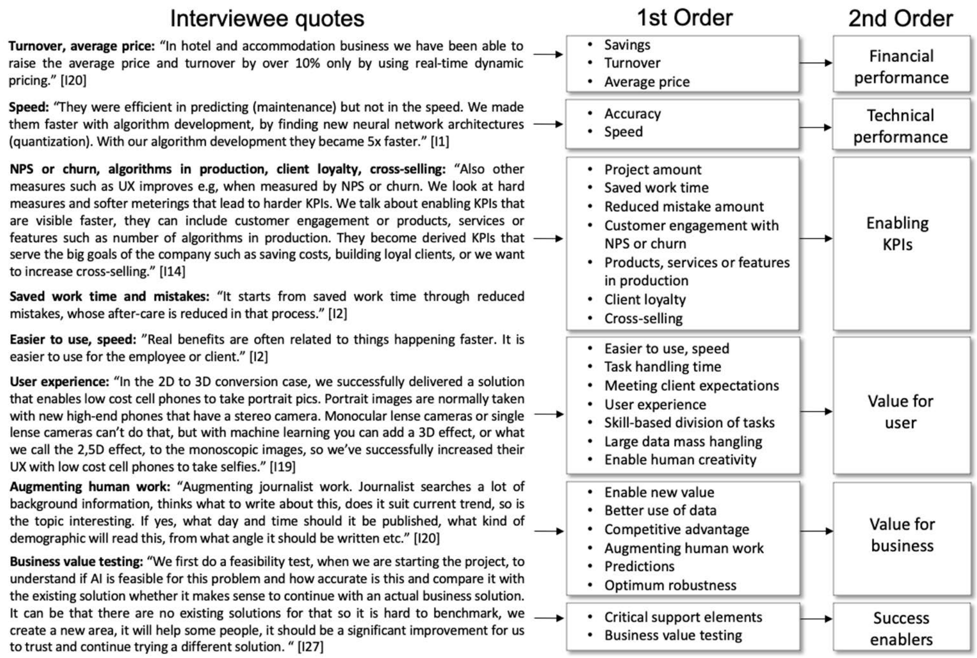

Figure 13. Measurable results in technical AI Consulting. *UX = user experience, NPS = net promoter score, KPI= key performance indicator, 2D/3D= 2/3 dimensions

As for the technical performance, measuring accuracy and speed were mentioned. An example of accuracy is given by one of the consultants: *“Human (work) is not even tried to be automated, because neither can alone reach the same (performance) level, but the combination is transcendent. Human does the rational thinking and final decision about some topic, but the machine supports in what it is good at. The image resolutions keep growing all the time, and if a human is responsible for each pixel, the eye gets tired. Physical limit is reached. So, if the machine can be used to handle the big data mass once, and then it is showed to the human that you could* *focus on these things; there is something weird in these (parts of the image). Then, the human looks at, and focuses on, what the machine does not know how to deal with. Then both are used for the right things."* [I20].

The consultants have measured also a number of other quantitative measures while working with their clients including the delivered AI project amount, saved work time, reduced mistake amount, customer engagement measured by e.g. net promotor score (NPS) or churn, the amount of products, services or features in production, client loyalty, and cross-selling.

Another big group of measurable results mentioned by the AI-consultants were related to the value for the user: the ease of use or task handling time in a process and the speed accomplished through them; or being able to better meet the client expectations; or nicer user experience; or more satisfactory division of tasks based on different set of skills between a human and a machine. These included, but were not limited to, the machine handling the large data masses and thus enabling more room for human creativity.

However, one of the consultants also problematizes the use of task handling time as a measurable despite its value creation: *"...but the real benefits are a little harder to calculate. For example, how many euros is it worth that the ticket handling time in client service drops from 4 hours to 3 minutes? It is harder to calculate in euros, how much you would be willing to pay for it versus if you save an hour, I have [X] euros to invest in this project. That's why it starts from there despite the benefit being something else."* [I2].

Consultants also mentioned business benefits in the form of new value creation (see more in chapter 5.3.5) that was AI-based, better use of data, competitive advantage, augmentation of human work, making predictions and optimizing robustness of operations. An example of AI enabling competitive advantage included producing a new whiskey recipe with the help of AI: *"The first consumer product that has been produced by a generative model: 40 000 bottles of whiskey will be distilled. It is the first big consumer launch."* [I20].

AI was also mentioned to have enabled new value e.g. through simultaneous ease-of-use and added security in payment situations: *"For the financial case, we successfully added a second layer of security to face payment transactions."* [I19].

Finally, the success enablers included business value testing at the start of the project to make sure the case was feasible technically and that it brought significant enough business value. In addition to solving an actual business need in a feasible way, critical support elements need to be set in place to enable the use of AI in an organization: *"With artificial intelligence or algorithm portfolio, business benefits are not achieved without enabling critical support elements such as working data infrastructure, capabilities, data-oriented culture, correct organization model,* *processes etc. In our client projects we aim to take all of these into account, not only the development of the algorithms."* [I14].

So, all in all, consultants seem to have achieved directly observable outputs through financial measures. However, they set importance also to observable outputs in technical performance, or through other quantitative measures, that are faster to observe than the ones directly on the bottom line.

The consultants even emphasize better client and business value, or other AI-based success enablers as measurable results despite the difficulty to quantify them. These observations are in line with those of Brynjolfsson and Hitt (2000), but bring better versatility and detail to what intangible benefits AI as an organizational resource might bring along with it. Thus maybe also these indirect measures should be included among the frequently discussed, ambitious, specific, and transparent (FAST) or the traditional specific, measurable, achievable, realistic, and time-bound (SMART) goals (Snyder & Quincy, 2020; Sull & Sull, 2018) of the company's objectives and key results (OKRs) (Che Ibrahim, Costello, & Wilkinson, 2018; Cwik, Kozlov, French, Shapiro, & Sewall, 2020; Ibrahim, Costello, & Wilkinson, 2015; Klanwaree & Choemprayong, 2019) and/or key performance indicators (KPIs) of the organization by its management.

I next move to the findings on measurable results achieved with AI in companies who develop AI-based products or services as their core business.

4.4.1.2 AI-strategy: Product

Companies with AI-based product or service as their core business were represented by 9 AI experts in this sample (see table 9 in chapter 3.2.3.4). Among this group (see Figure 14) the financial performance included both the revenue and funding; or AI had already enabled savings in different forms such as saved work time when the machine handles x percent of the bills automatically. In some organizations, savings were aimed for e.g. by putting the production measures in place or through ongoing development to reduce the service cost per case: *"We measure all the time how much time is spent per case. How many cases can be solved in a day and per service team member. How much the service costs, how much does one case cost us? We want them (the numbers) down with the help of automation, because the aim is to make this a profitable business."* [I5].

Compared to all the other AI expert interviewee groups, the customer benefits seem to be the most directly engrained into quantitative measures in AI Product organizations. This may be because in these companies all income is AI-based. All the benefits of each AI-based product or service are made tangible through some measure either to the customer or to the investors: following the development of time used per handling a case, how long it takes for a human to learn something, time required for the end user to take the system into use, or growth of company in employee headcount. These companies also increase the measuring abilities of the client and solve a real problem that the client had before.

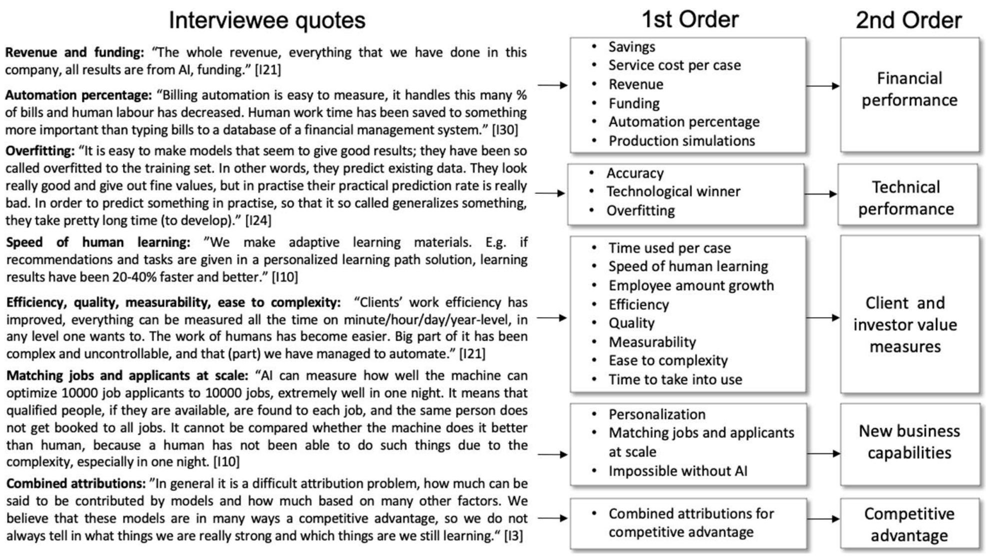

Figure 14. Measurable results while using AI in core Product or service.

However, the interviewees are also self-critical towards these measures: *"If recommendations and exercises are done in a personalized learning path solution, the reached learning results have been 20-40% faster and better, but they are laboratory tests. It cannot be said that this will always happen, because in the field the question is about motivation and many other factors"* [I10].

Another distinct thing about this Product AI strategy case is the emphasis on AI creating new value for business. This is often through new AI-based capabilities to do things that would not be possible without AI: *"Significant results in efficiency and differences in capabilities compared to before the use of AI. We do a lot of such things that would be impossible without AI."* [I18]. Such things include but may not be limited to personalized recommendations: to try to guess the content that the client might want to watch, or matching jobs and applicants at scale overnight in an optimal way.

However, even in these organizations algorithms alone are not enough. Additional success enablers are required to aim for competitive advantage. Yet the technology and measuring its capabilities can be used to prove one's competitive advantage over others: *"We made a press release when we got our NER (named entity recognition) to work better than Google or Stanford"* [I11].

Technical performance in this group is measured with accuracy as is the case with all the four other AI strategies. But what is distinct in this group, is to mention also the perils of reaching the so called too good or too accurate results through overfitting (Ren, Ma, Kong, Baltas, & Zureigat, 2022; Schueller & Saldaña, 2022). Overfitting may affect seeming accuracy in a deceiving way and, if used blindly, end up being useless or even harmful.

When comparing the findings between AI consultants and AI product or service companies, they seem to talk about similar measures on the second order concept level. However, the phase of development seems to be radically different. AI consultants talk about possibly having to set in place success enablers to the client organization. The consultants also test the business case potential before starting the consulting project. Whereas in AI product or service companies those prerequisites are already in place, maybe even up to a point of competitive advantage.

As opposed to the consultants, the AI product and service companies seem to be there where the consultants possibly end the AI project: when the consultants handover the AI development project to the customer organization. It seems that some sort of temporal or process aspects of measuring AI are starting to emerge.

I next move on to the findings of measurable results in autonomous robots as a special sub-category for the AI Product strategy.

4.4.1.3 AI-strategy: Robotics

A separate sub-case under the previous AI-product strategy is Robotics. These are the companies whose core business is to develop autonomous robots. This special sub-case group was represented by 3 AI expert interviewees in this study (see table 9 in chapter 3.2.3.4).

As visible in figure 15, the measurable financial performance results that have already been achieved by using AI in robotics include both generating additional revenue as well as efficiency through cost savings: *"The solution has saved a lot of money in training the rangers in Africa."* [I22]. The efficiency and savings derive e.g. from user centric personalization and intuitive usability of autonomous drones: *"We created a solution where the ranger will open a suitcase, log in and tell the drone where to go and what function to do, the drone will ask for some permissions and the rest is taken care of by the drone. When the drone wants to make a decision, it will either do a voice prompt or show a message on the screen, so the human can interact with the drone either by typing or talking. At any point the ranger can take control of the drone and do whatever he wants to."* [I22].

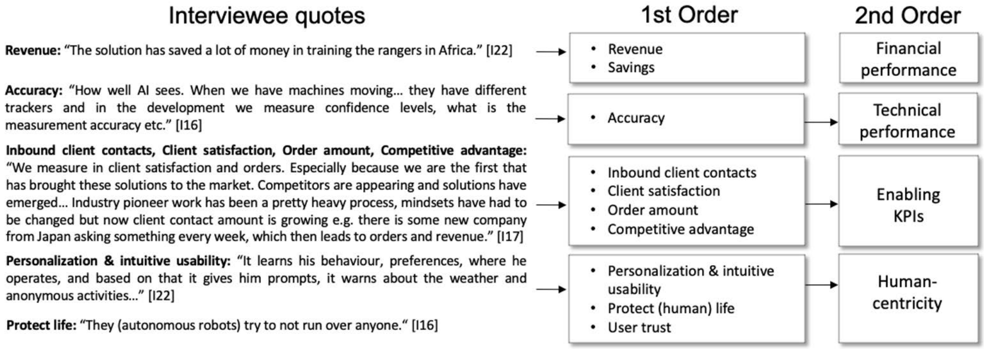

Figure 15. Measurable results by using AI in Robotics.

What sets this AI strategy case apart from the four other AI-strategy cases is that the experts developing autonomous robots seem to put particularly heavy emphasis on being human-centric. This may be because they need to gain human trust before doing business: *"By default, the human attitude is that IT will not work anyway. You cannot gain trust until the person has used the system."* [I17]. Heavy human-centricity can also be explained by the required co-existence of humans and robots in the same physical spaces. For that to be safe, the robot sensor fusion needs to work in real-time and be accurate enough to not run over anyone.

As with technical AI-consultants, also in autonomous robots the enabling KPIs for measuring performance have been used. The quantitative measures, that are neither directly financial nor technical, are used to predict future financial performance: *"Industry pioneer work has been a pretty heavy process, mindsets have had to be changed but now client contact amount is growing. There is some new company from Japan asking something every week, which then leads to orders and revenue."* [I17].

If we compare the Consultancy, Product and Robotics AI-strategies, in Robotics, the human-centricity stands out. If the other two AI strategies mostly focus on the potential benefits, it seems that in Robotics the first emphasis needs to be in ensuring safety for human lives and in building human trust; and ease of use. Robots also need to merge different data sources efficiently through sensor fusion in (nearly) real time. Only this enables the safe movement of the autonomous physical embodiment in its environment in a shared physical space with humans or other living creatures. Due to (nearly) real-time data processing requirements and protection of lives, Robotics seems to necessitate even more advanced and careful AI management and integration measures than the AI Consultancy or Product strategies. With robotics it is not only about how to get the solutions working but also how to always ensure safety of the solution for the surroundings of the autonomous robots.

In the following section I more from Robotics AI-strategy to overview the findings on measurable results achieved when AI is used as a key part of one or some of the products or services in an organization.

4.4.1.4 AI-strategy: Key part

Companies that use AI as key part of one or some of their products or services was represented by 5 AI experts in this study (see table 9 in chapter 3.2.3.4). In these organizations, AI is not necessarily a part of all the products or services that the organization offers.

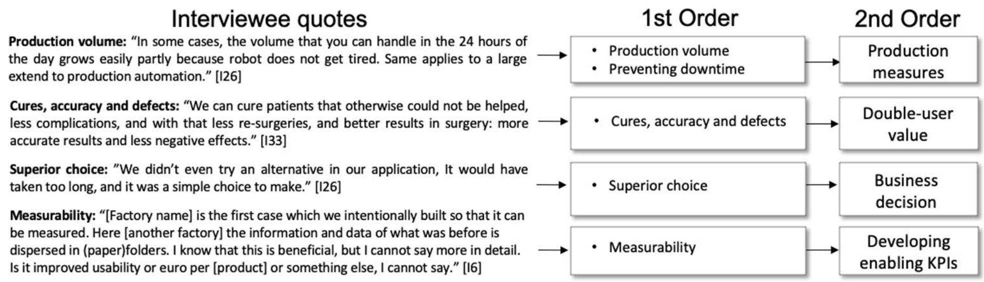

Figure 16. Measurable results while using AI as Key part in some product or service.

When organizations use AI as key part of some of their products or services (see figure 16), the closest to financial performance measures came the production measures of production volumes, and prevention of downtime: *"Reduced downtime. On the one hand, there is the precise book value of downtime, which is also affected by many factors that are not influenced by AI. It is a hard KPI (key performance indicator). Another is the calculated downtime that has been agreed together with the client, i.e. certain bigger events that have been identified. Together we agree that the system has found these (events) and warned about them, and what it might have led to, had they not been detected. And from that 10%, 50% and 90% classes have been calculated for the probability that the problem might have escalated, and what a day of downtime costs… Indication of value is challenging when your goal is that it (production downtime) does not happen."* [I28].

In a hospital, the user value can be two-fold. Then the AI-solution helps both the doctors or surgeons at their job and brings better value for the patients: *"We can cure patients that otherwise could not be helped. There are less complications, and with that less re-surgeries, and better results in surgery: more accurate results and less negative effects."* [I33].

Sometimes the choice to use AI or ML is an easy choice if an existing algorithm can already solve a specific business need. Or as was the case with client value measures in AI Product strategy, sometimes the value of enabling measurability can be used also in one's own organization. E.g. in a factory setting the digital transition to using AI can be made more tangible and thus enable more objective process development in the future. In this group that uses AI as a key part of some of the products or services, the organizations may or may not develop on top of AI technologically. They might simply use AI as a better tool to accomplish their goals. This makes the Key part AI-strategy group the most heterogenic.

But that heterogeneity also enables testing the temporal process logic (see chapter 5.1.7) that has started to emerge from the comparisons of the AI Consultants, AI Product and Robotics companies. The Key part organizations, who measure enabling KPIs as part of their AI development, seem to be at the same stage as where the Consultants might end their work with their clients. The Key part organizations, that develop and offer an AI-based product or service, seem to follow the same temporal process measuring logic as the Product AI-strategy. They start where the consultants might handover the AI project for the clients themselves for continuous process development: if AI consultants may have to focus on getting an AI development project started and they may, or may not, end in the handover to the client for maintenance and further development.

Based on the measuring logic, AI Product and service companies seem to continue further and already maintain an AI solution and develop it further for the market. Whereas based on the findings in the previous sub-chapter, it seems that the development of autonomous Robotics often requires an even more advanced human-centric focus and complex fusion of input from different sensors in real time; or that may be the case compared to most non-life-critical or non-time-critical knowledge work AI products or services. However, some of the Key part organizations use AI algorithms or AI-based products or services, because they provide the best tool for their need. Thus, where does the non-AI domain expert, such as a surgeon who uses AI simply because it is the best tool, fit in this continuum of AI development (maturity)? Is the AI product or service then the most advanced and polished and most ready for market? This might call for an addition to an emerging AI development temporal process that seems to have started to emerge from the data (see chapter 5.1.7).

In the next and final sub-chapter on measuring empirical impacts on AI, I introduce the findings in organizations with Ingredient AI strategy and compare them to the potential temporal process logic drafted above.

4.4.1.5 AI-strategy: Ingredient

Companies with the Ingredient AI-strategy, who use AI primarily to support some other non-AI core business or core function, were represented by 6 AI experts in this study (see table 9 in chapter 3.2.3.4).

Apart from growth as a financial measure, savings through saved human working hours was not considered a straightforward financial measure among these interviewees (see figure 17): *"Saved work time is a difficult measure. If AI can save 10 or 60 minutes per day, it does not replace a full human being, so how do you produce additional value with that time? This makes the business case definition challenging. Saved worktime is not shown in the profit and loss statement of the company. But on the other hand, it improves quality, better focus can be put to more essential things and in a more productive way, and then AI becomes visible at the large scale."* [I13]. Note that this is partly an opposing view compared to Consultancy in chapter 4.4.1.1.

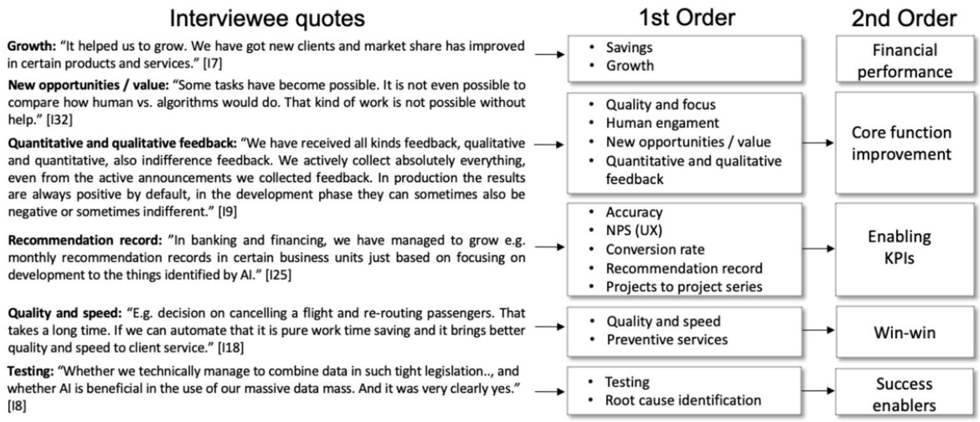

Figure 17. Measurable results while using AI as an Ingredient to other than AI-core business or core function.

So indirectly, core function of the organization might still improve and get the intangible[10] benefits of better quality and focus on the affected tasks and job descriptions despite the challenging measurability of the business case. However, all AI-features should be properly tested, and all sorts of quantitative and qualitative feedback should be collected in different forms before launch to production: *"With the chatbot test we measured the accuracy when the answer is provided by a human or the algorithm. We measured what kinds of answers were generated, how correct*

[10] Intangible investments are difficult to quantify (Brynjolfsson et al., 2017) and link to their macroeconomic performance. This is because *"traditional growth accounting techniques focus on the (relatively) observable aspects of output, like price and quantity, while neglecting the intangible benefits of improved quality, new products, customer service and speed"* (Brynjolfsson & Hitt, 2000). Yet they all seem relevant to be taken into consideration if performance is defined as an aggregate construct (Chet Miller et al., 2013).

they were, and what kind of feedback we got from the client. The accuracies were poor, we did not manage to teach the algorithm to generate proper answers. That of course showed in the client feedback quite fast. Even the test group did not give good reviews." [I32].

However, when successful, new organizational breakthroughs can be made with the help of AI in reaching new levels of human engagement: *"E.g. if you work with engineers in the client organization, we get them engaged too. They laugh with us, and we get more profiles involved in this (service design). It is subjective and very poorly measurable, but the kind of thing that has big implications: we get bigger support from the organization, and through that we get continuity to the project when also the board is onboard with things that are understandable in a matrix organization. We can turn the service design into business goals. It shows in a way that our projects become series of projects."* [I25].

Thus, projects becoming series of projects can be considered an enabling KPI (key performance indicator). Other enabling KPIs include but may not be limited to: conversion rates; or when recommendation records have been broken based on focusing development on recommendations provided by AI; or by quantifying user experience through the use of NPS (net promoter score). Accuracy as an enabling KPI can also be valuable to the business directly through managing potential risks: *"The accuracy has increased in fraud detection."* [I7].

In the best cases, AI enables potential for win-win situations by bringing value both for the organization and its clients simultaneously: *"E.g. decision on cancelling a flight and re-routing passengers. That takes a long time. If we can automate that it is pure work time saving and brings better quality and speed to client service."* [I18]. Or another example of win-win-situations was found e.g. in child protection services, and the development of their services and customer journeys: *"Whether it (AI) might work in development of preventive services? And that too became clear pretty fast, that yes it does work, and works pretty well in it." [I8]*

Much like the AI consultants, also organizations using AI as an ingredient emphasize finding the right problems to be solved by AI. This is to enable project success before it has even started: *"We use ethnographers to study this work that we do, so that in service design we can pick the right usage points. Even if we make an MVP (minimal viable product) and show it to the content producers and they say 'that is nice`, it is a problem if they do not use it. Now we tackle that by taking new methods into use. It gives us new types of problems and questions to be solved. Maybe that will help the development related to the root causes, and that is a step closer to real change."* [I9].

Like the Key part AI-strategy group, also this group that uses the Ingredient AI-strategy seems to be more heterogeneous than the AI Consultants, AI Product, or autonomous Robotics companies. Thus again, it can be tested how its measurable results compare to the other AI strategies and the potential continuum of the proposed AI development temporal process (see chapters 5.1.6-5.1.7): the problem feasibility testing for AI in these Ingredient organizations seems to share similar features as the success enabler measures that the consultants have before starting a technical AI project with a client. All the other measures seem to be placed somewhere in the continuum from handover to continuous development of the AI-solution to continue to improve the performance against the set measures. In this group, a noteworthy finding is the particular emphasis on generating win-win results, where both the organization itself as well as the client(s) win.

In the next chapter, I move from this fourth sub-research question on measuring the empirical impacts of AI to the fifth and final sub-research question, and its findings on the expected cumulative impacts of AI.

4.5 Expected impacts of AI to temporal dimensions

In this final chapter on findings, I explore the expected (cumulative) impacts of AI. More specifically I asked: *When approaching time as an organizational resource, which temporal dimensions are expected to be influenced by AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation?*

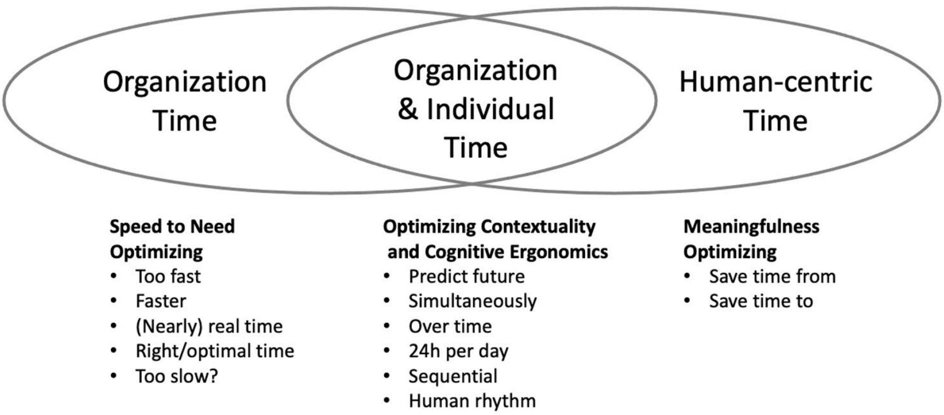

Figure 18. The proposed temporal changes influenced by AI.

When exploring the temporal aspects of how different AI-related technologies and ML may impact an organization's competitiveness or competitive advantage, three types of changes emerged. These changes may influence: the 1) organization time, both the 2) organization and individual time, and finally the individual 3) human-centric-time.

In the following sub-sections, each of these temporal change types (summarized in figure 18) are introduced more in detail.

4.5.1 Organization time

Organization time focuses on the need for organizations to optimize the speed to each internal or external need. As its conceptions of time[11] (Ancona, Okhuysen, & Perlow, 2001), organization time seems to follow the clock time and mostly unpredictable event time in relation to it. As the organization time events are highly contextual in nature, organization time does not seem to fit any of the previous activity mappings to time[12] specifically. Yet simultaneously, it may fit multiple different activity mappings to time. Thus, it seems that in the context of AI, a new type of more flexible mapping of activities to time, contextual mapping, seems to be called for.

In relation to optimal speed of the organization time, five types of temporal themes were identified ranging from potential negative innovation effects (Rogers, 2003) of too fast to too slow for an organization. However, positive innovation effects might be AI potentially providing opportunities for dynamic capability (Macher & Mowery, 2009; Teece, 2007) building based on increased speed; or reacting to needs in near real time or at the right time (see figure 19).
I next introduce the found five types of organization time mappings from what at least seems like the fastest to the slowest in relation to organization time and its speed to need optimizing and temporal dynamics on an organizational level[13].

11 Conceptions of time can be divided to different types of time and socially constructed time. Different types of time can be divided to linear clock time, cyclical time, event-based time, and life cycle of e.g. humans (Ancona et al., 2001).

12 Different activity mappings to time are divided into five sub-categories: 1) single activity mapping to the continuum, 2) repeated activity mapping of the same activity multiple times on the continuum, 3) single activity transformation mapping of change processes, where one activity changes in character in response to a marker, 4) multiple activity mapping of two or more activities on the continuum, and 5) comparison of multiple temporal maps with one another. (Ancona et al., 2001).

13 Previous literature has contributed to the temporal dynamics from the perspectives of strategic time dimension (Lei, 1989), conditioning by time (Chittoor, Sarkar, Ray, & Aulakh, 2009), optimal time to enter a market (Lint & Pennings, 1999), and timely commercialization of a new technology (Zahra & Nielsen, 2002). Another relevant temporal aspect in the context of competitiveness and competitive advantage is speed (Flier et al., 2001; Kessler & Chakrabarti, 1996; Macher & Mowery, 2009), shortening (Sasaki, 1991), decreasing (Hatten & Hatten, 1997) or speeding (Pittaway et al., 2004) time, being slow (Teece, 2000b), faster (Bhattacharya & Walton, 1998; Kapoor & Adner, 2012), or operating in a fast-moving environment or industry (Chatterjee, 2017; Chen et al., 2010; Cheng & Yiu, 2016; Hornbach, 1996; Newman & Chaharbaghi, 1996).

Too fast[14] speed came up in the context of combining both actors relating to time[15] and mapping activities to time, as AI enables faster than human speed to some problems. *"If you need to make decisions really fast so that you have 100 milliseconds, I, of course, can never do it. It is completely impossible for a human to solve. Actually, it is irrelevant how bad the model is. Domains can be done that have never been possible before. That naturally is a good success story every time."* [I3] However, this speed may also create problems in an organization, if it increases risks

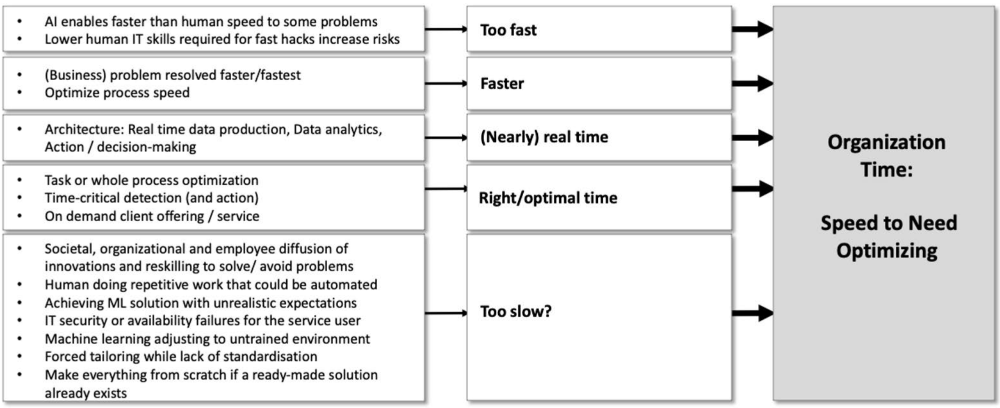

Figure 19. Summary of data-analysis leading to organization time and its five temporal themes.

in an organization: *"When people have good enough competencies for it to make at least half-ready hacks with no support from anywhere or without it becoming official, that is new. And when you add cloud computing to this mess, all you need is internet connection and a browser to use all sorts of things. There, staying alert with IT security is essential."* [I2].

Faster speed relates to accelerating speed in situations where problems are resolved faster or in the fastest possible way: *"It* (denoising algorithm) *was the best quality option to the time requirement, because it already existed. It did not have to be invented by us. It was fully a business decision."* [I26].

14 Too fast speed may be a problem: *"There are many instances where speed overrules quality, and rapid success can create a culture that stifles learning: concerns and warning signs are discounted or dismissed, and errors are not managed or learned from until it is too late (Lei, 2018)"* (see Carroll et al., 2018, p 390).

15 Actors relating to time focus on the relationship of actors to conceptions of time and different activity mappings to time (Ancona et al., 2001). They include how actors perceive the continuum of time (conceptions of time), and how actors act (activity mappings to time) with regard to the continuum of time.

But as was the case with too fast speed, also with faster speed there are both pros and cons. Process speed may be maximized, user expectations for speed may be influenced by competitors' performance, but when developing AI-based automation, speed should not blindly be the only indicator for success: *"Through AI a big new bunch of processes can be automated. It brings long-term cost savings; processes speed up. The benefits are eventually visible in the company operating profit, but a small gap always exists between the processes still produced by a human and a machine. This will be experienced by the end user. It is not totally simple. It can be a good and a bad thing: quality may be better or worse or shift… We (as humans) have got used to accepting a certain service level from humans, but we lack the skills to demand the benefits that a technology would provide. Yet, we will gladly receive them when they exist and refuse to accept a worse service level later."* [I31].

(Nearly) real time presents a possibly new dimension shared by both conceptions of time and mapping activities to time as with AI and ML machines start to be able to respond to a demand in nearly real time[16]. *"Now, it (website user content moderation) is done by message: as soon as someone writes something completely idiotic, an automatic message is received that this will not be published, because it relates to e.g. violence."* [I21].

For real-time action the IT architecture needs to be able to support the whole process of fast enough data production, data analytics and action based on them. The definition of real-time needs to be evaluated depending on how critical the use case is: *"For us everything revolves around real time when a robot moves in a real environment… Real time is defined by the time window in which something happens. Through that e.g. safety-related detection unravels. What is the maximum time that certain thing can take, and you calculate from there, whether the solution is safe or not."* [I16].

Right or optimal time is another time-critical and contextual dimension that emerged from the AI-related interview data and experiences of AI experts. This sort of timeliness is required to optimize tasks or whole processes: *"When you think of the life cycle of a movie or tv-series, it starts from someone pitching us something and then we decide to produce something. Especially during production phase there are a lot of different optimization problems e.g. where actors need to be at any given time, what are good shooting locations,... Different ML and other optimization methods can be used to optimize this whole process."* [I3].

[16] AI is already vastly used for real time decision-making in fields such as patent examination (Choudhury, Starr, et al., 2020), driverless cars, customer service, making different kinds of predictions and changing prices in real time (Davenport et al., 2020), marketing (Roberts et al., 2015) or influencing customer journeys with well-timed content on websites and mobile apps in different industries (Edelman & Singer, 2015).

Time-critical detection and possibly even action is required for business purposes such as safety and security, or even to preserve the lives of wildlife: "*We are working with drone manufacturers, who are deploying their drones to do surveillance for anti-pouching. The rangers don't need autonomous drones to do everything on their own, but the drones help them to be at the right place at the right time to see on the ground level when anonymous activity is detected. Or based on surveillance of the activities of this elephant herd, they were supposed to be at this waterfall but today they are not there, please deploy a permission to do a search and rescue."* [I22].

Optimal timing is required to serve clients on demand e.g. to detect the opening of a sales window before competitors, because the second sales person to offer a solution to a customer problem is already late. As AI has started to enable an increasing amount of optimal time solutions, even entire industries might have to be reinvented to serve customers radically better than before: *"The whole innovation frame should be rethought from scratch: how to renew core functions. E.g. when a travel agency reserves airplanes and tickets to Paris, it is not the client's problem to get to Paris rather it is the problem of the company to fill the plane. But how could a travel agency enable a person to travel where-ever s/he wants? With the help of a machine, you can co-ordinate how to solve the problem that linear travelling turns into on-demand travelling."* [I9].

Too slow is an interesting temporal theme which combines both actors relating to time and mapping activities to time. It refers to situations when, according one human actor, another human or some non-human actor is perceived to be too slow e.g. compared to competitors or expectations. These situations include societal, organizational and employee diffusion of innovations and reskilling to solve or avoid competition-based problems.

According to the interviewees, it is also too slow, if humans do repetitive work that could be automated either from the organization labour expense perspective or from the user experience perspective and/or in the case of IT security or availability failures experienced by the service user: *"If our lawyer has budgeted 10 minutes for this case and we have these A1, A2 and A3 (AI solutions) in use, and then for some reason it does not work, e.g. they are not available and because of it the case turns out to take 30-45 minutes instead, then it would probably be very frustrating."* [I5].

Sometimes the perceived slowness relates to unrealistic expectations: *"It (AI) was thought to understand everything in 6 months, to remember everything, to be able to react based on data and to produce really reasonable answers. Even after this long time it still is not in use because its development turned out to be surprisingly hard."* [I14].

A related problem is the slowness caused by the lack of standards and the problems caused by still trying to combine the different technologies for one's own use purpose: "*Everything needs to be tailored and that is time-consuming. And then there is the question, is it sensible work to get some small information grain from somewhere.*" [I17]. When the AI-solution has been developed, the algorithms might also learn a new situation too slowly: *"Local competition, which changes fast in some geographical area when the competitors make changes. In those situations, our data and AI model are late. They do not have the time to adjust to the competitive situation and we can start losing in competitions that we used to win before. Then we come precisely to this human decides -aspect. Human needs to save the situation when a client comes to ask for a mortgage in the bank."* [I7].

In the next sub-section, I move from organizational time to the zone where both organizational and individual human time intersect.

4.5.2 Organization and individual time

The second type of AI-related temporal change that seems to be emerging is situated in the interface of the whole organization and the individual people acting in the organization. Six types of temporal dimensions fall into this aggregated dimension.

Organization and individual time focuses on integrating and optimizing both the contextual needs of the organization and the cognitive ergonomics (Kalakoski et al., 2019) of the individuals working in it. Both might be required to be able to best adapt to the required business environment or competition.

Organization and individual time seems to follow the clock time and intends to predict changes in the future event time (Ancona et al., 2001) through strategic management and efforts aiming at 1) predicting the future and organizing different tasks 2) simultaneously in an organization accordingly (see figure 20). As the actors relating to time (Ancona et al., 2001) focuses on individuals rather than organization as a whole, an additional type of 'actors relating to time' seems warranted for strategic time and resource management of an organization.

Both the 'strategic time and resource management' and the cognitive ergonomics of employees seem to share the concept of cyclical time (Ancona et al., 2001): the tasks that AI can help take care of 3) 24 hours a day and 4) sequentially with different intervals between the repeated activity mappings to time. The cognitive ergonomics of employees could call for an additional conception of time called the cognitive time that takes the natural 5) human rhythm into account.

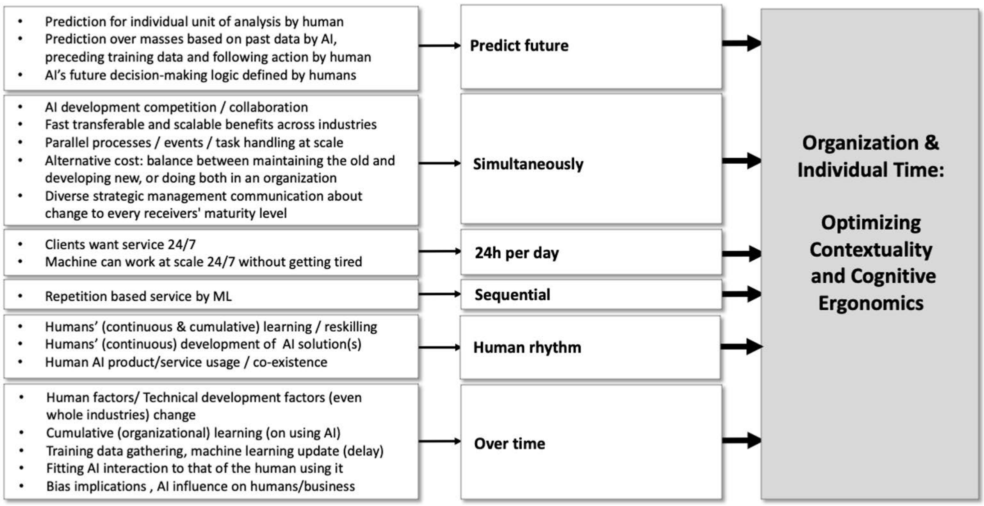

Figure 20. Summary of data-analysis leading to Organization and individual time.

The human rhythm can be defined with the help of slow ontology (Ulmer, 2017): it invokes time that is rooted in nature and thus "*inspires more natural rhythms for our spatial, temporal, and material localities*" and it could provide a respite in the local spaces and places in which we as humans might be slow. *"But to get the full benefit from the Slow movement, we need to go further and rethink our approach to everything"* (Honoré, 2004, p. 17, see Ulmer, 2017). Thus, slow ontology might be an interesting avenue for future research for helping people keep up with the continuously ongoing change and room for both human and organizational learning (Greve, 2020; Levitt & March, 1988). It is needed to keep one's own capabilities, as well as those of the whole organization, up to date, while optimizing both the organization's and individuals' time needs.

The cumulative skills and capabilities of both individuals and the organization develop 6) over time. This development over time takes place in relation to clock time, and the mapping activities to time transforms through the life cycle (Ancona et al., 2001).

Predict the future in the context of AI and ML is a temporally embedded process informed by the past in the form of the algorithm training data, but oriented toward the present and the future (Emirbayer & Mische, 1998). Actors in the organization aim to predict the future scenarios of the organization. According to the AI expert interviewees, some predictions are still better left for humans instead of a machine: *"AI is not better in e.g. predicting patient deterioration in intensive care unit, so if the condition will go bad in the next few hours."* [I1].

However, machines can be trained to make some predictions for a human to make decisions about the future, or the human expert can be guided or assisted by the machine based on past data: *“In the context of teaching image recognition: will this wind shield crack in the future? Should it be repaired or changed to a new one? It is new kind of knowledge work. It is quite tough and repetitive work. The amount of required training data is quite high to be able to change large volume processes.”* [I7].

It is noteworthy that when the AI or ML algorithms are trained and granted the permission to make decisions and execute action autonomously based on their algorithmic training, the decision-making logic of the machine has originally been defined by a human. Thus, also the responsibility and consequences of the mistakes made by the machine are left for humans to deal with: *“Naturally, a lot of all sorts of problems and side effects come with the complexity of a model. This is related to the fact that things might not work so well. Are we fine with it being a simple model, and everyone knows it is a simple model? It works 90% of the cases and will fail 10% of the cases, and how do we then deal with that?”* [I3].

Simultaneously refers to temporal situations when, while mapping activities to linear time, things happen in concurrence (Ancona et al., 2001). Simultaneous action may occur in and/or outside an organization in relation to its competition or collaboration and AI development. This may impact e.g. to the language-specific capabilities of natural language processing or other industry specific use cases of AI: *“The Chinese have a billion people who teach AI, whereas our AI is pretty stupid. A service (in China) has a billion people making the platform work: in the service you can buy teaching AI, and a billion people evaluate whether the decision and result of the AI is good or bad. Those kinds of populations can be created globally. In the Finnish scale probably not more than 10 000 could be made to do the same.”* [I12].

However, at the same time, AI as a general purpose technology (Brynjolfsson & Mitchell, 2017; Brynjolfsson, Rock, & Syverson, 2018) has potential to be transferred and scaled to bring benefits across industries easier and with less investments than ever before. This may even lead to societal changes and require the attention of policy makers: *”However, if you think of the progress made in the UK or the experiments by Google Deepmind, they got 20% more energy only by using an algorithm without any investment. Why is this a scientific experiment or a stunt made for a single company? Even when the idea could be that every time you find solutions that help fight climate change by using AI, some policy would rule that it will be taken into use for all in 2 months. We have never had a tool that is as transferable as AI is. You do not need to move a team or infrastructure there. Instead, you can move a piece of code and with that reach incredible benefits from the climate’s perspective.”* [I20]. Not only in transferability, but the machine is also superior to a human in handling parallel processes, events or tasks: *”Machine does natural things for machine learning algorithms such as simultaneously watching cause-and-effect relationships from over a million rows of data.”* [I24].

However, people and organizations might be slower in adapting to the ongoing technological change. The organizations need to balance between maintaining the old and developing the new in an organization. Managers need to continuously communicate about the change in different receivers' maturity level to enable required speed for the strategic diffusion of innovation (Rogers, 2003) and continuous development mindset throughout the organization: *"It is managing, taking care that they do not get forgot, and continuous driving of the opportunities, where machine learning can be used in the analysis and development of one's own business, and possibly most importantly, how can we develop new business." [I29].*

24 hours per day refer to situations where activities are mapped on clock time around the clock every day of the week and year. This might be required when machines are used to work at scale around the clock: *"When you have configured it to do something, it will scale to do the same with zero costs for an eternity. In that we humans are fairly bad at. Especially if you need to do the same thing every second, it starts to irritate you." [I4].* The processes or clients might require non-stop monitoring, where AI can help: *"That kind of (moderating) work no longer needs to be done in the middle of the night or on weekends. Office hours are enough. No need to stay alert all the time." [I21].*

This ability to use machines 24/7 may also enable the development of dynamic capabilities (Warner & Wäger, 2019) and new business opportunities with better service hours for the clients: *"Small companies take care of their banking in the evenings and at night time, when we do not have people at work. This kind of a service would not have been done before, but for AI it is an appealing case." [I7].*

Sequential or cyclical activity may be suitable for ML due to its repetitive nature and with that ease the mental burden of the human using a supportive system: *"E.g. it can detect local weather phenomena and warn that probably soon happens this, because the same thing has repeated 10 times before. Repeating phenomena exists, e.g. by the Brazilian cost usually at 2 o'clock the GPS signals are not right, when sun is in a certain position or currents or their influence etc. Local knowledge that is relevant for steering a ship, which currently is experience-based information."* [I17].

However, one needs to be careful with not scaring users with too timely action from the machines even if it was sequential enough to be predicted. This is because it might cause a little similar unnerving or creepy reactions as has been witnessed with too human-like humanoid robots with the uncanny valley (Gray & Wegner, 2012): *"When I was in the Netherlands, I used Google maps a lot so there always came a (message) 'Light traffic ahead, time to go home' or 'work'. I was like, help, I do not want these kinds of notifications about it knowing that I am heading home." [I5].*

Human rhythm or the natural rhythm (Ulmer, 2017) of a human refers to the purest form of actors relating to time (Ancona et al., 2001). It is related to natural pace of continuous and cumulative learning, or human's reskilling ability throughout the organization from top managers to AI project managers and domain experts training the machine. And despite the trained ML algorithms executing calculations and decisions fast, the preparation of the training data requires human time at human pace: *"It requires learning new tools, understanding of application development and use of knowledge, and it requires tough work on labelling the data."* [I7].

If no time is granted for learning and adjusting to the technological change and its impacts on one's own profession, the workload, stress levels and cognitive burden in general might rise: *"But in our work, time is not given at all for such things. We have asked for it and tried to arrange it, but such time does not exist. You have to have your own motivation and passion. You too have made this on weekends and on your free time (one interviewee to the other during the pair interview). In the public sector it just is so. Maybe later it will be so that time is arranged. Now maybe small work groups exist but too little still. It cannot be afforded. We are in the transition phase. It requires 'too excited' people that keep doing this on their free time and see that the change will come anyway."* [I33].

The AI solutions require human resourcing and enough allocated human work time as the AI-based services are never done, but require continuous development and updates for the algorithms: *"We did not use to have an AI building team before, but now we have one. Now we have a team that is responsible for teaching AI."* [I11].

AI impacts not only the people developing the AI-solutions but also the professionals using the AI-based products or services: *"The machine does not have the whole context but often it can analyze the accessible context significantly better than a human. At the same time, the human needs to have the context what the machine did and did not have, so that the human can bring his or her own contribution: in addition, I know these things. Machines can reach an equal diagnosis with doctors, but when you combine the knowledge of the machine and doctor to the same decision, then the quality of the reached decision is even better, significantly."* [I31].

Over time aspects of organization and individual time may happen continuously or cumulatively over time[17]. Some things that happen over time are external to an organization but the people in it may still need to react to that development. Such AI-related changes may concern humans, technology and/or even whole industries:

[17] *"Recent technological and statistical developments present error researchers with more tools than ever before for understanding error dynamics (e.g., system dynamics, cyclic relationships) over time."* This may happen with the help of simulations, big data and increased computing power. (Carroll et al., 2018, p 393-394).

"Business environment changes insanely fast. Even if you fix all today's processes e.g. in a bank, digitalization disrupts everything. Client expectation changes. Now everything is wanted in a minute in mobile. If the processes were perfect 5 years ago, now they are the wrong processes." [I2].

Some things require proactive attention over time also within an organization's management such as cumulative learning on what works and what does not work if AI is used. Training data needs to be gathered all the time over time for algorithm development, yet there may be delays for different reasons until the ML algorithms are (again) up to date when something changes: *"The machine will not learn in a day that the world changes. It will not change its way of working on its own. They are milestones in which the human needs to take over and e.g. show a new wanted outcome for the machine to learn from."* [I2] For that to happen, also the humans who monitor and train the machine need to stay alert continuously and mitigate the delays and develop the system to be better over time the best they can: *"Forming the response automatically is our next phase. Crime label and help need response will be formed based on earlier fairly similar cases. The challenge in this new domain and field is that we do not know, what is the population. How much crime takes place on the Internet and social media? We also do not know all the new teen fads. E.g. I myself just got acquainted with [social media service name]. I hear it is already an old thing, but I got to know it."* [I5].

Over time, also the interaction between the human and the machine needs to be developed to feel more intuitive and trustworthy for the human using the AI-solution. Also other potential implications and influence on humans and business need to be dealt with and thought of, if biased or otherwise problematic data has been used for training the machine: *"Almost all, 95%, of problems in AI solutions are derived from data. At least 50% of the time is used on fixing the mistakes in the data no matter where the data is received from."* [I21].

In the next sub-section, I move from the intersection of organizational and individual human time to human-centric time.

4.5.3 Human-centric time

Human-centric time focuses on alternative allocations of time among activities in relation to mapping activities to time. Additionally, human-centric time optimizes meaningful time use as perceived by the actor relating to time (Ancona et al., 2001). In the work context, human-centric time is closely related to work meaningfulness (Staaby, Hansen, & Grønli, 2021). Based on the findings, work meaningfulness is optimized through two logical categories consisting of things and tasks that the interviewees wanted to 1) save time from with the help of AI; and fulfilled with the logical second category 2) save time to which consists of things that the interviewees would rather spend their time for instead (see figure 21).

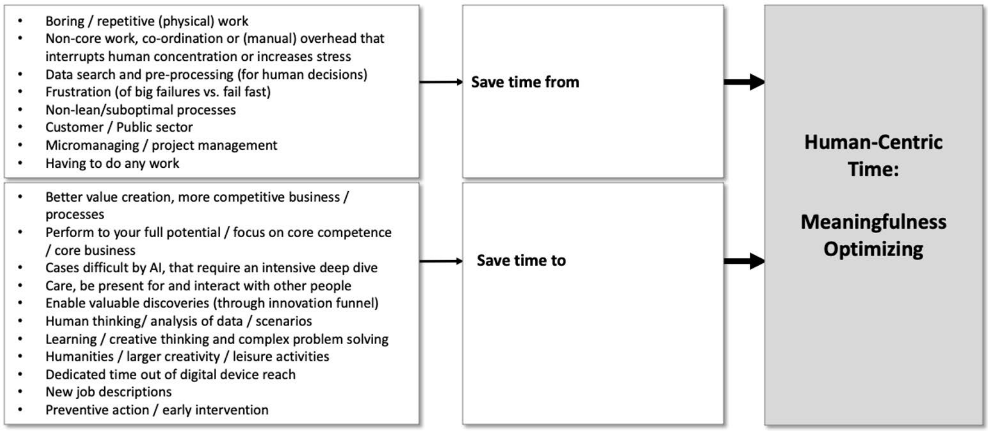

Figure 21. Summary of data-analysis of human-centric time and work meaningfulness.

Save time from included tasks that the interviewees wanted to be handled by some sort of an AI-assistant, such as boring or repetitive work or non-core work: *"Being a tech lead, a lot things that are not in your job description take a lot of your time, meetings, time management, scheduling, managing colleagues. I spend maybe like 25-30% of my time coding... I would want AI to write some boiler plate code for me. The base structures, it could take care of the mindless stuff like setting up project directories, etc. based on an exact project that you would like to start. Or more intelligent code completion, that would be really intuitive. Much like autocorrect, for it to be a helping hand for coding to be more productive." [I19].*

Some of the boring, repetitive and non-core work assignments increase frustration. Thus, time should be saved from these things both from oneself and from one's customers: *"E.g. if I'm going to a place x and need to be there 8-17, suggest and book me a flight and hotel so that I only say ok. The system then deals with the reservations and payments. Why everything still needs to be done manually? Hourly lists, travel billing, why do I need to explain what is this receipt and where did it come from? There are an infinite number of examples." [I2].*

Elsewhere, AI is already used to replace work tasks related to searching and pre-processing data, or even for making pre-decisions and taking action related to it for a human: *"In money laundering and fraud, AI makes use cases for us where conclusions are drawn by combining massive amounts of events and clients. A human could not do it with a reasonable time investment. In practice, it stops payments for more thorough human investigation." [I7].*

AI can be used to save time from the customer in different ways both on the private and public sectors by streamlining processes and collaboration between different players: *"Due to the fact that we collect data in a structured way, it is directly preliminary investigation material for the police. E.g. if charges were pressed, it (the collected data) could directly be mailed to the court. We have saved 20 hours from the police, which could be e.g. 200€/h. Or we are able to prevent a social media scandal or negative chain of actions in a school. How much is saved in healthcare expenses, when the child or adolescent does not have to go to treatment and does not have to skip school?" [I5].*

In the case of non-lean or suboptimal processes, time can be saved in pre-testing if the division of tasks between humans and AI is implemented in a smarter way: *"Another example is finding new molecular combinations of drugs. There is almost infinite number of combinations how molecules interact. It is very expensive to test it physically. Optimally you want to test the options that will behave as you want. So, you should implement in a lab the real molecules that are more likely to interact. It is impossible for humans, because it is extremely time-consuming, too expensive to test every combination. So, filtering out what to test and what to actually implement in real life." [I1].*

In other organizations, additional value creation (see more in chapter 5.3.5) is enabled by mitigating time wasted on failing things: *"That's why I have also built the infrastructure so that the whole organization can be in the mindset that things can be tested fast. You can also fail fast before making decisions on what will be done in the future. Because it is in fact a desperate recipe that you start making AI and then it becomes an expensive project. It takes several months and in the worst case, even years. Then it gets deployed for the first time and it does not work at all so well. It takes desperately long time, and it is desperately expensive. And that brings organizational frustration." [I3].*

The interviewees mentioned also that time should be saved from micromanaging, because there is simply no time for it, but some went as far as to saving time from having to do any work: *"Now we think that, oh my God, what if I lose my job. What will I do if I am unemployed? It would be worth asking the ancient Greek aristocracy. All the people we know of were unemployed based on our definition. They have had AI, aka slaves at their service, who did what they asked. They invented all sorts of exciting things: wrote plays, philosophy and developed all sciences, sculpture art,… Anything they just happened to think of." [I30].*

Save time to are the things that the interviewees prefer to do instead if AI can offload time consuming tasks that create frustrations at work. When AI helps saving time from current tasks, the AI experts would rather use time for better value creation (see more in chapter 5.3.5) e.g. through valuable innovation discoveries, to perform one's own full potential, and to handle cases that are difficult for AI: *"Clinicians* *have been able to use the saved time to patient treatment and care, research, and to cases that are difficult by AI, that require an intensive deep dive."* [I1].

For surprisingly many of the AI-developers, AI is wanted and already used to enable more time for human-to-human care and interaction: *"I spend more time trying to understand people, their goals and to find opportunities for people to be more content and want to continue working here for us; and for them to be able to achieve good outcomes and experiences."* [*I7].*

If pre-work was done by AI, the human could have more time to think and analyze different options or scenarios before having to make a decision: *"If you think of it through job descriptions of the people who have been recruited here to make decisions: the decision-making may be fast, but for that you have to dig information from different places. If the information arrived in anticipation, the whole decision-making process speeds up and time is left to analyze different scenarios."* [I13].

Related to thinking is, people longing for time dedicated for learning, creative thinking and complex problem solving. Sometimes it is required even because of AI, e.g. in the case of deciding on AI-related governance and legislation: *"How do we improve, when we start building completely new kinds of institutions that are purely built on digitalization in the next 20 years? So how do we create responsibility and governance to be able to control products and services that use or do not use AI?"* [I23].

At work, more time is wanted for new or changing job descriptions: *"While job descriptions change, time needs to be reserved for development in our small unit. But in the public sector, for it to be officially on paper, it takes so long that it is never done. The clinic itself needs to dedicate time for it."* [I33]. In a bit similar manner, time allocation was wanted for preventive action or early intervention: *"Now we can see in what groups and services the factors are shown before (we have) a child protection case. Then we need to be able to react earlier before people become clients of the child protection services. One finding was that this kind of risk assessment model could work in any service, or in any diagnosis or forecasting anything."* [I8].

Some time was wanted to be saved within or from work to humanities and leisure activities: *"Creating new is the salt, sugar and whipped cream of this job. That is what I want to do myself, and that is why I do this job: to create new."* [I15].

In the context of increasing digitalization and AI, it should also be taken into consideration that people might need or want dedicated time that is out of digital device reach: *"Driving a car has been dedicated time, and the audience wished that it would not be taken away. Driving is (was) the last fortress where you are (were) not reachable by electronic channels."* [I9].

This is the end of the findings chapter. In the next chapter, I discuss and conclude the contributions, implications, limitations and identify avenues for future research.

5 Discussion and conclusions

The main research problem of this study is: *What makes artificial intelligence -based value creation challenging from the management and organization perspective?* When approaching this main research problem from the perspective of five sub-research questions related to management and organization, at least some value creation challenges to be overcome can be identified. They may partly start to unravel the reasons behind the productivity paradox of AI. However, as with down-the-road theorizing, further studies are required to question or verify the validity and reliability of these qualitative findings in different contexts and settings.

In the following sections, I discuss the contributions and managerial implications related to the main research problem as a whole and to each sub-research question separately. In these sub-chapters of contributions, I also introduce most of their limitations, avenues for future research, and managerial implications. After the contributions and implications section, I move onto summarizing the main limitations of this whole study in a separate sub-chapter. Finally, I end this dissertation by discussing what might AI and this whole doctoral dissertation a be case of within the future studies on general management and organization studies.

5.1 Contributions and implications

In this section, I discuss my contributions, as well as the theoretical and managerial implications of this study. I start with the contributions of the theory section of this study. I used the literature review first and foremost to position this study to the literature on AI within the fields of general management and organizational studies, but this work also offers my first theoretical contributions.

Thereafter, I discuss the contributions and managerial implications per empirical sub-research question. Finally, I combine all the learnings from the literature and empirical studies to answer the main research problem of this study.

5.1.1 AI in management and organization literature

I conducted a literature review on AI as a phenomenon in the premium outlets on general management and organizational studies (see chapter 2). This helped to position all the sub-studies of this doctoral dissertation in relation to it. As the literature review on AI as a managerial and organizational phenomenon could only be conducted last, the analysis of the literature was partly influenced by the empirical studies I had conducted before it. In this dialogue between empirical findings and existing theory, several contributions are proposed to help scholars better position their future studies on AI.

Firstly, elite management and organization scholars have already adopted three types of research approaches to AI: 1) using AI as a novel method to make new contributions to existing theoretical discussion streams, 2) approaching AI as the subject of study with traditional qualitative or quantitative research methods, or 3) combining the two into a hybrid form and using AI as a method to study AI as the subject of study. Thus, all three research approach options remain for future contribution making in relation to AI.

Secondly, the empirical, conceptual, and editorial papers on AI can be categorized in relation to AI use phases and (impact) scope. In this analysis phase, the final decision for the categorization criteria and order of these categories was tested against the findings of my empirical papers. Having already conducted the empirical studies, they needed to be tested and logically align with the insights from the literature. This practical testing of the identified AI use phases and particularly the testing against the (expected) impact scope helped to order the phases more logically: based on both the literature and the empirical findings the phases were finally organized in relation to impact scale as the determining criteria.

The five categories start from the smallest impact scope on task level with 1) the antecedents of AI use. The impact and scope of AI starts to grow with 2) the actual use of AI, and 3) the empirical impacts of using AI. These three first categories are easy to study with traditional methods within an organization.

The last two categories try to grasp something that is not quite here yet; they are oriented towards the future and thus might require or benefit from teaming up with experts from futures' studies. Among the contemporary literature, a lot of room for future contributions remain especially on the practical and empirical use and impacts of AI. Since the 1970's, and even more so recently, 4) the expected impacts of AI especially on the societal level of analysis have intrigued the intellectual interest of management and organization scholars. Among these conceptual papers and editorials, simulations and scenario building might offer interesting avenues for future contributions on different levels of analysis.

Finally, 5) the AI-related paradigm shift already seems to be among us. This might have a significant impact on how AI-related research is conducted as a whole, methodologically. When AI is used as a research method, the paradigm shift refers to the emergence of AI-enabled methods for predictive analysis (Bhatia et al., 2021; Sheng et al., 2021). AI may enable individualized practices and personalized recommendations (Kaibel & Biemann, 2019), or be used for analysis in (nearly) real time (Antons et al., 2021; Bhatia et al., 2021).

At the same time, the scope of what can be studied can develop to enable findings that are more detailed, such as specific leadership traits (Bhatia et al., 2021; Doornenbal et al., 2021; Spisak et al., 2019; Truninger et al., 2021). This is enabled by AI, because AI enables researchers to handle larger amounts and different combinations of structured and unstructured data (A. Lee et al., 2020), or big data. AI even enables building scenarios with partly uncomplete datasets with methods such as Bayesian inference (de Oliveira & Barbosa, 2021) to analyze the probability of a hypothesis. Additionally, with the ever-increasing amount of data collected in real time, the boundaries of how research is conducted and what kind of new findings and contributions this might enable are likely to radically expand.

Thus, the research community should start to prepare for the expected changes e.g. by building reviewer competences to be able to evaluate the reliability and validity of studies where AI has been used as the research method. This is because of the shift in demanded skills when AI is used as a research method (A. Lee et al., 2020; Leonardi & Treem, 2020), and because the AI-related research methods differ in the degree to which their results may be easily explained (Putka et al., 2017). This is particularly important, because the use of AI can magnify difficult-to-spot biases present in the training data and because ML models are more difficult to interpret than traditional statistics (Shrestha et al., 2021).

Another interesting aspect of AI relates to the expected changes in temporality: will the real-time data collection and scenario building impact the types of contributions that can be made in the future? The industry is already giving agency to AI to take action in real time (Choudhury, Starr, et al., 2020; Davenport et al., 2020; Roberts, Roberts, Danaher, & Raghavan, 2015). If this is the case, how might this change in time management or time allocation, and the given agency to AI in the industry side, translate into doing research, or the contributions it enables in the future?

Another change that is increasingly called for by management and organization scholars is the need for multi-disciplinary skills when writing a paper (Doornenbal et al., 2021; Glikson & Woolley, 2020; Raisch & Krakowski, 2021). They call for the collaboration of both technical experts on ML modelling and management and organization scholars. However, as mentioned before, collaboration with experts on futures studies might also be required. In the industry, multi-disciplinary collaboration is required to build any AI agent, thus the need for even wider multi-disciplinary or cross-disciplinary collaboration in research might also be called for in the future: "*Addressing these and doubtless many more questions will demand cross-disciplinary research ranging from philosophy to management research to computer science, and many fields in between*." (Johnson et al., 2021, p 306.)

As the third contribution in the theory section of this dissertation, I provide an overview of the contributions already made by the elite scholars in general management and organizational studies, as well as their suggestions for future research. They are organized and introduced in relation to the contributions one and two presented above: in relation to the three research approaches adopted in relation to AI, and in relation to the five identified AI use phases and (impact) scopes.

Taking a closer look, I hope this proposed positioning of the contemporary and the suggested future research related to AI in management and organization (see figure 22) helps other management and organization scholars: firstly, to identify to which direction AI-related research might be evolving in the future, secondly what gaps there still are, and thirdly to be able to better position their own future studies in relation to AI and argue their research design and contribution choices related to AI in the fields of general management or organizational studies. Hopefully this will enable and inspire new scholars to create and introduce a deeper understanding of AI as a managerial and organizational phenomenon.

Future research	AI use antecedents	AI use	AI use impacts	Expected AI Impacts	AI-related paradigm shift
AI as method					
AI as subject					
AI as method and subject					

Figure 22. Proposed positioning of future research on AI as a managerial and organizational phenomenon.

In addition to the three research approaches adopted in relation to AI, and in relation to the five identified AI use phases and (impact) scopes in figure 22, I invite management and organization scholars, as well as multi-disciplinary and cross-disciplinary scholars to use this proposed positioning, and to explore new additions to it. Additional new dimensions could be e.g. different levels of analysis, other management and organization theories being contributed to, or possible other aspects related to their own expertise to develop this exciting stream of literature together with the potential of not only gap spotting but actual novel research problem solving, or even taking the giant leap towards a new management and organization research paradigm.

In the next sub-section, I move to the contributions related to the sub-research question one.

5.1.2 Defining artificial intelligence

The first sub-research question of this dissertation explored the definitions of AI: *How is artificial intelligence defined in the management and organization literature and in multiple-industry settings?*

The first striking and the most obvious observation was that both in the literature and in the multiple-industry settings the variety of AI definitions seems almost infinite (see chapters 2.1 and 4.1). No one definition includes all perspectives brought up by the literature and/or how AI is defined and explained in the multiple-industry settings. This made conducting the literature review challenging, but it adds confusion not only in the research community but also among practitioners.

The versatility of AI definitions is also likely to increase confusion and make it harder for non-AI experts to understand what AI really is, and what can it do. As both a scholarly and a managerial implication, it is important for each researcher and/or organization's AI experts to explicitly define, what is it that they mean by AI in their papers or in their organization. Only this way, AI is demystified as it is clear for the reader or for the whole personnel of the organization, regardless of the work title, what do we talk about, when we talk about AI.

Regarding the sub-research question one on the definition of AI, the contributions of this study are twofold: discussing the AI definitions in the literature and discussing the AI definitions in multiple-industry settings.

Firstly, I have aimed to clarify the relationship between the different terms: artificial intelligence, machine learning, and other terms related to them that include either AI or ML as an embedded part in the literature on general management and organizational studies. When approaching the premium management and organization literature, one of the main emphases was put on first understanding the relationship between the terms 'artificial intelligence' and 'machine learning'. Based on the literature, scholars either 1) use the term 'machine learning' or 'artificial intelligence' alone, or 2) they use both terms interchangeably, or 3) ML is considered as a part of AI. Additionally, 4) AI is often used as an embedded term as part of some other key term that is in the research focus of a specific paper.

The second contribution related to the sub-research question one, is exploring and offering a multiple-industry view on how AI is defined (see chapter 4.1). Based on the empirical interviews and basic information surveys on how the industry experts themselves define or explain AI within their organization, or for their clients, AI was found to be defined along the lines of:

AI consists of a combination of many different technologies and fields that may or may not enable artificial narrow, general or superintelligence, and/or the use of AI starts to have an increasing amount of human colleague (seeming) features.

When combining both the empirical findings on how the industry AI experts define AI and the literature from management and organization, as well as several papers from other fields, we start approaching the complexity of AI as a phenomenon: AI can be approached at least from eight different perspectives. The first three approaches relate to the creation and development of AI:

1) Firstly, AI can be approached purely technically by defining what it consists of and what is technically required to develop an AI solution, a product, or a service. What makes this challenging is that AI means different technologies for different people in different industries.

2) Secondly, AI can be approached through people and their expertise in different fields of study or disciplines that have been required to enable AI technically such as mathematics, statistics, and information technology.

3) Thirdly, AI can be approached through the amount human involvement required to develop AI algorithms (supervised, unsupervised, semi-supervised or reinforcement learning (Jha et al., 2021; Xu, 2019)).

The fourth approach to AI relates to explaining AI to non-technical people within organizations. Thus 4) fourthly, to explain what AI is to the non-technical experts, often both scholars and AI developers in the industry side explain what machines can do with the help of AI, and/or they tell examples of how AI has already been used in practice in a specific industry context. These examples often compare the agency of machines to that of humans by explaining the humanlike features that machines may start to have with the help of AI. This seems natural also from the original AI definition point-of-view of Turing's test on whether a machine is able to think (Turing, 1950).

When comparing the machines to humans, 5) a fifth approach relates to the performance of AI in relation to a human. AI can be divided into artificial narrow intelligence, artificial general intelligence, and artificial super intelligence as is the three-step performance scale in information system sciences (Panda & Bhatia, 2018; Pennachin & Goertzel, 2007). With the current sophistication and performance level of AI solutions, and if using the Turing test as the measure of performance (Cohen, 2005; French, 2000; Hayes et al., 1995; Turing, 1950; Whitby, 1996), only weak or artificial narrow intelligence level has been reached. With artificial narrow intelligence, a machine or intelligent AI agent is able to perform a single task extremely well, but the achieved solution is non-transferrable to other data sets even in the same use purpose (Panda & Bhatia, 2018; Pennachin & Goertzel, 2007). However, when the heterogeneous intelligences of a human and artificial agents are combined, these socio-technical systems achieve *"a performance in a specific task that none of the involved agents, whether they are human or artificial, could have achieved without the other"* (Dellermann et al., 2019, p. 640).

However, the industry experts were often explicit that in the context of their own organizations, and when developing AI solutions for their internal or external clients, they did not refer to artificial general intelligence rather only to artificial narrow intelligence. Yet, what is considered AI has been a moving target (Grudin, 2009) and up for debate since the 1950's[18], thus this perception and expectation to AI

[18] Turing's article on his imitation game and the Turing test was published in the Mind journal in October 1950 (Turing, 1950). The Turing test has ever since been the object of debate and controversy. Despite of this, the Turing test is commonly used as the definition of AI. Even among some of the interviewees of this doctoral dissertation study, the Turing test had the role of de facto definition whether something was AI. Although AI has been defined with dozens of different definitions, none of them has been able to replace the Turing test as the generic definition of AI. French (2000, p 9) depicts the first fifty years of AI history in the following way: *"From its inception, the Test has come under fire as being either too strong, too weak, too anthropocentric, too broad, too narrow, or too coarse. One thing, however, is certain: gradually, ineluctably, we are moving into a world where machines will participate in all of the activities that have heretofore been the sole province of humans."* Whitby (1996, p 59) claims that the Turing test is just a distraction: *"It should be clear that at this stage in the development of AI there is nothing to be gained by clinging to the notion of the imitation game as an operational test for intelligence. It is now clear that we need AI for a number of practical purposes including the development of computing machinery towards being more useful. To imagine, for whatever reason, that this involves making computers more like human beings may well be a distracting vanity. In conclusion it is worth repeating that the last thing needed by AI quasi science is an operational definition of intelligence involving some sort of comparison with human beings."* Also Cohen (2005, p 62) thinks in the same way and criticizes the Turing test for hampering the progress of AI: *"It is valuable to be reminded of the breadth of human intellect, especially as our field fractures into subdisciplines, and I suppose one methodological contribution of Turing's test is to remind us to aim for broad, not narrow competence. However, many find it easier and more productive to specialize, and, even though we all know about Turing's test and many of us consider it a worthy goal, it isn't enough to encourage us to develop broad, general AI systems. So, in a way, the Turing test is impotent: It has not convinced AI researchers to try to pass it. Paradoxically, although the proxy function is the test's most attractive feature, it puts the cookie jar on a shelf so high that nobody reaches for it."* Hayes et al. (1995, p 974) go even suggesting that the Turing test is harmful: *"But if we abandon the Turing Test vision, the goal naturally shifts from making artificial superhumans which can replace us, to making superhumanly intelligent artifacts which we can use to amplify and support our own cognitive abilities, just as people use hydraulic power to amplify their muscular abilities. This is in fact occurring, of course, and has been clearly foreseen and articulated by others; our point here is only to emphasize how different this goal is from the one that Turing left us with. AI should play a central role in this exciting new technology, but to do so it must turn its back on Turing's dream."* The interesting aspect of the Hays et al. suggestion is that moving away from the Turing test approach, we should combine the intelligence of both humans and AI to gain superhuman performance.

performance level may change in the future with further technical development of AI[19].

In summary, AI definitions can be approached technically (1-3), by comparing the capabilities of AI agents to those of humans (4), and by rating the AI algorithms' performance against that of humans (5). However, also the impacts of AI to humans and organizations have started to be addressed (6-7).

The AI impacts to humans can be approached at least from task, individual, organizational and societal levels 6) through the amount of human involvement, when an AI solution is being used (automation, augmentation, hybrid intelligence, conjoined agency). AI has also different 7) workforce implications depending on whether AI replaces or supplements people. AI may either take away work (tasks) from humans or augment human work if AI agents complete tasks that are not humanly possible.

The eighth, and final 8) approach to the division of labor between people and AI relates to the power dynamics between humans and machines, where humans decide whether to give the AI algorithm(s) the permission to execute tasks. Here the involvement of management and organization scholars have been especially called for to gain the value and benefits of AI while mitigating the negative side effects (Raisch & Krakowski, 2021) of this potentially powerful technology (Byrnes, 2017; University of Cambridge, 2016).

19 The technical components used in the quest to reach AI are mentioned in a multitude of journal articles, but a structured hierarchy or taxonomy of the technologies and their inter-relationships were at best found only in non-academic blog posts or speaker presentation slides (De Spiegeleire et al., 2017; Garg, 2015; Kainth, 2019). Some initial efforts to create a hierarchy or taxonomy in journal articles was made by Paschen, Pitt and Kietzmann (2020) who focused on the building blocks of AI systems consisting of inputs, processes, knowledge base and outputs. The required inputs for ML consist of both structured and unstructured data. Natural language understanding and computer vision were categorized under pre-processes and problem solving, reasoning and ML under main processes. In their building blocks model, the outputs are in the form of information consisting of natural language generation, image generation and robotics (Paschen et al., 2020). The process and output items were used as an initial base for AI definitions' technology categorization. A very old classification of information systems on applied AI consisting of scientific computing, CAD/CAM, and manufacturing robots was found from almost 30 years ago (Ein-Dor & Segev, 1993). As advances in AI have been made, more contemporary journals mention ML, deep neural networks, machine translations, image recognition, voice recognition (Brynjolfsson & Mitchell, 2017), object recognition, problem solving, natural language processing (NLP) (Dellermann et al., 2019), knowledge reasoning, ML, NLP, computer vision, and robotics (Coombs, Hislop, Taneva, & Barnard, 2020). Specifically AI is mentioned to not be synonymous with IT, ML, analytics or big data (Ågerfalk, 2020), or on the contrary, some papers only directly mention ML, but may imply to the use of additional technologies indirectly (Huysman, 2020; Schuetz & Venkatesh, 2020).

Thus, based on the literature and the empirical findings, I propose that when defining AI as a managerial and organizational phenomenon AI can and/or should be approached both technically and by explaining AI agency and its impacts in relation to humans.

As managerial implications, a few suggestions can be given both technically and by explaining AI agency and its impacts in relation to humans within organizations. Simultaneously, these proposed questions for managers also open potential avenues for future research.

Technically, AI can be approached through three questions: 1) what is technically required to develop an AI solution, 2) what fields of expertise and their (human) skills are required to enable AI technically, and 3) what is the required human involvement to develop AI solutions based on algorithms (both in the short and in the long term)?

To explain AI agency and its impacts in relation to humans, 4) the non-technical experts should be given practical examples of AI use, and more specifically answer 5) what is the realistically to-be expected performance level of the AI solution. Additionally, people developing artificial agents and/or people made to collaborate with artificial agents need to understand: 6) what is the amount of human involvement, when AI solution is being used? 7) what is the scope of the workforce implications on task, individual, team, organization, and society levels, when AI solutions are taken into use? And finally, 8) who supervises the decision-making when artificial agents are given an increasing amount of agency within an organization, and in society as a whole? How should the artificial agents be supervised to gain the value and benefits of AI while mitigating its negative side effects?

In the next sub-section, I recap the contribution of the identified AI strategies that served as the basis for casing and the analysis in sub-research questions two to four.

5.1.3 Strategies for artificial intelligence

As a result of the methodological choice of casing research questions two to four (see chapters 3.2.3.4 and 4.2.1), I propose five to seven AI strategies already adopted by different organizations.

The first five AI strategies include: 1) Consultancy, where consultants provide tailored AI solutions to their customers; 2) Product, where companies have an AI-based product or service as their main core business; and a special sub-category of Product AI strategy 3) Robotics, where the physical embodiment of an autonomous robot is the core business. If the AI strategy is 4) Key part, companies use AI as part of one or some of the products or services in their product portfolio. Finally, some have adopted the 5) Ingredient AI strategy, when AI is not directly part of the core function of the organization, but when AI is still strategically used to support the non-AI core business or function (see table 13, and the more granular breakdown of casing interview source information is shown in table 8 in chapter 3.2.2.2.).

Table 12. Summary of organizational AI strategies.

AI strategy	Organizational AI strategy definition
Consultancy	AI-consultancies providing tailored AI solutions to their customers
Product	Companies with AI-product or service as their main core business
Robotics	Physical embodiment of an autonomous robot as core business
Key part	AI as part of one or some of the products or services in the product portfolio
Ingredient	AI primarily supports some other non-AI core business or core function

The above were the five AI strategies used as part of the analysis for the empirical findings for sub-research questions two to four. However, it is possible that at least two more AI strategies could be proposed: 6) the organizations with no or reactive AI strategy that were absent among the collected empirical informants, and 7) AI keynote speakers / influencers, who were included to the analysis of sub-research questions one and five but were excluded from the analysis of sub-research questions two to four in this study.

Despite these initial findings on AI strategies, a lot more research is called for to draw managerial or theoretical implications related to them. Even though these findings may have more limitations than not (see chapter 3.4), they may offer a valuable contribution for the down-the road theorizing in the future. And even with these initial findings and first draft of proposed AI strategies, it is worth considering that organizations may adopt very different AI strategies. The adopted AI strategy is likely to significantly influence what kind of managerial and organizational phenomenon AI is within these organizations. Additionally, AI as a managerial and organizational phenomenon is likely to differ at least to some extent from organizations who have adopted a different AI strategy.

It is also possible that within the same organization, different functions or departments have adopted different AI strategies. Thus, it is possible that categorizing the whole organization under only one AI strategy will be impossible in some organizations. Rather more than one AI strategies are represented in different departments within the same organization. This could be the case e.g. between the core business or core function of the organization and its support functions. However, this remains to be studied further by future research.

Despite all this uncertainty, one managerial implication can be suggested for all organizations: managers should start thinking what kind of an AI strategy their organization currently has, and should it be changed somehow for the future to better serve the core business or core function of the organization.

In the next sub-section, I move to the contributions related to the sub-research question two.

5.1.4 Managing anticipated (non-/)value of AI agency

The second sub-research question of this study focused on AI use antecedents. I was curious to explore the multitude of different factors that may precede the managerial decision-making on whether to invest in developing AI for an organization. More specifically, the sub-research question two asked: *How are the managerial decisions formed on whether to invest in AI-based technology development?*

During the analysis, I approached AI as the subject of study from the AI use antecedent phase perspective (see chapters 2.3 and 2.4). The level of analysis was on a task or use case level in an organization that has adopted a specific AI strategy (see chapters 4.2.1 and 5.1.3).

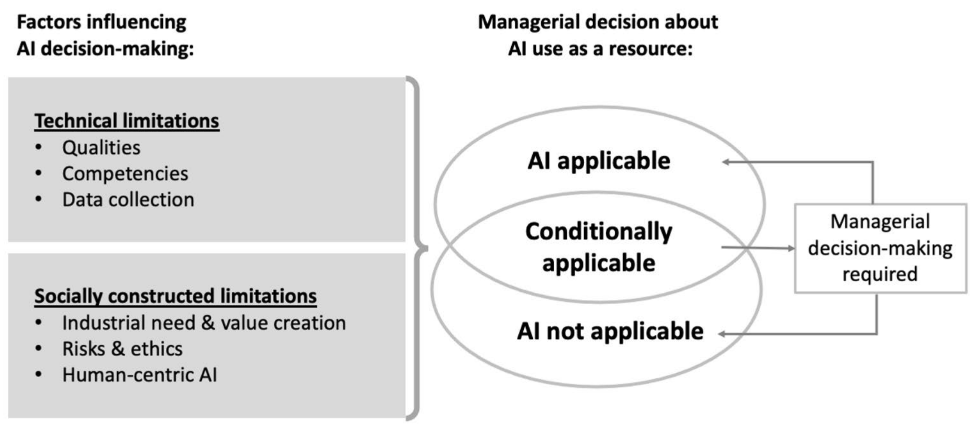

Figure 23. The intertwined technical and socially constructed limits or criteria for investing in developing AI as an organizational resource.

The main contribution of this empirical study is to propose three types of technical and three types of socially constructed decision-making criteria (see chapter 4.2.2) for whether to allocate resources to AI development as an organizational resource for a specific task in a specific use case. The technical decision-making criteria on whether to allocate resources to AI development as an organizational resource in a specific use case depend on whether the AI 1) qualities, and 2) competencies match the use case needs, and evaluation of whether the 3) required data collection prerequisite for training the ML algorithms can be met sufficiently.

The socially constructed limitations that serve as the decision-making criteria for whether to invest in AI development as an organizational resource or not, are found to be set based on evaluating the 4) industrial need and value creation potential, 5) risks and ethics, and 6) impacts on humans (see figure 23). However, at least in this sample, there seems to be variation especially in the socially constructed decision-making criteria *details* depending on the chosen AI strategy (see chapter 4.2.2). Future studies are required to further investigate these early findings.

While analyzing the types of technical and socially constructed limitations, a second complementary finding was made. Sometimes, based on the technical and/or socially constructed decision-making criteria the managerial decision may be clear, whether to invest in AI development as an organizational resource or not. Then the decision-making category is either that 1) AI is applicable, or that 2) AI is not applicable. However, often further analysis of the applicability of AI is required. Then the decision might be 3) conditionally applicable.

Sometimes it is clear that one or more critical technical or socially constructed limitations are not met, and then the investment decision is clear: AI is not applicable as a resource or to be developed into an organizational agent. It is expected to bring contextual negative or non-value.

Sometimes, all the required limitations are met, and then the positive investment decision for AI is made. In such a case, the expected AI-based contextual value in the future is positive and AI starts to be developed as a future resource and an organizational agent. In this situation the managers with budget decision-making power are investing in the value creation potential of AI.

What is noteworthy, that even with the positive investment decision, the AI development initiative may fail, and AI may end up bringing negative or non-value. However, despite these uncertainties AI might be invested in because of the potential effects that AI might have on competitiveness (van Rijmenam, Erekhinskaya, Schweitzer, & Williams, 2019), performance (Akhtar et al., 2019; Harrison, Thurgood, Boivie, & Pfarrer, 2019; Tidhar & Eisenhardt, 2020), or productivity (Choudhury, Starr, et al., 2020) of an organization. More generally, strategic IT-related organizational capabilities (Park & Mithas, 2020; Peppard & Ward, 2004; Ravichandran, 2018) and resources (Bharadwaj, 2000; Vannoy & Salam, 2010) have been studied to gain understanding of how organizations can navigate in hyper competitive business environments or how competitive advantage could be achieved. Thus, managers might take a risk and try to develop AI into a competitive advantage or to mitigate the negative effects if the competitors already develop AI. So even though *"(a)dded value is the yardstick for measuring efficiency in the use of resources"* (Wood, 1979), some managers might still take the risk and invest in developing complementary innovations for AI in attempt to turn it into a future resource or capability for the organization.

However, it was found that often the AI investment decisions might be conditionally applicable. Managers and/or AI experts need additional analysis and/or testing of one or more decision-making factors before they make the final decision on the applicability of AI in a specific organization and in a specific use case context.

Technically, the decision-maker needs to 1) be aware of the qualities that contemporary AI agent can bring along with it, and 2) evaluate that the AI competencies match the needs for which the AI agent is planned for. Thirdly, the trickiest decision without testing is evaluating whether the 3) required data collection pre-requisite for training the ML algorithms can be met sufficiently. Therefore, many of the AI developers often suggested a conditional investment decision, so that the data can be tested before the manager makes the final decision on whether to proceed with developing AI further as an organizational agent and resource. For this data applicability testing also other experts such as a data scientist and people working in the IT department are likely to be needed.

On the business or organization core function side, the manager needs to be the expert and take a stand on the socially constructed limitations. S/he needs to evaluate the value creation potential of AI in relation to the 4) industrial need, but also evaluate the potential 5) risks and ethics when agency is given to AI, as well as the 6) impacts that the new AI solution will have on employees and the users interacting with the AI solution in the future. Thus, the AI investment decision may depend on multiple limitations for managerial decision-making simultaneously, as well as the chosen strategy of the organization. Future research is warranted on understanding these AI-related decision-making boundaries, combinations of factors impacting the decision-making, and their variations more in detail.

In summary, through the Gioia analysis, a multitude of technical and socially constructed factors were identified in this study. Further research needs to focus on how the single factors and/or their combinations may or may not impact the managerial decision-making e.g. in the form of expected suitability and value for the organization. As the expected suitability and value for the organization is context-dependent, this is likely to pose a challenge for the manager with the investment decision-making power.

Additionally, there seems to be indications within this study, that many of the managers need technical consultancy to understand 1) the capabilities and competencies of contemporary AI as well as 2) the technical minimum requirements for AI even on a theoretical level.

The lack of understanding AI technically may complicate and/or slow down the managerial decision-making. Also, based on the empirical interviews, the technical requirements to test whether e.g. the available data for a specific use purpose or a business problem are likely to be multi-disciplinary. This is in line with previous research, where big data-driven teams, their actions and performance are found to depend on multi-disciplinary skills such as computing, mathematics, statistics, ML, and business domain knowledge to turn traditional business operations into modern data-driven insights e.g. on real-time price changes and customer preferences (Akhtar et al., 2019).

As collaboration between teams and organizational silos is likely to be required, that may also slow down gathering the needed team even to test an AI use case. When this is done for the first time, finding the right people, and allocating work time for them may slow down the decision-making and project start for an AI investment. When the processes and people are in place, the decision-making and variables influencing an AI investment may be different e.g. when calculating the expected costs of developing an AI solution for a specific task. The first AI project is likely to be the slowest and to require the highest tangible and intangible investments (Brynjolfsson et al., 2017) such as to find the right people, and to create all the required technical and people processes. However, future research is required to better understand the break-even point, or where the AI investment-decision-making speed or AI development project success rate start to increase. All these uncertainties open intriguing avenues for future research.

Also, the contextual value depending on the adopted AI strategy, or other contextual factors, requires further scholarly attention. Particularly interesting are the conditionally applicable cases, where the decision is not clear, why, and how, in a specific context at a given time, the combination of the technical qualities, competencies, and data collection (are expected to) match the use case technically. But also, the socially constructed factors deserve further analysis and better contextual understanding on why the (to be developed or adopted) AI solution or AI agent fits the industrial need well enough to create (enough) expected value to justify the investment. It should also be studied whether the risks and ethical concerns are in fact considered in the managerial decision-making process, and how. When making the AI investment decision, are the industry managers aware of socially constructed factors such as mitigating the direct and indirect risks related to human safety, or protecting people's private data, or the transparency of fair decision-making versus discrimination when AI is used? How do they balance the organizational learning (see chapter 5.3.4) of AI to the perceived external competition in developing this powerful technology into a potential competitive advantage? If the managers operate in global markets, how do they balance their AI-investment decision-making to different political climates and legislations on AI use?

Based on the early findings and identified avenues for further research, it seems that AI decision-making is preceded with a multitude of complex human decision-making.

Longitudinal studies could provide interesting insights e.g. on how long a temporal horizon is taken into account when the AI agent investment risk level is evaluated. Ideally these studies would focus on both the antecedent phase, when the AI investment decision is made, as well as the impact phase to find out if any risks have in fact realized inhouse or in the business environment, and through that potentially impacted the risk evaluations of future AI investment decisions. As the literature review indicated a potential relationship between the antecedents and impacts of AI use (see chapter 2.5.3), future research might need to start studying AI as a process rather than just identifying typologies as a specific part of the process. This way also the value or non-value and return on investment over time could be studied.

Similar longitudinal study approach might fit the future studies on whether and how the human-centric aspects of developing AI solutions are considered in the investment decision-making phase. But also, how these decisions might evolve over time, as organizational learning (see chapter 5.3.4) on AI increases with cumulative experience and user feedback, or with other intangible investments (Brynjolfsson et al., 2017) on AI.

Up until now, the management and organization research community has heavily focused on educating other management and organization scholars about AI/ML as a method (see chapters 2.4.1 and 2.5.5). In the AI-related literature, future research has been suggested for further analysis on AI's research related fundaments and/or concerns. Scholars have taken a role to educate others and increase method understanding before other scholars are advised to take AI into use as a research method.

In previous research, other technical and practical antecedents have included the creation and collection of the required data for ML (Leonardi, 2021), which was one of the technical AI investment decision-making criteria also in this study. Other scholars have contributed to the AI antecedent understanding and literature through the user-centric (technical) antecedents of data network effects (Gregory et al., 2021), the required AI-related skills (Akhtar et al., 2019), and the factors influencing workers' trust in AI (Glikson & Woolley, 2020). The technical and socially constructed AI investment decision-making criteria complement these previous findings, but the previous literature also complements my findings and through that indicate that more (non-)value (see chapter 5.3.5) decision-making criteria are likely to be discovered in the future.

When top publishing management and organization scholars have approached AI as both the research method and the subject of study, they have contributed to the practical utility decision-making before implementing AI (Pantano et al., 2021). To this stream of literature, the proposed types of technical and socially constructed types of AI investment decision-making criteria of this study bring novel and valuable managerial understanding. Additionally, these findings may guide the scholarly community a step closer toward a better understanding on which criteria should be used for the AI investment decision-making to realize the benefits of AI and mitigated its negative side effects (Raisch & Krakowski, 2021).

In the next sub-section, I move to the contributions related to the sub-research question three.

5.1.5 AI use value vs. wanted AI use and value

The third sub-research question of this study focused on exploring the potential reasons behind the differences between the actual use of AI and the use cases to which the AI developers themselves would want to use AI, but for a reason or another could not do so at least yet. More specifically, the third sub-research question of this study focused on the reasons *why might the actual and wanted use of AI differ.* The findings contribute to the AI use phase (see chapter 2.4.2), when AI is being used or implemented in the daily work of an organization and/or on person specialization (Keon & Carter, 1985) level.

Table 13. The spectrum of six categories on AI applicability, and its use or wanted use.

AI applicability	Use AI	Want to use AI
Applicable	Can use & AI in use currently	Want to use AI & already applying / developing AI solution
Conditionally applicable	Can use AI with prerequisites	Want to use AI but something still missing
Not applicable	Cannot use AI	Do not want to use AI even when it is possible

For the analysis, I asked the AI developers how they themselves use AI in their work, or how would they want to use AI in their own work. These findings build on the findings and contributions of sub-research question two, and they widen the spectrum of AI use to six categories depending on the different mix on whether AI is used or wanted to be used, and whether AI is applicable, conditionally applicable, or not applicable (see table 14).

Based on the initial observations during the interviews, there seemed to be a heavy contrast between the AI developers developing AI solutions for others' work, but them not necessarily using AI themselves in their own work. Additionally, some of the AI solutions they mentioned were already in use, some were still in different phases of development for different reasons, and some had already decided to not use AI even if it was technically possible to do so. I was curious to know the reasons why. This also seemed theoretically interesting, as up until now, the AI literature on management and organization has been framed first to automation (Fleming, 2019; Furman & Teodoridis, 2020; Johnson et al., 2021), and then to augmentation (Raisch & Krakowski, 2021). However, based on the literature, adopting both automation and augmentation might be complementary options. By adopting both rather than either automation or augmentation, the paradoxical tension between them is expected to be possible to be solved, and through that be able to benefit business and society (Raisch & Krakowski, 2021).

Thus, to expand this discussion and to explore the initial observations of AI use in the multiple industry settings, it was necessary to include the answers of both when the AI developers use and want to use AI. Based on the on the practical experiences of 30 interviewed practitioners, who themselves develop AI solutions in various roles in 17 different industries (see table 8 in chapter 3.2.2.2), as the first contribution of this study a continuum of six types of AI usability categories seemed to emerge: 1) use AI, 2) use AI with prerequisites, 3) want to use AI and already applying it, 4) want to use AI, but something is still missing, 5) cannot use AI, and finally 6) do not want to use AI even when it is possible to do so (see table 13).

All the second order themes under these AI use type categories call for additional studies to fully understand the complexity of AI use as a resource (see chapter 5.3.1), dynamic capability (see chapter 5.3.2), or as an artificial agent within an organization. This explorative study and the reasons why the actual and wanted AI use differs may open a multitude of future research directions related to the six different types of AI use. I will next discuss some of the potential avenues for future research. I start from the AI solutions that are already being used by the interviewees in their role as an AI solution developer.

AI in current use is more versatile or fine-tuned than just automation and/or augmentation based on the findings of this study. When AI is already being used, it is often used as a hidden part of a process or a service so that the user does not necessarily think, or even know, that s/he is now using AI. On the other side of AI use, whether its nature being automation, augmentation, or hidden part of some product or service, the AI developers had already experienced and/or witnessed changes to human work on individual and organization levels.

At the individual level, future studies should explore the practical effects of 1) hybrid intelligence or work augmentation, where humans work together with an AI agent[20], and 2) how the simultaneous multitasking of work tasks with the help of, or

[20] Look also the discussion on conjoined (Murray et al., 2021), interdependent (Raisch & Krakowski, 2021) or intertwined (Leonardi & Treem, 2020) agency when using AI for work automation (Fleming, 2019; Furman & Teodoridis, 2020; Johnson et al., 2021) and augmentation (Raisch & Krakowski, 2021).

because of AI agents is perceived by the user. This exploration could focus on the effects of AI use on things such as human well-being or cognitive ergonomics (Kalakoski et al., 2019), productivity (Akhtar et al., 2019), team level collaboration and leadership implications (Larson & DeChurch, 2020), where the team consists of multiple humans, some of whom might work with different AI agents, while others might only work with humans. What are the technical skills that are required from people with different roles within an organization as individuals, or on a team level (Akhtar et al., 2019)? How does the use of AI agents change work time reallocation, not just for the person using the AI solution, but in the multi-disciplinary settings of different experts all over the organization?

On the organization level, there are also many other new avenues for future research that this explorative and phenomenon-driven study has opened and implied. How might work roles change at both individual and organization levels (Carter & Keon, 1986; Keon & Carter, 1985; Larson & DeChurch, 2020) because of implementing AI agents as part of the organizational resources and with increasing work (task) agency (Larson & DeChurch, 2020; Murray et al., 2021; Raisch & Krakowski, 2021)? AI is expected to impact organizing because technologies with capacity to exercise intentionality are affecting organizations in new and distinct ways, thus organizations may evolve differently based on the type (or types) of conjoined agency on the chosen technology they adopt (Murray et al., 2021). This raises interesting research questions such as what is the good balance for an organization: where AI agents can or should be used as opposed to where the agency should be left entirely for humans? How does this differ in different industries or different kinds of organizations, and why? What factors influence the diffusion of AI as an innovation (Rogers, 2003) in different organizations, and why? What might be its positive as opposed to its negative side effects? How could AI agents support and help people in their work? Despite the conceptual expected impacts of AI in the previous literature, findings on the empirical impacts of AI use are still to be explored to a large extent (see chapter 2.4.3).

Finally, one more factor seems to radically impact AI use: the AI development phase as a technology: how mature is AI as a technology? What can and cannot be expected to be achieved with the help of AI in general, and/or in a specific use case context? How can a needed AI agent be created and maintained to stay up to date? What is the maturity of the organization in relation to developing and maintaining AI agents as part of the organization's resources? When the maturity of AI as a technology develops, who in the organization understands and can detect the new opportunities it might bring to the organization as a potentially new resource, or even as a competitive advantage before the rivals?

But these are all just questions, when the decision has already been made to use AI, and the solution has been implemented into use. What about the five other types of AI use decisions? At the other extreme of the six types of AI use are the types of AI use cases, where it is technically and otherwise possible to use AI, but one decides not to use AI anyway, the decided non-use of AI. What are these cases?

AI is refused to be used by the AI developers themselves in situations or cases of final decision-making, human-to-human connection, and interaction, or in things that give themselves pleasure, or that they themselves find meaningful. Yet a major category in which the interviewees refused to use AI were the cases, which contradict with the ethics and morals of the user. A lot more research is required to understand the refused or non-use of AI in different contexts: how might these decisions differ between organizations, or even between individuals within the same organization? And how do the personal values of an individual impact the decision-making of whether to use AI, or not? Can an individual even refuse to use AI, if it is already a hidden part of daily used products and services in and out of work? What if the AI is in use in an organization, but the individual is convinced that the AI is wrong? Can s/he refuse to use it if the organization has decided to use an AI solution? Who has the power to decide whether an organization uses AI or not, how, and for what purpose?

Multiple interviewees had faced a situation where a lot of money was offered to the company to help them develop an AI solution, but for ethical reasons the interviewees and their companies either pulled out of the project or refused to work with these clients. Interesting ethical and moral questions arise, how much is an ethical or moral decision worth? What if the individual or the organization is in financial trouble? What drives the destructive use of AI in society? Concerns already exist:

"A very dangerous question to humankind is, what do you want? That is a decision humankind needs to decide, when there exists an extremely powerful technology with which we could suddenly get what we want." (Interviewee 30, CEO, empirical interviews 2019)

"What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity." (Tim Cook, CEO of Apple, Byrnes, 2017)

"The rise of powerful AI will either be the best or the worst thing ever to happen to humanity. We do not yet know which." (Stephen Hawking, theoretical physicist, University of Cambridge, 2016)

This brings us to the questions related to the second most usable AI solutions: **use AI with prerequisites.** A multitude of questions remain to be studied empirically on the AI implementation issues (Brynjolfsson, 1993; Brynjolfsson et al., 2017; Pachidi et al., 2021; Pantano et al., 2021) and general hybrid intelligence (Dellermann et al., 2019), or conjoined (Murray et al., 2021), interdependent (Raisch & Krakowski, 2021) or intertwined (Leonardi & Treem, 2020) agency issues, where humans work together with machines with increasingly amounts of given agency. Who has the final say, and when, and why? The human or the machine? How should the AI solutions be tested before taken into use? Who monitors and develops the AI agents in an organization so that they are up to date with the (potentially abrupt black swan) changes in the real world? Or who has the power or courage to question the numbers just based on human intuition, or a hunch? What if the machine is wrong? What if I know something that the machine does not, something its training data did not include? What if there is a virus or a hacker interfering the AI agent(s)?

The future studies on AI implementation, might focus on how organizations form their AI strategies, or whether they even have one(s). Or how organizations handle the change and/or expectation management, when AI solutions are being implemented as contextually adaptive organizational resources and as artificial agents who execute new work tasks? What AI-related skills are required in an organization to implement AI solutions? What is the level of AI understanding, or AI related skills and competencies that are needed in different parts of the organization to handle questions such as: how to handle the AI-related expectations versus reality? What are the new or changing multi-disciplinary collaboration skills required across traditional organizational silos? How should the organizational processes be changed; and who is in charge for this change? How does the potentially increasing number of artificial agents change the work organizing on different levels (see chapter 5.1.8)?

If these were open questions on the organization level, some similar and overlapping issues relate to individuals in the specific case of them working together with AI agents: how mature is the AI solution, what can and cannot be expected from the AI agent? In what decisions the artificial agents can and cannot be trusted (Glikson & Woolley, 2020; von Krogh, 2018)? How do I know the difference? When should or can I over-rule the decision, the machine has made, or the solution it is suggesting as the best option? How does the AI agent communicate[21] the reasoning, why it suggests the outcome or a specific conclusion as the best option in this situation? Do I agree or disagree? Can I have a conversation with someone else to learn to understand what is the data on which the ML algorithm has been trained on? What are the goals that have been set for the algorithm(s)? How do I as a human fit into this human-machine collaboration? What can I learn from the machine, and what

[21] See more about explainable AI (e.g. in Barredo Arrieta et al., 2020).

should the machine learn from me as the domain expert in this specific expertise field (Dellermann et al., 2019)?

So, the three AI use type categories above, 1) AI in use, 2) use AI with prerequisites, and 6) do not want to use AI even when possible have opened many avenues for future research as well as numerous managerial implications. The three other AI use type categories may be AI development specific: 3) want to use AI and already applying, 4) want to use AI but something is still missing, and 5) cannot use AI (see figure 24). I will discuss these remaining three AI use type categories next. I will start with the fifth one 'cannot use AI', because that may increase the managerial understanding on clear cases, where AI cannot be given agency, yet.

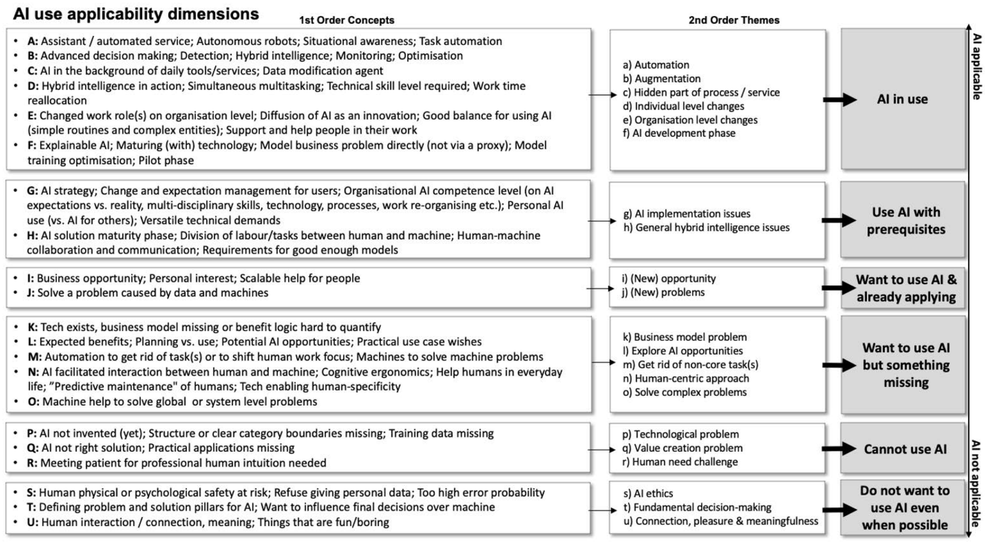

Figure 24. Overview of the six AI use applicability dimensions found.

Cannot use AI are the second last applicable use cases out of the six AI use type categories. They include the cases to which AI simply cannot be used. These cases are second last after the AI use cases to which the AI developers simply do not want to use AI. The 'cannot use AI' use cases are second last because, over time, there is a chance that these AI use cases may become usable. However, with the contemporary maturity of AI as a combination of technologies, AI cannot be used if the need simply does not fit the technological demands, AI does not create enough value (see more in chapter 5.3.5) to be used, or there is a human need that cannot be overcome with technology. Yet, all these mismatches that prevent AI use may change over time. Thus, like managers, also scholars should keep their eyes open and follow the fast-paced development of AI-related technologies and changes in relation to the business or core function needs of different organizations. It may well be that AI can suit something else than originally intended or strived for when the AI-related experience, skills and competencies increase, and people realize what other problems AI might solve.

Thus, there might be a surprisingly fine line between the use cases to which AI cannot be used for (both for business and technical reasons), and the AI use cases to which the AI developers would want to use AI in their work but there is still something missing that prevents its use.

When AI developers want to use AI but cannot, something critical is still missing that prevents the use of AI. Yet, often in these cases, the technology already exists. However, the business model remains to be invented by someone to develop the technology into a working everyday solution. For these types of AI use cases, the AI solution developers had a multitude of wishes where they knew that the technology was already suitable. These tasks included e.g. a variety of support function or other non-core work tasks. These were tasks that the AI developers had to take care of in their daily work, but the kind of tasks which they considered a distraction from their core work. Thus, the AI developers considered these tasks a waste of their work time (in their own opinion).

This may have surfaced a bigger phenomenon, where secretary work was first replaced by IT-based self-services, and now everyone is a secretary: *"I wish that for my own work, already in the near future, there would be an AI assistant or a business assistant for the kind of things that human assistants used to do 15-20 years ago; then when no self-services existed yet. Now they actually consume time for real during the workdays both in our own (company) and in our client companies."* [I2, Consultancy]. Many of the interviewees shared these views. They wanted a full automation of tasks that first used to belong to secretaries but have then been developed into self-services. They were wished to be fully automated in a smart way.

Developers as these interviewees are, many of them were also curious to explore the AI opportunities for use cases to which they expected that AI would bring benefits already now, or they wanted to explore new technical opportunities that AI might have. AI was also hoped for more human-centric solutions in the interactions between humans and machines, and to help humans in different ways and in a more personalized manner. So, AI might enable a shift in sociotechnical human-technology relations, if instead of humans adapting to machines, would it finally be time for machines to adapt to people instead?

These exploratory findings and wishes for AI use might be the first weak signal for additional other interesting work life phenomena. Future studies could focus on how AI is or could be used to offload unnecessary burden from humans, and through that enable more humane work and cognitive ergonomics (Kalakoski et al., 2019) with the help of AI: *"At its best, AI trims away irrelevancies: a lot of disturbance is* *related to work that does not create value. It frees time for creative work. Everything that is away from the state of free association or that interferes with it, AI may clean away. I believe that the human brain capacity is currently way too loaded; and that AI would have a lot of opportunities to help people with this. When the number of stimuli or irritants is heavily reduced, different mechanisms are born for interaction and for the ability to be present. It would be great, if only we could still reach such a state in working life someday."* [I9, Ingredient].

This is a particularly interesting new perspective, where AI is not only wanted for increased efficiency and performance but to help people, when they suffer from the contemporary work life task number and pace. Thus, AI seems to open potential new avenues for work wellbeing-related research.

One more thing to which AI was hoped for, but cannot at least yet be used for, is solving large complex problems on global or system levels. Could it be, that we start to see AI in the context of wicked problems and global grand challenges? Maybe parts of these big and complex societal problems could be intended to be solved with human and machine collaboration in future studies?

Last, but not least, interesting AI use cases to which the AI developers could contribute to are the use cases, to which they both **want to use AI and are in fact already applying AI for**. As was the case between 'cannot use AI' and 'want to use AI, but something missing', the latter might be a step closer to applicable if the something, that is missing, is found and thus it is possible to start applying AI for it. Thus, managers or at least someone in the organization needs to constantly stay alert: *"Technology develops so fast. For us it means that we stay on the map what is possible and what is not possible specifically today. There is a fairly big difference, whether something can be done by 90 percent or by 98 percent. And then it can change from a useless solution to a great solution."* [I2, Consultancy].

This can be key, because AI has already enabled new business opportunities[22] that were not possible before AI. Exploration of these opportunities alone opens potential for new and interesting scholarly discoveries, as well managerial implications for how different industries might be disrupted as happened e.g. with cell phones entering the camera market. Thus, what is also interesting about AI, is its nature as a general purpose technology with a need for people to develop complementary innovations for it (Brynjolfsson et al., 2017): *"AI solutions just exist, and they can be put to use anywhere. The more AI is used, the more generic the*

[22] Premium management and organization scholars have focused on the AI opportunities, but from a different angle than the more technically oriented AI developers interviewed for this study. The management and organization scholars have e.g. been interested in how to realize data-driven learning scale and improvements with AI in the context of data network effects (Gregory et al., 2021).

situation can be viewed as. It is everyone's responsibility to think where else this same solution could be used, when you think of a solution to something." [I20, Consultancy].

Even though, the AI solution developers are likely to have a strong pro-innovation bias toward AI, also first side effects were identified. As a side effect with increasing amount of data overflow, AI solutions are already being developed to solve problems caused by digitalization, data overflow, and e.g. sensors collecting more data than what people can analyze, or make sense of, with a reasonable time investment. *"At the moment there are so many measures and variables. Humans are surrounded by machines, but human eye has difficulty to interpret a single variable."* [I33, Ingredient]. Thus, the initiatives that are already being developed, whether focusing on the new opportunities or solving problems that AI brings along with it, deserve further investigation in future studies.

All these examples are just surfacing the explorative tip of the iceberg, and all six types of AI use type categories deserve further investigation in future studies. It would be particularly interesting to conduct case studies where all the AI use type categories could be examined from the organizational AI agent use portfolio management and organization perspective, where all these AI use categories may or may not be represented simultaneously[23]. Even though, or maybe particularly because of, the six kinds of AI investment decision categories were related to the AI use of AI developers, future studies could and should test whether the same or similar categories could describe the entire AI solution portfolio of an organization. Also, were the AI use studied further from someone else's perspective than from the perspective of the AI solution developers, the AI use categories might be different from the AI users' and usability perspective, or from the perspective of senior managers looking at AI as an investment or as an organizational resource.

The actual use of AI also surfaced additional managerial and organizational factors to be taken into consideration, when AI solutions are being used and implemented within an organization: is there someone who manages the whole organizational AI agent portfolio, the chief AI officer perhaps? Or does it require a multi-disciplinary team of experts? What might be in the job description of such roles? How should the whole life cycle of managing the organization-wide AI agent portfolio be managed? What legal contracts are required and who bears the responsibility if or when AI agent makes a mistake?

[23] Portfolios can be used to manage strategic objectives, not through temporary organizing but through continuous strategic management of ongoing projects and programmes within an organization. Portfolios represent a platform that remains alive and enables the emergence of new projects and programmes. (Geraldi et al., 2022).

Also, other interesting questions remain to be answered when increasing amount of AI agents are already in use within an organization: what happens to the power dynamics[24] and organizational hierarchies[25] within an organization if machines gain more power and agency? Does it mean that the experts who work with AI agents also gain more power as they oversee that the AI agents stay up to date and keep doing the wanted things? These people might start to expand their domain expertise and even replace other human experts with the help of AI as has already happened with work computerization (Frey & Osborne, 2017). Future studies are needed to explore, how might experts be able to leverage from this new technology by increasing their productivity with the help of big data and ML. How might this change affect their compensation bargaining power and/or other power position within the corporate ladder? What kind of other side effects might this potential shift in power dynamics have between people and work roles within an organization? How does work need to be re-organized because of both developing and maintaining AI agents simultaneously? What processes are needed, when a multitude of different AI agents are used daily both by employees and customers?

This study has focused and contributed to the understanding of why the actual use and wanted use of AI may differ by proposing and discussing six different AI use type categories. However, the practical experiences of the AI developers may serve as the first step on starting to understand the complexity of the potential AI impacts on individual knowledge worker as well as on organizational level more in general.

This study joins the theoretical discussion on AI in work automation (Castro Silva & Lima, 2017; Fleming, 2019; Furman & Teodoridis, 2020; Johnson et al., 2021; Lundvall, 2017) and work augmentation (Raisch & Krakowski, 2021) in the context of workforce implications (Brynjolfsson & Mitchell, 2017). More specifically, this study offers an important human-centric, yet pro-innovation biased, view to the emergent discussion on human and AI collaboration termed hybrid intelligence (Dellermann et al., 2019), (hybrid-) augmented intelligence (Pan, 2016; Zheng et al., 2017), intelligence augmentation (H. Jain, Padmanabhan, Pavlou, & Santanam, 2018), and/or conjoined (Murray et al., 2021), interdependent (Raisch & Krakowski, 2021), or intertwined (Leonardi & Treem, 2020) agency.

24 *"By gradually uncovering AI as a fundamental organizational phenomenon, we may distinguish and offer tentative explanations of the emergence and interaction of human and machine authority regimes in organizations"* (von Krogh, 2018, p 406).

25 Technicians' work has been found to cause trouble for vertical form of organizing because it decouples the authority from position from the authority of expertise (Barley, 1996).

Up until now, the premium management and organization literature has mostly focused on business process re-engineering (Shadbolt & Milton, 1999), or in developing an expert system for strategic marketing planning (McDonald & Wilson, 1990). The more contemporary scholars have focused on specific AI use cases such as to analytically detect emotional responses from customers' static images (Pantano et al., 2021), or to analyze expert sentiment from text at scale regarding high risk capital allocation decisions (Nauhaus et al., 2021). Scholars have studied the enactment of data-driven actions in big data-savvy teams (Akhtar et al., 2019), whereas others have focused on using ML to study the adoption of an expertise search tool per employee type (Wu & Kane, 2021). Yet, at least among the premium literature, an overall understanding of AI use and AI as a managerial and organizational phenomenon seems to be missing.

I hope my findings serve in providing an initial understanding for both scholars and practitioners alike on the breadth of questions associated to AI use, and why its actual and wanted use may differ. In the next sub-section, I move to the contributions related to the sub-research question four.

5.1.6 Measuring value per AI strategy

As my fourth sub-research question, I asked: *how are the impacts of AI-based technology development investments measured?* I analyzed the findings from five AI strategy perspectives. The measurable impact types seem to have variation between the five different AI strategies adopted, at least based on the initial qualitative findings. However, they seem to also have significant overlap and similarities, if comparing only the second order themes that are to a large extent based on the traditional quantitative performance measures. At a closer look and with a more detailed analysis, there seems to be variation in the maturity between measured impacts of AI development on multiple levels: between projects, between AI products or services, but also between organizations. Despite the similarities between the second order theme names among different AI strategies, they seem to reflect different phases in AI maturity development.

In the management and organization research, the expected impacts of AI have been speculated since the 1960's (Meinhart, 1966), yet the studies on the empirical impacts of AI have still been relatively scarce (Akhtar et al., 2019; Furman & Teodoridis, 2020; Nauhaus et al., 2021; Nguyen & Malik, 2021; Pachidi et al., 2021; Wu & Kane, 2021).

To the best of my understanding, the overall measurable impacts of AI have not yet been empirically studied in multiple industry settings. This is where the main contribution of this sub-research question lays. I was curious to explore the empirical impacts that are already taking place in organizations that develop AI solutions.

In this study, my contribution focuses on identifying the different types of measurable impacts of AI development investments. Yet, the typology as a contribution type (Cornelissen, 2017) seems limited for what I was studying. Thus, future studies should focus on analyzing the AI impacts not only based on measurement type but as parts of the AI development process, and potentially the different phases in it. At this relatively early phase of AI diffusion as an innovation (Rogers, 2003), it could be argued that rather than focusing on analysis per adopted AI strategy, the focus instead should have been put on comparing the AI development maturity phases on different levels of analysis as well as the measurable impacts associated with each AI development phase.

In this study, as my *"plausible hunch that dissolves anomaly"* (Van de Ven, 2016b, p 223), I give a rather bold yet rough first draft suggestion of AI development phases in the form of the temporal process development framework (see figure 25 in chapter 5.1.7). However, the robustness and methodological reliability and validity of the temporal process development framework might be questionable. This is because rather than being based on process analysis methods (Langley, 1999) it is mostly build on the typologies found by applying the Gioia methodology (Corley & Gioia, 2011; Gioia et al., 2013), even though Langley's temporal bracketing (Langley, 1999) was also partly applied. Thus, future studies should explore AI maturity development phases using a wider variety of process analysis methods as well as with a more suitable dataset for analyzing AI development as a process.

Despite all, this study may still have touched upon a potentially valuable discovery related to the AI maturity development phases, and the potential management and organization requirements associated with them. Whether this really is the case remains to be studied in future research. Potentially this may open a multitude of avenues for research including but not limited to questions such as what similarities and differences there might be in the AI development phases between different AI strategies adopted? How might the financial performance and value creation (see more in chapter 5.3.5) vary between AI strategies adopted, or between AI maturity development phases?

How might the management and organization requirements within an organization change in different AI development maturity phases? How might the minimum investment requirements vary between different kinds of AI development projects? When and how do the AI investments reach a break-even point on a single AI development project level versus on a bigger AI portfolio management level? How can that be measured? Is it possible that some AI investments must be made just to stay in business without the value of the investments ever becoming fully captured from clients (see more in chapter 5.3.5)?

When AI investments are made, how might the processes and organizing of multi-disciplinary experts change within an organization in different AI maturity development phases? Who are the people as actors in the new organizational processes? Whose job descriptions change because of increasing use of AI agents? What parts of specific processes are taken care of by artificial agents?

Or depending on potentially different kinds of AI agent portfolios, where some AI agents are developed into products and services by other service providers, some solutions are developed and maintained inhouse: which AI solutions should be developed inhouse, what can be outsourced and why? When do AI agents become, or not become, a core capability of an organization, and why might that be? Where does AI then have agency? Why? To what extent[26]? Where should AI no longer have agency, and why? Who has the power to question the agency of AI? Can AI agents question human decisions?

When reflecting these measurable AI impact findings against the earlier studies of this doctoral dissertation, it is noteworthy that the findings on AI antecedents, and more specifically the technical and socially constructed limitations for AI investment decision-making, are only partly reflected in these findings on measurable impacts of AI (see chapters under 4.2.2). The findings on different types of AI use are also only partly reflected in these measured impacts of AI (see chapters under 4.3.1).

The AI developers still seem to have a need to adjust the arguements of the measurable impacts of AI to the so called traditional and quantitative top management measures, even though they themselves problematize this approach (see chapters under 4.4.1). Based on their practical experiences with AI solution development, the value generation of these solutions seems to be much more versatile than just the quantitative financial performance measures, or even contradictory to the value of the calculated human working hours saved (see more in chapter 5.3.5).

If AI completes tasks and enables business opportunities that have never been possible before AI, is it possible that new AI-related measures are required also for performance? What about the strategic management of the agency of the AI agents and their effects on multi-disciplinary humans? How should the performance of their collaboration be measured, when a team consists of human experts with a

[26] *"Moreover, to better understand and explain the delegation of decision-making authority to AI, it is important to gather qualitative and quantitative data on delegation failure (e.g., is there such a thing as moral hazard by machines?). For example, trading algorithms reduce information-processing costs and decision-making time, but a wrong trading decision may risk the survival of a financial firm in a split second. A medical AI assistant reliably processes complete data and the experience available, but a false diagnosis based on an undetected data flaw may risk a patient's life. Through abductive reasoning, we may better understand what it means to delegate authority to AI in organizations, what the role of human responsibility and accountability is in such delegation, and how organizations, organizational members, and machines learn how to improve AI decision-making in various situations."* (von Krogh, 2018, 406).

background from different disciplines as well as the AI agent portfolio that they work with?

The performance of AI might be positive but also negative, and this may vary on the short and long term: who monitors the risks of all the AI agents? Who monitors the contract portfolio of the different AI agents? If AI makes a mistake, whose responsibility is the financial loss: the one who provided the data, or the one who trained the model, or the company that sold the system, or the company that bought the system, or the end user of the system? It seems possible that AI impact development measures would need to include a significantly wider range of measures than just financial measures.

Scholars have been worried about the expected impacts of AI taking human jobs (Brynjolfsson & Mitchell, 2017; Castro Silva & Lima, 2017; Frey & Osborne, 2013, 2017). Job creation dynamics are expected to shift based on new technologies (Lundvall, 2017), and work descriptions are to change (Fleming, 2019). Could it then be that AI also provides new jobs, or even increases the amount of human work needed, this calling for a larger variety of people with multi-disciplinary skills and capabilities? How should the AI-related multi-disciplinary skill and competence requirement portfolios be managed and measured for different AI maturity development phases and/or per different AI strategies adopted in an organization? Numerous open questions remain for future studies related to the empirical impacts of AI, and how they should be measured.

In summary, a potentially new and interesting avenue for future research would be the potential change requirement needs in measuring the AI impacts in relation to AI antecedents and AI use. This might offer an interesting addition to the so called traditional financial performance measures of the AI impacts. Future studies could focus on exploring, whether measuring AI (and its development and maintenance) needs to include not only traditional (financial) performance measures, but also intangible new measures, even though intangible investments are difficult to quantify (Brynjolfsson et al., 2017) and link to their macroeconomic performance. This is because *”traditional growth accounting techniques focus on the (relatively) observable aspects of output, like price and quantity, while neglecting the intangible benefits of improved quality, new products, customer service and speed”* (Brynjolfsson & Hitt, 2000). Yet they all seem relevant to be taken into consideration if performance is defined as an aggregate construct (Chet Miller, Washburn, & Glick, 2013).

AI might require new and potentially innovative supporting measures to help people to constantly monitor the value or value generation of AI, but also when different kinds of business focused, and context-dependent AI risks generate non- or negative value (see more in chapter 5.3.5). This might be particularly important in this early phase of AI-related transformation within organizations and in the society.

And when better technologies are developed, AI-solutions can and might need to be replaced or cannibalized by other artificial agents, or sometimes agency might need to be given back to humans. All these potential scenarios deserve scholarly attention in the future in addition to other intangible measures such as: is the AI solution being developed or used human-centric, what bias might it have, how is its usability from the user's point-of-view? Can the solution be trusted by the users (von Krogh, 2018)?

Thus, in addition to measuring the value of the AI agents, potentially also their non-value or negative value (see more in chapter 5.3.5) should constantly be measured and monitored. This would help in the decision-making of whether to not only start but also end AI agency for a specific task in an organization. This might include, but not be limited to, the theoretical and empirical early findings of this study on the relationship between the antecedents and impacts (see chapter 2.5.3): how e.g. the use of particularly sensitive data in training ML algorithms (AI use antecedent decision) might have legal and ethical concerns and impacts the short or long term? This potential antecedent-impact-loop perspective opens interesting avenues for future research. They could relate to the impacts of the decisions on which AI strategy has been adopted in an organization, and/or how the technical and socially constructed AI investment decision antecedent limitations may (or may not) be directly (or indirectly) reflected on the contemporary use of AI and/or in the measured impacts of AI.

What seems interesting, is the contrast between AI performance in the industry and in academia. The AI developers have a need to justify the financial results either directly or indirectly when they were asked about the measurable impacts of AI. Yet they also mentioned a lot of intangible or indirectly measurable results. In literature however, the focus to a large extent has been focusing on the performance level of AI compared or in combination to human (Cohen, 2005; Dellermann et al., 2019; French, 2000; Hayes et al., 1995; Panda & Bhatia, 2018; Pennachin & Goertzel, 2007; Turing, 1950; Whitby, 1996). The AI developers, instead of comparing AI to humans emphasized that what they deal with is at most artificial narrow intelligence and often *explained* what AI can and cannot be used for in practice in the users' specific field (see chapters 4.1-4.1.3).

Especially in information system sciences, in some cases, the performance of AI alone already exceeds that of humans. This has happened mostly in games (Bard et al., 2020; Brown & Sandholm, 2019; Fortunato et al., 2017; Schrittwieser et al., 2020; Tian et al., 2019), but the superhuman performance of AI has started to grow interest also outside games e.g. in autonomous scientific discovery of materials (Gomes et al., 2019) or in improved efficiency, diagnosis and prognosis in medical tasks such as cardiovascular imaging (Siegersma et al., 2019). When the measurable impacts of AI were studied empirically, the performance compared to a human was sometimes present, but among these potentially pro-AI-innovation-based interviewees, the negative impacts of AI were never mentioned to be measured.

However, from previous studies we know that AI not only enhances employee productivity (Nauhaus et al., 2021); it may also harm employee productivity. Or what makes this challenging from the measuring point of view is that employee productivity has been found to both increase and decrease with AI as both effects have been found to co-exist (Tong, Jia, Luo, & Fang, 2021). We also know, that despite the massive investments in AI (Tricot, 2021; Zhang et al., 2021), their effect on the productivity statistics can be paradoxical (Brynjolfsson et al., 2017). Thus, the empirical impacts of AI and how they could or should be measured both theoretically and empirically deserve a wide variety of further investigation.

In addition to all the theoretical and managerial implication questions presented above, I want to highlight the need for and importance of adopting a process perspective in AI solution development initiatives in an organization. With my potential discovery on the different phases in AI development, and a need for a process perspective in measuring the empirical impacts in the future, I next introduce and discuss my *"plausible hunch"* (Van de Ven, 2016b, p 223). I present the initial proposal for the temporal process development framework for down-the-road theorizing: a proposed framework to be tested and developed further by future research.

5.1.7 Measuring maturing AI development

In this sub-chapter, I first summarize the findings and the early observations of the measuring typology findings from chapter 4.4. Based on the summary (see table 15), I then propose a first draft of potentially emerging AI development phases. These proposed initial phases are based on comparing the within case and between case findings on how the impacts of AI development have been measured in different organizations with different AI strategies (see chapters 3.2.3.4 and 4.2.1). Finally, based on the emerged AI development phases, I propose a temporal process development framework (see figure 25).

In this study's sub-research question four, I explored how five different types of organizations that already use AI, measure the AI-based performance already achieved in their organizations. By first using the Gioia methodology (Corley & Gioia, 2011; Gioia et al., 2013) to analyze the within case findings, temporal dimensions started to emerge. This became clearer when I compared the similarities and differences of the types of measures used in organizations with different AI-strategies. The aggregate levels that derived from the 2nd order measure themes with the help of temporal bracketing (Langley, 1999) are summarized in table 15. The details on how this table's temporal dimensions emerged from the data, and the more detailed findings and interviewee quotes about each case and comparison between findings of different cases, are explained in the per strategy findings section of this study in chapters 4.4 and its sub-chapters.

Table 14. Summary of the 2nd order themes, based on which the proposed AI development temporal process framework was formed.

AI strategy	Before start	AI project	Fine tuned business	User-centricity	Cumulative performance
Consultant	**Success enablers**	**Technical performance** **Enabling KPIs** **Value for business** **Value for user**			**Financial performance**
Product			Technical performance Client & investor value New business capabilities		Financial performance Competitive advantage
Robotics			**Technical performance** **Enabling KPIs**	**Human-centricity**	**Financial performance**
Key part	Business decision Developing enabling KPIs		Production measures	Double-user value	
Ingredient	**Problem feasibility**		**Core function improvement** **Enabling KPIs**	**Win-win**	**Financial performance**

I next explain how the temporal process development framework was formed based on the learnings on hybrid intelligence (Dellermann et al., 2019) and the empirical findings. I also introduce, what the temporal process development framework is, and how managers could use it in organizations, when they develop AI solutions.

In the study on the sub-research question 4 on the measurable impacts of AI, the interviewees rarely directly mentioned impacts related to hybrid intelligence (Dellermann et al., 2019), where humans and AI collaborate. This was even despite the previous literature, where increased performance is conceptually proposed with the help of hybrid intelligence. In hybrid intelligence, humans and AI complement one another's capabilities and learn from each other in an iterative manner. Over time, this leads to a cumulatively superior performance.

Even though this was rarely directly mentioned by the interviewees, the cumulative learning was indirectly visible, when the interviewees mentioned different measured results and impacts when they had already used AI. Thus, building on the mutual learning over time based on hybrid intelligence and on the within case and comparative findings between cases (see table 15), I propose a temporal process development framework for measuring AI (visualized in figure 25). Further studies are needed to test this initial and proposed grounded framework.

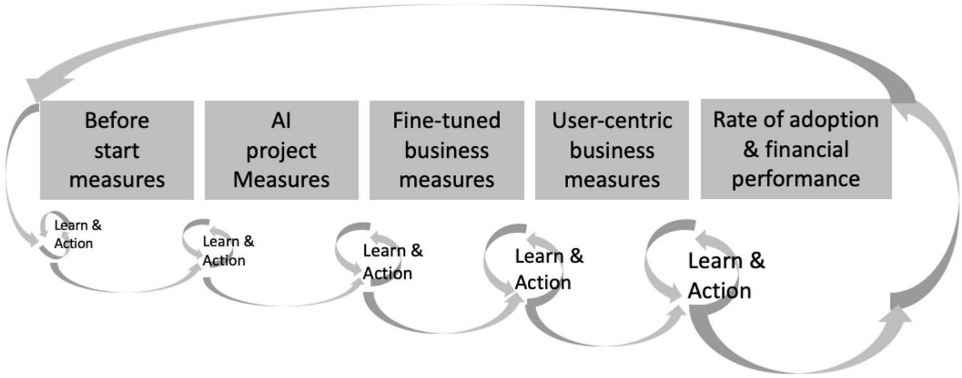

Figure 25. The proposed temporal process development framework for measuring AI.

The iterative measurement framework starts with the 'before start measures' to test the technical feasibility to solve the chosen business problem (AI use antecedents, see more in chapter 4.2.2 and its sub-chapters). This should be done before committing to an AI project, thus the first 'learn and action' gate is the kill or continue -decision. If the project is killed, some other project feasibility should be tested instead.

The second set of initial measures should be defined for the start of the AI project. These measures can be technical e.g. testing which model to use, and the outcomes of the use of each model should be evaluated against the predefined objective/quantifiable measures. Once this iteration is complete, the first or good enough first version of the AI solution can be launched e.g. for the test audience for feedback collection. At this point, the project team might typically hand-over the AI solution: the further development of the AI solution changes from consultants or from the project team to the business side. At this gate the most important 'learn and action' is to make sure that the domain expert learns how to collaborate with AI to develop it further against the enabling KPIs that react relatively fast, the 'fine-tuned business measures'. At this phase the first experiences and learnings of collaboration with AI and user feedback should be available to adjust the initial softer/intangible business measures or enabling KPIs to better fit the set organizational goals for the AI agent.

After this phase, the experience and skills of the human domain expert working with AI starts to grow. Hopefully this will free capacity and time resources to learn more about the AI-solution user reactions and make improvements based on them at this 'learn and action' gate. Measures can be adjusted again, away from technical skills required from the end user towards ease-of-use, pleasant user experience, and building user trust toward using the AI solution. Thus, while developing AI-solutions, it should always be remembered to keep human in the loop: not only to increase the implementation efficiency, but to carefully rethink and redesign human-centric processes, division of labor, and interactions between humans and the machines. Organizations and individuals also need to take responsibility of the trainings regarding the reskilling requirements when domain experts and organizations start to allocate more agency to machines.

The final fifth 'learn and action' gate focuses on reflecting on this whole cycle and defining possible new features, product or service needs to move again a step closer to the direct financial measure KPIs (key performance indicators). Consultant interviewee 14 explains this nicely: *"Also other measures such as UX (user experience) improves e.g., when measured by NPS (Net promoter score) or churn. We look at hard measures and softer meters that lead to harder KPIs. We talk about enabling KPIs that are visible faster, they can include customer engagement or products, services, or features such as number of algorithms in production. They become derived KPIs that serve the big goals of the company such as saving costs, building loyal clients, or that we want to increase cross-selling."* [I14].

In the next sub-section, I move to the contributions related to the final sub-research question, the sub-research question five.

5.1.8 Expected temporality re-organizing needs

With my fifth and final sub-research question, I asked: *when approaching time as an organizational resource, which temporal dimensions are expected to be influenced by AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation?* This question was not part of the original scope of this study; it was not even asked in the interviews. Including the temporal dimensions as a phenomenon to be part of this study is entirely based on a grounded (Glaser & Strauss, 1967) observation or a potential discovery among the interview data. When collecting and analyzing the empirical interview data, different temporal aspects started to repeat across the interviews. Thus, building on and staying faithful to the grounded data analysis approach that relies on emergence (Glaser, 1992; Glaser & Strauss, 1967) these temporal aspects could not be ignored.

In this study, I explored the multitude of different temporal aspects that emerged from the experiences of practitioners developing AI solutions in and across different industries. The interviewees either had already witnessed, or expected, or hoped for a wide variety of changes related to time and speed in organizations because of AI. I was curious to explore them more in detail to create a better managerial understanding of the expected impacts of AI: how the temporal dimensions might be changing because of AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation.

I analyzed the answers by the combined use of the Gioia methodology (Corley & Gioia, 2011; Gioia et al., 2013) and the integrated temporal framework (Ancona et al., 2001). Based on the findings four contributions are made. First by using the Gioa methodology, I identified 13 AI-related temporal dimensions (see chapter 4.5 and its sub-chapters for details). Secondly, by comparing the 13 temporal dimensions, I identified three core categories of temporal changes that have already been influenced by AI: organization time; organization and individual time; and human-centric time. Based on this analysis, thirdly I propose the following additions to the integrated temporal framework (Ancona et al., 2001): First, an additional conception of time (see chapter 4.5) called the 'cognitive time' that takes the natural human rhythm (e.g. in learning or doing work) into account. Second, an additional mapping of activities to time, called 'contextual mapping' for events that are highly contextual in nature (such as something happening in real-time or at the right/optimal time). Finally, for the whole organization as an actor an additional type of 'actors relating to time' seems warranted for 'strategic time and resource management', which relates to the potential (even disruptive or radical) changes in future work re-organizing and not only work time allocation but also task specific allocation between humans and machines [27]. (See chapter 4.5 and its sub-chapters for details.)

Out of the 13 emerged AI-related temporal dimensions, at least three speed-related temporal dimensions seem relevant in the context of dynamic capabilities (see chapter 5.3.2): faster, nearly real time and right or optimal time of action. Either independently or as a sub-category of dynamic capabilities could also be studied the temporal dimensions of 24/7 and sequential action through the lens of cognitive ergonomics (Kalakoski et al., 2019), and how AI could help humans to better follow their natural rhythm[28] for things such as sleep and work, if AI can handle or help

[27] *"Consider another example of hospital emergency departments. Sorting "high-risk" from "low-risk" patients is a difficult problem for such departments, and research has found that compared with human operators, machine learning can under some conditions predict faster and better the likelihood that patients who call in will experience cardiac arrest, simply based on the sound and tone of the voice (Blomberg, Folke, Ersboell, & Lippert, 2018). Yet, treatment includes choices about methods to jump-start the heart and whether or not to perform surgery. Such choices require experience and physicians' on-site judgment of the patient's condition. In this problematic situation, a "creative assemblage" (Orlikowski, 2007; Suchman, 2007) of team problem-solving and automated solution generation seem to offer the greatest benefits. However, understanding the nature of these assemblages and when and how AI augments task performance in such organizations may require the collection and analysis of rich data on the problematic situation, including how physicians collectively interpret, justify, and ultimately build "trust" in AI solutions."* (von Krogh, 2018, p 407).

[28] According to Ulmer (2017), slow ontology invokes time that is rooted in nature and thus *"inspires more natural rhythms for our spatial, temporal, and material localities"* and could provide a respite in the local spaces and places in which we as humans might be slow. *"But to get the full benefit from the Slow movement, we need to go further and rethink our approach to everything"* (Honoré, 2004, p. 17, see Ulmer, 2017).

with the tasks that need to be taken care of at night time, or when many tasks need to be executed simultaneously either in one's own job or on the organizational level.

Studying organizational learning (see chapter 5.3.4) together with the AI-related events that occur over time may be interesting. To better understand the positive, negative, and neutral effects that AI as an innovation might have to the competitiveness of an organization, further research is warranted on the action potentially taking place too fast, too slow or in human rhythm. Again, either as part of the innovation effects or as a potential sub-category of it, the AI-related effects of saving time from old things to new things may be interesting to study also from the perspective of work meaningfulness (Staaby et al., 2021). How might AI enable a person, on an individual or even on an organization level, to focus on the kind of work that s/he personally finds meaningful? And what ripple effects might that have on the work well-being on individual and organizational levels? How would that impact the work performance of the individual and the organization as a whole?

An additional new avenue for future research could relate to the further testing of the proposed three core categories of temporal changes that have been influenced by AI: the organization time; organization and individual time; and human-centric time. Future studies could focus on the work re-organizing needs related to all these three core category levels. The AI-related changes in temporal dimensions may influence the work descriptions and time allocation in an organization. It is possible, that the changes caused by AI in temporal dimensions can change time allocation and cause (even radical) work re-organizing and time re-allocation needs[29] already now or at least in the future once we start to experience the cumulative impacts of AI in organizations.

This research has implications both for managers and the academia by exploring the versatility of the ripple effects that AI solutions are already starting to have to the different temporal dimensions inside and outside the organization. This is another reason that makes this exploration interesting: these expected impacts in temporal dimensions might not be organization-specific, rather they might help scholars and especially managers to understand the weak signals that might be happening in the operating environment, or in the society at large. It is possible that one mechanism through which AI might start to affect all organizations, regardless of the adopted AI strategy, is time. Thus, it might be the first step toward also understanding those organizations, that have adopted a passive or a reactive AI strategy. Even though

[29] Researchers expect AI to affect workforce (Brynjolfsson & McAfee, 2012; Brynjolfsson & Mitchell, 2017; Ernst et al., 2019; Fleming, 2019; Forum, 2018; Frey & Osborne, 2017; Furman & Teodoridis, 2020; Johnson et al., 2021; Lundvall, 2017; Phan et al., 2017; Raisch & Krakowski, 2021; Susskind & Susskind, 2015; Wu & Kane, 2021).

they were excluded from this dissertation, they might nevertheless be in-/directly affected by AI. To answer the question "how" is left for future research to explore more in detail.

New interesting avenues for future research open also in the context of competitive advantage (Adner & Zemsky, 2006; J. Barney, 1991; Jenkins, 2010; T. C. Powell & Dent-Micallef, 1997; Sun & Tse, 2009; Walsh, Schubert, & Jones, 2010; Wiggins & Ruefli, 2002). For example, what happens to the clients' and employees' individual expectations and competitiveness as a firm with increasing use of AI? What might be the AI effects on the different temporal dimensions that have the biggest impact on an organization's competitiveness?

Previously, research attention has already been given to time and competitive advantage. Previous studies have studied how to reach sustainable or enduring competitive advantage (Adner & Zemsky, 2006; Drew, 1997; Greve, 2020; Liu, van Jaarsveld, Batt, & Frost, 2014; T. C. Powell & Dent-Micallef, 1997; Wiggins & Ruefli, 2002; Zeng & Glaister, 2016), competitive advantage on the short- and/or long term (Andriopoulos & Lewis, 2010; Choi & Wang, 2009; Franko, 1989; J. Y. Lee, MacMillan, & Choe, 2010; Lin, Oh, Liu, & Hsu, 2016; Roos & Roos, 1997; Shenhar, Dvir, Levy, & Maltz, 2001; Siggelkow & Levinthal, 2003; Sun & Tse, 2009; Vaidya, 1993; Yu, Minniti, & Nason, 2019), or over time (Barnett & McKendrick, 2004; Hajli, Shirazi, Tajvidi, & Huda, 2020; Klassen & Whybark, 1999; Swamidass, 1987; Wibbens, 2019; Wiggins & Ruefli, 2005; Zaheer & Mosakowski, 1997).

Related to both time and speed, researchers have been interested in contributions related to shortening (Sasaki, 1991), decreasing (Hatten & Hatten, 1997) or speeding (Pittaway, Robertson, Munir, Denyer, & Neely, 2004) time, being slow (Teece, 2000b), faster (Bhattacharya & Walton, 1998; Kapoor & Adner, 2012), or operating in a fast-moving environment or industry (Chatterjee, 2017; Chen, Katila, McDonald, & Eisenhardt, 2010; Cheng & Yiu, 2016; Hornbach, 1996; Newman & Chaharbaghi, 1996).

When taking a closer look at the temporal aspects of AI, organizations already use AI as a time-critical dynamic capability in real time decision-making related to marketing (Roberts et al., 2015), pricing (Davenport et al., 2020), and patent examination (Choudhury, Starr, et al., 2020). AI also serves as the (nearly real time) contextual intelligence in driverless cars or customer service (Davenport et al., 2020), just to give a few examples identified in the literature. Yet, research on the temporal aspects of AI seem to have been relatively scarce (Choudhury, Foroughi, & Larson, 2020; Ding et al., 2019; Farjoun, 2019). This is even despite temporal aspects of competitive advantage having been of interest to management and organization scholars. Further research could explore the relationship between the

13 temporal dimensions identified in this study and the competitiveness and/or competitive advantage of organizations more in detail.

In the context of AI as a managerial and organizational phenomenon, and AI potentially gaining increasing agency (Larson & DeChurch, 2020; Murray et al., 2021; Raisch & Krakowski, 2021), building on earlier research on goals, events and/or action that occur simultaneously (Holgersson, Granstrand, & Bogers, 2018; Kennedy, Whiteman, & van den Ende, 2017; Kyrgidou & Spyropoulou, 2013; Niesten & Jolink, 2020; Vassolo, Anand, & Folta, 2004; Y. Zhao, von Delft, Morgan-Thomas, & Buck, 2020) seems relevant both based on my empirical findings and previous research. Thus, the future studies in the context of AI could focus particularly on AI's effects on not only temporality but also on the competitiveness or competitive advantage or an organization, and the change requirements in organizing related to it.

Based on previous research, we know that new realities of the digital age are expected to have implications for corporate strategy related to corporate (competitive) advantage, firm scale, scope, and boundaries, and internal structure and design (Menz et al., 2021). Thus, I suggest further research building on strategic management (Akhtar et al., 2019; Tidhar & Eisenhardt, 2020; van Rijmenam et al., 2019) and on at least two of the temporal dimensions identified in this research: predicting the future and simultaneous action.

Additional interesting avenues for further research on the AI, temporality and competitiveness of an organization could be opened also by using the lenses of dynamic capabilities (Teece, 2007; Warner & Wäger, 2019), organizational learning (Greve, 2020; Levitt & March, 1988), and innovation effects (Furman & Teodoridis, 2020; Rogers, 2003). Future research could also take a more human-centric approach like the one of job crafting and work meaningfulness (Staaby et al., 2021), or cognitive ergonomics (Kalakoski et al., 2019) of the employee. These could be studied as strategy options when the employers compete for the best employees now and in the future.

Similarly further testing related to AI and competitive advantage is required for impacts of the proposed additions to the integrated temporal framework (Ancona et al., 2001), which I propose to be the 1) cognitive time, 2) contextual mapping for events, and 3) for the whole organization as an actor relating to time through 'strategic time and resource management'. In the context of competitive advantage, either quantitative research or mixed methods could be interesting and relevant ways to test these proposed core categories of temporal change further as additions to the integrated temporal framework.

Maybe related to competitive advantage, but from another perspective, future studies could focus on what are the impacts and inter-relations between user expectations and the AI-development to organization's performance or even competitive advantage over time. More holistically, it would be interesting to investigate further whether the level of integration and/or maturity of AI development in organization time; organization and individual time; and/or human-centric time effect competitiveness or competitive advantage in an industry-specific context.

When building on previous research and especially the human-centric time, the focus might partly be turning from pure productivity enhancement to reordering of value creation and appropriation by human effort and the nature of work itself (Phan et al., 2017). Thus, the interlink between perceived value creation with AI in and out of work context seems to deserve further research attention (see more in chapter 5.3.5). Now we only know that the perceived value may consist of a combination of data network effects and direct network effects (Gregory et al., 2021), but how might the ‘save time from’ translate to ‘save time to’ when an increasing amount of AI solutions or AI agents are taken into use?

Other than competitive advantage, the temporal dimensions could be studied further with the empirical focus on implications to work organizing and compare the findings to the conceptually found and proposed 12 leadership implications of AI (Larson & DeChurch, 2020), and/or in relation to the types of conjoined agency on the adopted technology (Murray et al., 2021). Also empirical research could study (with the more detailed temporal dimensions found in this study), how augmentation and automation might be interdependent across time and space (Raisch & Krakowski, 2021).

In the next sub-section, I move to the contributions related to the main research problem of this doctoral dissertation and discuss the learnings of each sub-research question in relation to the main research problem.

5.1.9 Complexity of AI-based value creation

The main research problem of this doctoral dissertation asked: *what makes artificial intelligence -based value creation challenging from the management and organization perspective?*

In this sub-chapter, I intend to tie together all the learnings from each of the five sub-research questions from the main research problem’s perspective. By combining the main findings of each study, I propose an initial process model that may start to explain why AI-based value creation might be challenging from the management and organization perspective (see figure 26).

The first study related to sub-research question one asked (phase 0 in figure 26): how is artificial intelligence defined in the management and organization literature and in multiple-industry settings? As this definition seems to have variation both in the literature and in the industry side, AI is always to be clearly defined: what is meant by AI whether it being in a scholarly outlet or in a specific organization on the industry side (see chapters 2.1, 4.1, and 5.1.2).

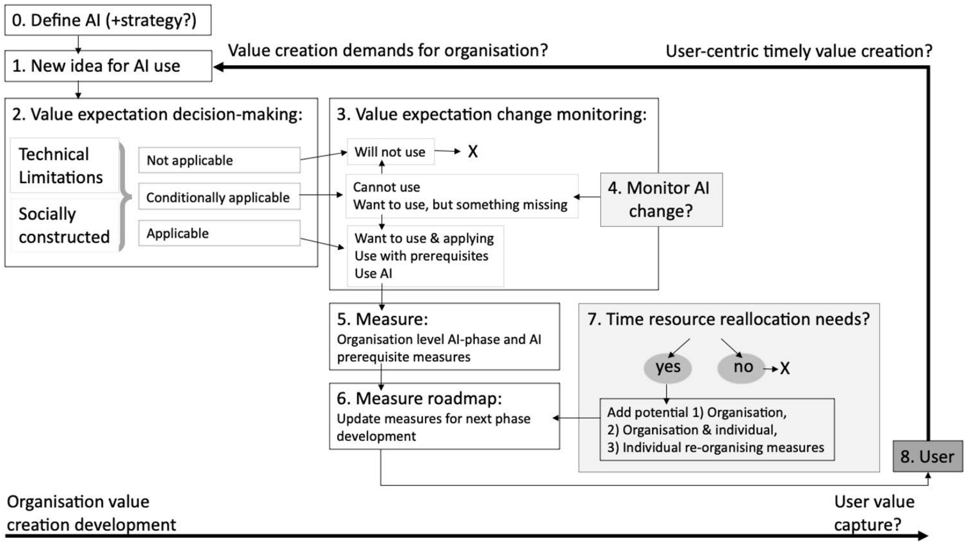

Figure 26. An initial process model to explain why AI-based value creation might be challenging from the management and organization perspective.

Depending on the AI maturity of the organization, an organization may or may not already have an AI strategy (see chapters 3.2.3.4 and 4.2.1) defined. Ideally, the AI strategy supports the core mission or core business of the organization, and/or solves a business-critical problem. Further studies could focus on how an explicitly defined AI strategy can be aligned to the business or core function of an organization, and whether this leads to better business outcomes[30].

Figure 26 proposes that the clearly pre-defined AI definition and the potential AI strategy may guide the ideation of how AI could be used within the organization (phase 1 in figure 26). The idea can come from within or outside the organization. The benefit of the ideas coming from within the organization might be the domain expertise, especially if that is combined to enough technical understanding on what is or is not realistic to be expected from an AI solution, or an AI agent. If the idea comes from outside the organization, it may come through other people such as sales consultants or media giving the idea where AI might bring value (see more in chapter 5.3.5), were it to be given agency within the organization. In any case, *"a better*

[30] Compare the results to the findings on strategic alignment of IT and business strategies (Park & Mithas, 2020; Peppard & Ward, 2004; Ravichandran, 2018).

understanding of the precise applicability of each type of ML and its implications for specific tasks is critical for understanding its likely economic impact." (Brynjolfsson & Mitchell, 2017, p 1534).

Thus, the second sub-research question asked: *how are the managerial decisions formed on whether to invest in AI-based technology development?* The findings suggest that there are both technical and socially constructed limitation criteria that may impact whether AI is not applicable, conditionally applicable, or applicable (see chapters 4.2.2 and 5.1.4) in a specific industry and its intended use purpose context (phase 2 in figure 26). The findings of this second empirical study also influenced the setting for the third sub-research question that asked: *Why might the actual and wanted use of AI differ?*

This relationship also opens an interesting dialogue between the antecedents and actual use of AI (phase 3 in figure 26). In the antecedent phase, AI might not be applicable and thus not be invested in if one or some of the critical technical or socially constructed limitations are not met. In the use phase (see chapters 2.4.2, 4.3. and 5.1.5) the not applicable cases are those, where the AI developers do not want to use AI even if it was technically possible to do so. Conditionally applicable cases are those, where AI cannot technically be used, because the use case simply does not fit or match with the contemporary technical capabilities of AI. Similarly, conditionally applicable AI use might include the cases to which the AI developers themselves would want to use AI, but they cannot. This can be because something is still missing such as the business logic for developing the solution into a product or service, or because e.g. company policies prevent the use of an existing AI solution. However, in these conditionally applicable cases, someone in the organization might want to monitor whether the AI solutions meet the organizational needs in the future (phase 4 in figure 26).

When an idea for AI use first passes the technical and socially constructed antecedent decision-making phase, the AI use can be divided into three categories: 1) want to use AI and the AI solution is already being developed, 2) AI can be used with pre-requisites, or 3) AI solution is already launched and in daily use. Out of these three types of cases, where AI is already taken into use, it is likely that organizations need to implement different kinds of measures (phase 5 in figure 26).

In the fourth sub-research question I asked: *How are the impacts of AI-based technology development investments measured?* Based on those early findings (see chapters 4.4, 5.1.6 and 5.1.7), it seems possible that the set measures for AI development might be different depending on the chosen AI strategy (see chapters 3.2.3.4, 4.2.1 and 5.1.3) or the AI development maturity phase of the organization. However, future research might explore more whether some new AI-specific measures should also be put in place for different parts of the whole AI development process: starting from the AI antecedent decision-making criteria, follow-up measures for those decisions in the actual AI use development portfolio management phase, and both their alignment to the measurable implementation effects. And all these process measuring chains might be project specific, or similarities between projects might be found in future studies.

As it seems that AI solutions are not typical IT solutions, where you buy the plug-and-play-kind of solution rather someone continuously needs to work to develop the AI agent(s) to stay up to date in the organization-specific context, it might be beneficial for organizations to define measurement roadmaps (phase 6 in figure 26). This might need to be an iterative and living collection of measurements, where relevant multi-disciplinary experts define: the goals for the next iteration development for a better performing AI agent, and how should the measures be re-defined towards the defined goals in the AI solution development. In future studies it could be interesting to explore how this affects the power structures within an organization, as control might be moving from top-down to all experts of the organization who work with AI, and the success might depend on their ability to collaborate seamlessly across organizational silos and/or in multidisciplinary teams.

Thus, in addition to only measuring the AI solution development, it seems that measures should be set also for the changes in the organizational processes in relation to a specific or whole AI agent portfolio management, because achieving significant performance gains requires rethinking of how the business can be redesigned to take advantage of new technologies: *"Creativity and organizational redesign are crucial to investments in digital technologies. This means that the best way to use new technologies is usually not to make a literal substitution of a machine for each human worker, but to restructure the process… Compared to simply automating existing tasks, this kind of organizational co-invention requires more creativity on the part of the entrepreneurs, managers, and workers, and for that reason it tends to take time to implement the changes after the initial invention of and introduction of new technologies. But once the changes are in place, they generate the lion's share of productivity improvements."* (Brynjolfsson & McAfee, 2014, p 138).

Also based on the empirical interviews, it is possible that even a small task agency change from humans to AI may cause multi-disciplinary changes in multiple organizational silos. Thus, with the illustration in figure 26, I propose one way, how organizational process change management, and its measuring could potentially be implemented into an organization. Based on the findings of the fifth sub-research question of this study on the expected (cumulative) AI impacts (see chapters 2.4.4, 4.5 and 5.1.8), I propose including the time resource reallocation needs as part of the measuring roadmap (see phase 7 in figure 26). This is because as part of the measuring roadmap it might be beneficial to re-evaluate the potential time resource reallocation needs as part of each AI solution development iteration round. If no time resource reallocation needs are identified, then they have no effect on the measure roadmap development. However, if the answer is yes, the answers to the sub-research question five might need to be taken into consideration. As the fifth sub-research question of this study, I asked: *when approaching time as an organizational resource, which temporal dimensions are expected to be influenced by AI, and thus might have to be taken into consideration in future work re-organizing and work time allocation?*

Three aggregate level dimensions were found, on which AI might already cause temporal changes and potentially also require evaluation of changes in time resource reallocation needs. These three dimensions are on 1) organization level, 2) on the intersection of the organization and the individuals working within the organization, and 3) individual human-centric time management and personal time allocation levels. Future studies are needed to explore the potential time resource reallocation needs as well as the impacts of time resource reallocation, and how might all this need to be considered in the organization-level measuring.

Finally, all the above should somehow focus on the end-user (phase 8 in figure 26), whether it being the internal customer and end user of the developed AI solution or the customer of the core business or core function of the organization. As part of the sub-research question five, also potential temporal changes in the expectation of the clients were identified such as delivering products or services on demand in (nearly) real time, or getting a diagnosis faster, or at the right or optimal time. Thus, it is possible that at least some industries and organizations might be in transition towards more user-centric and timely value creation (see more in chapter 5.3.5) demands and/or expectations. If this is the case, organizations might face new value creation demands from the operating environment outside the organization. All this is still speculation, for future studies are needed to either verify or prove these initial observations and guesses at least partly right or wrong.

With the help of the figure 26, I suggest future studies on whether through all this development 1) there is potential to create more user-centric and timely value, and/or 2) a potential for value capture from the user (see more in chapter 5.3.5). Yet, even if all the above was theoretically understood, one key aspect remains to be studied: who are the people in this process? Who are the people, who generate the most valuable ideas for AI use within the organization? Do the ideas ever reach a manager with the budget and decision-making power? If yes, can this person evaluate the realistic value creation potential of the suggested AI use idea? What and who are required to develop the idea into a working solution?

Based on the analysis of this study, I am not able to say who else the AI use ideas might come from except the AI solution developers, potentially working inhouse or as external service providers to sell AI projects, products, or services (see phase 1 in figure 27). Future studies could explore who generates AI use ideas for an organization. How is the idea development process? Who are the people in the process from the person who generates the AI use idea to the decision-maker? Who decides whether to invest in the AI use idea development or not?

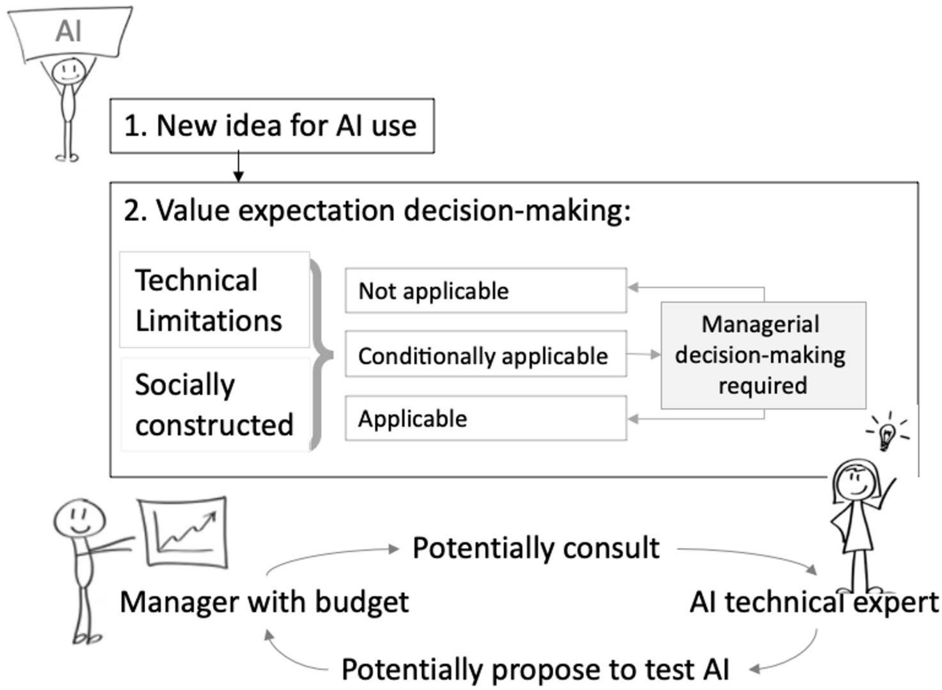

Figure 27. A first draft for further research on who might be the people (needed for) creating AI-based value in an organization.

An early observation based on the findings of this study is that the managers with budgets and AI initiative investment decision-making power might consult technical experts on AI (see phase 2 in figure 27). Many of the empirical interviewees implied that because of AI, they as technical experts have had to start teaching CEOs and business managers, lawyers, and other domain experts about AI on a general level as part of their job. It is possible that if managers do not understand even the basics of AI as a general purpose technology, and are afraid to consult those who do, they cannot organize the people and business to create value with the help of AI-based technologies. Further studies are required to analyze this phenomenon and its potential impacts more in detail. Yet, based on the study on sub-research question two, one can observe that even for the technical experts the expected value of AI is hard to evaluate because of multiple (technical) uncertainties. Thus, the technical experts might propose to test AI suitability with the data and resources and organizational pipeline structures available in the organization.

When moving further than phase two in the figure 26, nothing can be said of the people in the proposed AI development process because other than AI developers with both technical and industry expertise were not included in the empirical scope of this dissertation. However, as many of my interviewees called for a multi-disciplinary collaboration when developing AI solutions, future research on all the people participating in the AI development process is warranted.

So, what might it be that makes AI -based value creation challenging from the management and organization perspective? We do not know who are all the people needed for multi-disciplinary collaboration to create the AI-based value. We do not even exactly know, what is the value of AI (see more in chapter 5.3.5), for what, who, and why. Also, at least based on this study, we do not know what the challenges of the required multi-disciplinary collaboration might be. We also do not know how the processes in an organization (need to) change because of AI. But based on this study, we do know early findings on the types of technical and socially constructed decision-making criteria that may affect the decision-making on the AI antecedent phase. However, future research and scholarly attention is required to study how these proposed decision-making criteria affect the AI investment decision-making as individual criteria and as different combinations of decision-making criteria. Thus, it seems that with the current maturity of AI-related research, a lot of uncertainty remains on how the AI investment decisions are made, and how could they be made to generate or capture value (see more in chapter 5.3.5).

As from the AI use perspective, the early findings of this study identified six types of AI use. In one of them, AI might not be used even when it would bring significant monetary value if the use of AI in a specific use case causes ethical concerns. Thus, the value creation of AI might be contradictory to some extent. Based on the findings in sub-research question four, we know that even if an AI solution is developed and we measure the impacts of the AI solutions developed, many measures related to AI value creation development might be required before measurable financial performance is visible.

From the fifth and final sub-research question perspective, we also notice that there might be uncertainty about the user expectations that change in relation to temporal aspects in the operating environment of an organization. Some solutions might have to be developed because the competitors already use AI and have already set a new standard for the industry's clients, how long can something take. This might increase the pressure for the organization to develop AI solutions just to keep up with the competitors. Yet, in this situation it might be hard to capture the value of the required investment. Further studies are required to understand the AI investment need -related details and their relation to value creation and value capture (see more in chapter 5.3.5).

Even though this study is not able to answer how to overcome the challenges of AI-based value creation, I believe that this study can serve as a valuable start for AI-based value creation discoveries from the management and organization perspective. This study has collected qualitative data on situations where decision-making authority is starting to be delegated to AI in different industries. I have explored the antecedents, AI use, AI impacts and expected cumulative impacts (see chapters 4.2-4.5) of AI to better understand the AI-related decision-making and artificial agent development toward value creation (see more in chapter 5.3.5). The focus has been set on situations, where people and organizations have already started to delegate, or not delegate, decision-making authority to machines. This continues the work of von Krogh (2018, p 406), who explains that through researchers describing the features of these situations of AI use in terms of task input and task processes *"we can gain deeper understanding of the constraints on AI authority across the organization"*.

In this study, I have explored the fundaments of developing artificial agents and the first steps of revealing the decision-making, management and organizing processes required for AI-based value creation. My focus has been to offer tentative explanations of the emergence and interaction of human and machine authority regimes in organizations (von Krogh, 2018) from the AI solution developer perspective. Future studies need to focus on other perspectives of this human and AI-applying machine collaboration in the future.

5.2 Limitations of this study

In this chapter I discuss the limitations of this doctoral dissertation. I start by limitations related to the chosen mode of reasoning and the criteria on making abductive discoveries. Then, I move on to overview the limitations of the chosen phenomenon-driven research strategy as a theoretical framing and the empirical data collection.

5.2.1 About the mode of reasoning and discoveries

From the perspective of those, who are quantitative or positivist researchers, the main limitation of this doctoral dissertation is that my phenomenon-driven doctoral dissertation represents neither. I even shifted from the originally inductive research towards abductive research in the analysis phase.

According to Bamberger (2018, p 3), compared to induction and deduction, *"abductive reasoning is the weakest form of reasoning of the three, allowing the researcher to emerge with only a plausible conjecture and some insights into what this conjecture might mean for the development of new or alternative conceptual frameworks (Shapira, 2011) and down-the-road theorizing. Although abduction* *offers a logic for considering conjectures about complex phenomena, it does not produce simple or clear answers".*

Table 15. Differences between deduction, induction, and abduction in (Bamberger, 2018, p 2).

TABLE 1
Differences between Deduction, Induction, and Abduction

	Deductive Reasoning	Inductive Reasoning	Abductive Reasoning
Objective	- To demonstrate that if premises are true, it is impossible for the conclusion to be false - To demonstrate the situational validity of a generalizable rule or claim	- To generate a knowledge claim where "it is improbable that the conclusion is false if the premises are true" (Hurley, 2000) - To demonstrate the probable generalizability of a situational reality	- To generate plausible, conjecturable explanations - Discovery
Strength of knowledge claim	Strongest (certain)	Strong (probable)	Weak (plausible)
Role of theory	Provides *a priori* explanations (hypotheses) to be challenged empirically	Provides a guiding framework and systematic approach to generate a generalizable explanation from the data	Provides assumptions to be challenged and frames anomalies to be explored and suggests the variables on which to sample
How data are used	- To disconfirm the null - To disconfirm alternatives	To confirm a generalizable outcome when premises are met	- To describe phenomena - To elicit tentative claims - To narrow range of possible explanations
Type of reasoning and how used	Necessary reasoning Used to test falsifiability of presumed means-ends linkages	Probabilistic reasoning Used to demonstrate generalizable means-ends linkages or processes	Contrastive reasoning Used to identify patterns indicative of alternative dynamics, processes, mechanisms, or means-ends linkages

Primary sources: Campos (2011), Folger and Stein (2017), Okhuysen and Behfar (2017).

Looking at table 16, deductive reasoning could not have been applied as no hypothesis could be formed upfront based on the literature on AI as a managerial and organizational phenomenon. This is because that literature was, and still is, only emerging. Yet, the definition, of whether this study is inductive or abductive is debatable. I started off with inductive reasoning, but when reading more about the phenomenon-based and phenomenon-driven research, I learned more about abductive contributions, down-the-road theorizing and making discoveries. Thus, I think this doctoral dissertation is not fully inductive anymore, but it is not fully abductive either, as I am still looking for the plausible theory what might explain the synthesis of AI as a managerial and organizational phenomenon (see table 15 for further details on the comparisons between deductive, inductive and abductive reasoning).

I think there is also variation between the studies on different sub-research questions. When chosen to do so, sub-research question one on defining AI could have been the closest to the deductive reasoning. This is because previous literature on AI definitions would have been possible to have been formed into a hypothesis on the complexity of AI definitions (however, mostly from outside management and organization).

Sub-research questions two, three and five are most likely closest to inductive reasoning as they provide a systematic approach to generate a generalizable explanation from the data. The biggest abductive leaps might occur in relation to sub-research question four, where I propose a temporal process development framework (see chapter 5.1.7).

However, in their current state, all the empirical studies in the five sub-research questions' findings are grounded in the data and have iteratively been formed when engaging with wide variety of theoretical discussions. This follows the advice from von Krogh (2020, p 161): *"Although the search for social facts can be broad or deep, it makes sense to start broadly. Searching broadly and comparing instances across measures and categories may reveal novel, unanticipated connections and effects...This strategy cannot confirm or disconfirm a theory or even inductively develop it but instead aims to uncover (unreasoned) facts that point to novel questions (what are these data telling me about a phenomenon?) and limits to existing theory and show whether or not it would be beneficial to conduct further study."*

Up until now I have read broadly, and the depth of the grounded studies of each sub-research question have only narrowed the range of possible explanations (Bamberger, 2018). Thus, based on that definition this whole study is abductive, and based on Bamberger (2018, p 3), my proposed contributions could be considered as down-the-road theorizing or pre-theory: *"But for the most part, abductive reasoning is applied in the context of pre-theoretical inquiry, when—whether by chance or intention—we confront new, puzzling facts which cannot be easily typed into some existing category nor parsimoniously explained on the basis of extant theory. As noted by Dunne and Dougherty (2016: 135), 'scientists cannot confirm hypotheses deductively when knowledge is limited and fragmented, because experiments will likely fail and the results provide no indication of where else to explore.' It is in such situations that we enter the realm of empirical exploration, digging deep into patterns embedded in our data to generate the tentative and fallible conjectures that may eventually lay the groundwork for innovative theorizing and subsequent hypothesis testing. Abductive reasoning in management research, although perhaps rare, is by no means absent. Indeed, much of the research aimed at generating grounded theory (Glaser & Strauss, 1967), although typically framed as inductive, is in fact often driven by abductive reasoning. This is because those engaging in grounded research often work as scholarly detectives, unbounded by the constraints of extant theory (Czarniawska, 1999). Starting with a question for which extant theory offers an inadequate explanation, they 'follow the trail of evidence,' narrowing the range of alternative explanations until they can offer a plausible, data-grounded conjecture (Weick, 2005)."*

So, what about the synthesis of this doctoral dissertation? Have I made any abductive discoveries as my contributions? Do my findings expand or push against established paradigms (Tucci et al., 2019)?

As my main research problem, I asked: *what makes artificial intelligence -based value creation challenging from the management and organization perspective?* I look at the AI-based and human-centred value creation as a managerial and organizational phenomenon. Is the human-technology collaboration new? No. Is the implementation of a new technology new? No. Is the resourcing and division of labour or work tasks between people and machines new? No. Is the need of innovation or change management new? No. Is the multi-disciplinary collaboration within an organisation across organizational silos and/or with external service providers new? No. But what might be new is that all the above need to be co-ordinated simultaneously, and the machines with increasing agency cannot correct the mistakes unless it is taught to do so and given the authority to do so. Also, with the promise of AI being able to do some single tasks better than any human ever could, this performance might enable competitive advantage for some. Yet, to enable even a small one task by AI, all the above needs to change. Thus, the first change to use AI is likely to be slow and difficult, but if an organization is already used to using AI and has all the necessary technical and human skills and competencies, and all the processes in place the change is incremental, not disruptive. However, to transform all my phenomenon-driven findings and observations into a theoretical discovery is still a long road ahead for which I will need the help of reviewers and editors, because *"(d)iscovery requires bold conceptual leaps. It can be hard to abstract up from the empirical phenomenon to unpack its implications for future theorizing"* (Tucci et al., 2019, p 214).

Only through the interactive scholarly dialogue with journals, such as Academy of Management Discoveries, I will ultimately know whether I have surfaced significant new or emerging phenomena, or identified and explored surprising relationships, or offered empirically driven insights into and/or a plausible resolution of critical anomalies and discrepant findings (Tucci et al., 2019). My current understanding is that this dissertation and all its empirical studies, when combined, best fit to offering empirically driven insights into critical anomalies and discrepant findings. Through the interplay between previous research and empirical phenomenon-driven research, my contributions provide new qualitative insights. They enable a step toward theoretically explaining the AI productivity paradox and its complexity from the managerial and organizational perspectives.

But to qualify as a discovery, I still need to gather new qualitative data. This is to verify whether I have in fact made a discovery, because for that it is required to collect data at multiple points in time, collect different kinds of data, make continuous comparisons between data, hunches, and evidence, and to use a process of elimination to rule out alternative explanations and narrow down the range of plausible explanation (Tucci et al., 2019).

Next, I move on to the other limitations of this study related to the research design, empirical data, and theory building choices made in this dissertation.

5.2.2 About theory and empirical data collection

Some of the most noteworthy empirical limitations of this doctoral dissertation is that all the empirical data is based in the Nordic country context, or more specifically in the cultural context of Finnish values. In other cultural contexts, the decision-making categories related to AI might or might not be the same, but it is likely that at least some of the values driving the managerial decision-making may be different e.g. in the context of ethical concerns. Thus, future research could and should be extended e.g. to the different cultural contexts of AI superpowers such as the United States of America and/or China, and could be compared against those of this empirical data from the high-technology applying Nordic country context. Yet, as empirical studies on the impacts of AI from the management and organization perspective have been scarce overall, this study not only offers initial down-the-road theory as a potentially valuable contribution for others to build on but also diversifies this emerging body of literature by offering a chance for comparative studies to other cultural contexts.

Another key limitation throughout this dissertation relates to the chosen scope of the interviewees for this study: the findings of this study are limited only to the people in AI-based solution development role. The interviewees were chosen to be single representatives from a specific organization. Future studies are needed to extend the empirical scope to other experts, preferably to whole multi-disciplinary teams that work around or with AI in an organization.

Thirdly future studies could develop the explored and proposed typologies further and study AI development and maintenance of artificial agent portfolios in an organization from a process perspective, or to produce specific propositions (Cornelissen, 2017) for down-the-road theorizing. That is likely to reveal interesting new insights related to AI as a managerial and organizational phenomenon as well as to bring deeper insights into AI-based value creation, value transformation and value capture (Bowman & Ambrosini, 2000) of an organization, or how value can be captured at different levels of analysis related to both use value and value exchange (Lepak et al., 2007).

I summarize some of the main limitations for the literature review and per sub-research question shortly here below. More specific limitation and identified avenues for future research are discussed in each of the contributions and implications sub-chapters (see chapters 5.1.1-5.1.9).

The main limitation of the literature review and the theory section of this dissertation is that it is limited to the premium outlets in general management and organizational studies up until the end of 2021. Future studies should extend the literature review to the outlets on strategic management and lower ranked journals, or maybe even consider conducting cross-disciplinary literature reviews including for example the outlets in the information system sciences. There is also a constant need for updates as AI-related papers have started to emerge at an increasing pace in the past few years.

The limitations of the first sub-research question on the definition of AI are along the same lines as the limitations related to the literature review stated above. Future studies could analyze deeper the AI-related definitions with a wider variety or search terms than just artificial intelligence and machine learning. Depending on the focus of the future studies the scope of AI definitions could include words related to automation and/or augmentation, even robotics, or specific algorithms and their names to widen the understanding of the whole scope of AI impacts. Additionally, the empirical differences in the AI definitions could be analyzed further for example by chosen AI strategy, or per country, or per industry, and compare the differences to create a deeper conversation between theory and industry practices related to AI.

The contributions on the identified AI strategy types are limited with only few interviewees per AI strategy (see chapters 3.2.3.4 and 3.4). Thus, now that the proposed AI strategies have been identified, future studies should expand and test the proposed AI strategies. Some AI strategies are at least likely to be missing. Already during the analysis phase of this study some AI strategies were identified and excluded from the scope of this dissertation. Out of the empirical scope are at least the organizations with no or reactive AI strategy, and AI keynote speakers or influencers. They were excluded from the analysis in relation to sub-research questions 2-4 where the analysis was conducted per AI strategy (see chapters 3.2.2.1, 3.2.3.1, 3.2.3.4 and 3.4). Especially during the analysis of sub-research question 4, it seemed that the AI development phases might form an additional or an alternative casing opportunity to the chosen casing per AI strategy. Thus, future studies might focus the casing per AI development phase, or both per AI strategy and the different development phases and then compare their differences within an AI strategy and compared to other AI strategies.

The main strength of the sub-research question two on the decision-making criteria on whether to invest in developing an AI solution is that I propose the different types of limitation criteria for AI investments. However, future studies should focus on testing and identifying potential other missing key decision-making criteria, and on understanding the multitude and complexity of the different combinations of these decision-making criteria. It could be explored further how the managers take them into consideration before deciding whether to invest in AI in a specific context or not.

The findings of the sub-research question three expand the understanding of sub-research question two, and the multitude of AI investment decision-making criteria. Future studies could test the proposed six categories on organization-level AI initiative development and maintenance portfolio management. Additionally, it would be interesting to know, what additional AI use categories might have been identified in organizations that are applying AI. What sub-categories might they have for the artificial agent portfolio management and based on what grounds? What different processes might they have implemented related to different types of AI use within the organization and why?

In sub-research question four, the main limitation is the focus on the chosen analysis per AI strategy. Firstly because of the only one individual from each organization, and secondly because of the small number of representatives from organizations who have adopted each of the AI strategies. Thirdly, based on the analysis and findings, it seems that future studies are warranted on what development phases might emerge from the empirical interviews. It might be interesting to study how the measurable AI-results differ between adopted AI strategies and different AI development maturity phases. In future studies with more interviewees, it might also be interesting to dive even deeper into the analysis and focus on the measurable results achieved in both a specific AI development phase and with a specific AI strategy adopted, and then compare these findings between the different AI strategies and/or their AI development phases.

In the study of sub-research question five, the main limitation relates to the boundaries of what might be the expected (cumulative) impacts on temporal dimensions that relate to AI alone versus e.g. to digitalization, or other changes in the society, or in the operating environment as a whole. Maybe also methodologically collaboration e.g. with the futures studies could make the research related to the expected future more rigorous.

Finally, the main limitation of the main research problem of this study relates to identifying the people as actors in developing AI-based value. Who does what and why? How might the multi-disciplinary collaboration and organizing in an organization change when AI solutions are being implemented in it? And the most striking limitation relates to AI as a managerial and organizational phenomenon: what is this whole study a case of? Which theoretical discussion(s) or streams of literature are contributed to (other than the literature on artificial intelligence and machine learning that serve as the main theoretical framing of this study)? I discuss different aspects of this limitation in relation to future studies in the next section.

5.3 What could AI be a future case of?

As typical to exploratory abduction, first the researcher is confronted with puzzling facts, but unable to cleanly apply a theory or theoretical perspective to readily explain them (Bamberger, 2018). My puzzling fact was the seeming contradiction between the massive investments in AI (Tricot, 2021; Zhang et al., 2022, 2021) versus the understanding what is AI (see chapters 2.1 and 4.1). Later I observed that AI further embodies a productivity paradox (Brynjolfsson et al., 2017). This was even despite AI starting to outperform people mostly in game settings (Bard et al., 2020; Brown & Sandholm, 2019; Fortunato et al., 2017; Schrittwieser et al., 2020; Tian et al., 2019), though AI has outperformed people also outside games (Knobbe et al., 2022) in a single task with robots. So, despite the monetary investments in AI and technical AI performance these efforts somehow did not seem to translate into productivity and added value on the bottom line. I was curious to explore why: what is it about AI that makes value creation based on it challenging from the management and organization perspective?

In exploratory abduction the pattern of results is used to *"conceive a plausible explanation, or at least identify the criteria that an explanation would have to meet to be plausible. Engaging in exploratory abduction, the researcher must herself conceive the general rule and use the pattern of findings to argue for its plausibility."* (Bamberger, 2018, p 3.) When it comes to AI as a phenomenon, I think I have succeeded in this. Within four AI use phases from AI use antecedents to anticipated cumulative impacts of AI, I have identified one specific point in each to identify and propose 1) the criteria for AI investment decision-making (antecedent), 2) the categorization for AI portfolio management (use), 3) the categorization of AI measures and how the measures of AI-based solution development might evolve over time (impacts), and 4) how cumulative impacts of AI are expected to change requirements and resource allocation needs related to temporal dimensions such as time, timing, and speed on different levels within an organization. For the latter, I even started to form a contextual understanding of both the supply and demand side of the reasons why. However, from the management and organization theory perspective, my exploratory abduction in relation to identifying patterns of results in relation to a specific management and organization theory is still a limitation in this study that calls for further research.

Since the beginning of this doctoral dissertation research journey, I have been asked by management and organization scholars who are not familiar with AI, what is this a case of. Thus in the following, I move toward a plausible conjecture. It involves contrastive reasoning: comparing what I have observed to what would have been expected to be found if other than AI-related theory had been applied (Bamberger, 2018). To do so, I compare my findings with five theories in management and organization in attempt to anchor AI as a phenomenon to 1) resource-based view, 2) dynamic capabilities, 3) sociomateriality, 4) organizational learning, and 5) value creation and value capture. This is to help me in attempt to contrast and narrow the range of plausible explanations for my grounded observations and for down-the-road theorizing (Bamberger, 2018).

I next discuss to which direction the findings of this phenomenon-driven research could be taken further in future studies in the field of management and organization. I start with resource-based view.

5.3.1 Resource-based view

Resource-based view (RBV) focuses on the firm level as the unit of analysis and explores the resources and resource positions, rather than the products of a firm, over time (Wernerfelt, 1984). From this perspective, AI seems to at least partly fit RBV in this dissertation. The different resource strategies of the firm may be related to diversification, resource positioning or their barriers, balancing between exploitation and exploration, and acquisitions. In this study, the focus is set maybe more on exploring than exploiting AI at this early phase of AI development.

AI skills and competencies can be either developed inhouse (Product, Robotics, Key part AI strategies) or acquired e.g. though consultancies (Consultancy or Ingredient AI strategies). Resources that are tied semi permanently to the firm may be tangible or intangible. Resources include, but are not limited to, brand names, in-house knowledge, contracts, machinery, procedures and capital (Wernerfelt, 1984), or resources may be physical, human, organizational and used to implement value-creating strategies (Eisenhardt & Martin, 2000). It seems that despite AI consisting of various technologies and physical machines, it also requires the human and organizational resources to be able to implement AI as part of the organization's value creating strategy. However, the brand might also impact the choices related to AI use: *"In the context of [Organization name], a peculiar problem is that despite us generally being open about everything that we do, all these themes related to AI are really sensitive at the moment because the brand is wanted to be kept very humane and human-centric" [I3, Product].*

The key question in RBV is *"under what circumstances will a resource lead to high returns over longer periods of time?"* (Wernerfelt, 1984, p. 172). However, resource portfolios should be managed and evaluated both in the short and long term (Wernerfelt, 1984), but not all resources need to be in-house. Interfirm resources and routines may also influence performance and competitive advantage depending on relation-specific assets, knowledge sharing routines, complementary resources or capabilities, and effective governance (Dyer & Singh, 1998). Knowledge sharing may include information or know-how; out of which know-how is harder to imitate and transfer. Thus, know-how may be more likely to result in advantages that are sustainable: *"As a result, alliance partners that are particularly effective at transferring know-how are likely to outperform competitors who are not"* (Dyer and Singh, 1998, p. 665). Whether this also applies to AI as a GPT would be interesting to study further.

In the case of interfirm resourcing, transaction costs need to be minimized and mechanisms that preserve the relational rents need to be in place. In other words, in RBV, firms with superior systems and structures are seen to be profitable because of their markedly lower costs or because of their markedly higher quality or product performance, and their competitive advantage is seen to rest on the idiosyncratic and difficult-to-imitate resources (Teece, Pisano, & Shuen, 1997). This perspective opens interesting new avenues for studying AI as an organizational resource while aiming for competitive advantage.

Recently, the research tradition on RBV has been proposed to have three types of pathways for additional contributions. These RBV-contribution pathways include: 1) finding synergies between RBV and other theories such as human resources, economics, entrepreneurship, marketing, and international business. Secondly, RBV could be contributed by 2) leveraging it with greater content knowledge, on human resources-related firm heterogeneity, best practices in human resource management, microfoundations issues, competitive parity and firm-specific human capital, investigating whether human resources *"truly are a firm's greatest asset"* and opportunities to build bridges from RBV to competitive dynamics (Barney, Ketchen and Wright, 2021, p. 4). Thirdly, future RBV contributions have been suggested to be found by 3) expanding the strategic resources concept from the valuable, rare, inimitable, and non-substitutable resources to more multidisciplinary foundations e.g. with stakeholder theory or with strategy creation view. The strategic resources concept could also be expanded by finding the optimal amount of resources for avoiding them to change from a strength to a weakness instead; or solving other resource-related paradoxes (Barney et al., 2021). This dissertation could best be taken towards the first and third new contributions for RBV-theory. The first type could build on the bi-disciplinary view on merging AI-related theory to RBV and the third type of suggested contribution to RBV could build on the strategic choices on using AI as a resource through the lens of stakeholder theory or the strategic resources concept to study further the resource-related paradoxes. Also the second contribution might be possible, if the focus of the future studies was set on the human and AI collaboration especially from the mutual learning perspective of hybrid intelligence (Dellermann et al., 2019).

I next move to reflecting the findings of this study in relation to the theory on dynamic capabilities.

5.3.2 Dynamic capabilities

If RBV looks inwards to a firm and focuses on securing resources either inhouse or through interfirm resource rents (Dyer & Singh, 1998), dynamic capabilities focus on internal technological, organizational and managerial processes inside the firm that operates in a business environment of rapid technological change (Teece et al., 1997). Dynamic capabilities (DC) are the antecedents based on which managers alter the resource base of the firm to generate new value and drive *"the creation, evolution, and recombination of other resources into new sources of competitive advantage"* (Eisenhardt and Martin, 2000, p. 1107). This could apply to the organization that the interviewees work for, but not directly AI as a general purpose technology (Brynjolfsson & Mitchell, 2017) and as a managerial and organizational phenomenon, because AI in fact might be the cause for rapid technological change. Yet, DC might offer an interesting view for developing AI into a new source of competitive advantage.

In research, the DC approach is used to analyze the sources of wealth creation and capture by the firms with the aim to gain competitive advantage. Dynamic capabilities refer to analyzing the capacity of the firm: 1) to renew competencies and through that achieve congruence with the changing business environment and 2) to appropriately adapt, integrate, and reconfigure internal and external organizational skills, resources, and functional competencies *"to match the requirements of a changing environment"* (Teece, Pisano and Shuen, 1997, p. 515). A longitudinal multiple-case study could be interesting avenue for future research to study whether, or how, organizations are able to use AI to match the requirements of the changing business or operating environment. This could build further e.g. the study on sub-research question five and focus on the requirements that change related to temporality in the business or operating environment.

According to DC, the renewal and adaptation to the changing environment relate to three kinds of key issues: the business processes, market positions, and expansion paths of the firm. Especially the changes in organizational processes could be an interesting avenue for future research related to AI to not only match but also create a market change: *"The firm's processes that use resources -specifically the processes to integrate, reconfigure, gain and release resources – to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die."* (Teece, Pisano and Shuen, 1997; Eisenhardt and Martin, 2000, p. 1107).

However, dynamic capabilities are not in themselves found to be a source of long-term competitive advantage, rather they are often short-term. Thus, *"strategy in high-velocity markets is about creating a series of unpredictable advantages through timing and loosely structured organization. The strategic logic is* *opportunity and the imperative is when, where, and how often to change."* (Eisenhardt and Martin, 2000, p. 1118). Again, here continuing further the study on sub-research question five on temporal aspects and AI seems interesting.

As dynamic capabilities in dynamic markets need to rely increasingly on real-time information, cross-functional relationships and intensive communication is required among those who need to be involved with a specific process related to the external market (Eisenhardt & Martin, 2000). Again, the sub-research question five on the expected cumulative impacts of AI (see chapters 4.5 and 5.1.8) seems to touch at least partly the core of this need.

In the study of the temporal aspects already influenced by AI, DC could be applied to explore further at least the temporal dimensions and situations where action is required faster, in (nearly) real time and at the right or optimal time for a given internal or external need. Related might also be the need to predict the future and the requirement for simultaneous cross-functional action within the organization. Real-time information could alert people on the need to adjust different action(s): their own, that of the AI agents or maybe even that of the whole organization. As with DC, monitoring real-time information could enable quicker understanding of the changes in the marketplace and enable starting to adjust to them (Eisenhardt & Martin, 2000). This is found to be useful in firms operating in high-velocity markets, where *"dynamic capabilities rely extensively on new knowledge created for specific situations"*. This is also why in high-velocity markets analysis is quickly replaced by experimenting, because it generates immediate knowledge. Also in the organizations that make such an adaptation, routines need to be iterative and cognitively mindful. (Eisenhardt and Martin, 2000, p. 1116-1117). Future studies could explore the usability and/or ability of organizations applying AI to match these demands.

Since the early days, the DC research has developed from macro level towards more complex microfoundations to explore the multidimensional challenges and specific tensions such as those of sustainability-driven hybrid organizations, and through that complement the sensing, seizing and transforming of dynamic capabilities (Vallaster, Maon, Lindgreen, & Vanhamme, 2021). Sensing refers to discovering and shaping opportunities. Seizing is used to mobilize resources to capture value from the identified, filtered, and calibrated opportunities and threats. Finally, transforming is used *"to combine, recombine and reconfigure assets, resources and structures to align with the strategic decisions identified by the sensing mechanisms and determined by the seizing mechanisms"* (Vallaster et al., 2021, p. 914). Thus, organizations developing and/or implementing AI might benefit from the learnings already found in DC. Future studies are needed whether also AI could in fact contribute to the theoretical discussion on DC.

When using the terms of the DC framework (Teece et al., 1997), AI could possibly be considered an undifferentiated factor of production until it is implemented and trained by the firm-specific data. After that and when the required organizational processes, routines, and competencies for AI are put in place within the organization, AI could become a resource of the organization. This making it *“difficult if not impossible to imitate”* (Teece, Pisano and Shuen, 1997, p. 516).

If the firm has successfully implemented or adopted hybrid intelligence (Dellermann et al., 2019), which combines both the capabilities of humans and AI, both the human and the machine learn from each other over time. This can enable the organization to achieve a task level performance that neither the human nor the machine could achieve without the other (Dellermann et al., 2019). Depending on what these tasks are where AI and hybrid intelligence are adopted, the task handling by AI or hybrid intelligence might even become one of the core competencies of the organization, or AI might serve as a complementary for the core business or core function of the organization. Thus, an interesting avenue for future research would be, to what extent organizations are already able to use AI as their dynamic capability, or its *“ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments”* and *“achieve new and innovative forms of competitive advantage given path dependencies and market positions”* (based on Leonard-Barton, 1992, see Teece et al., 1997).

I next move to comparing what I have studied to the theory on sociomateriality.

5.3.3 Sociomateriality

In sociomateriality, every organizational practice is considered always to be bound with materiality. Materiality is proposed as an integral part of organizational everyday life and its organizing, because materiality is increasingly constituted by multiple, emergent, shifting, and interdependent technologies (Orlikowski, 2007). Unlike the techno-centric perspective that focuses on the technology effects, or the human-centered perspective that focuses on the interactions with technology, sociomateriality is interested in the view that *“the social and the material are constitutively entangled in everyday life”* and considered inextricably related so that neither exists without the other (Orlikowski, 2007, p. 1437). Thus, could sociomateriality be used to study the entanglement and mutual learning of humans and AI in hybrid intelligence (Dellermann et al., 2019) in the future?

With a more practice theory lens on sociomateriality, 1) the empirical focus has been set on how people act in organizational contexts, 2) the theoretical focus has been set on how are the relations between the actions people take and the structures of organizational life, and 3) a philosophical focus has been set on understanding the constitutive role of practices in producing organizational reality (Feldman &

Orlikowski, 2011). In the context of this doctoral dissertation, the pure AI solution developer view for sociomateriality seems too narrow, but in deeper multiple-case studies this would be possible to be studied in the future.

An interesting question related to RBV, dynamic capabilities, and sociomateriality is the question, whether something can be called a resource before it has been used in some way (Feldman & Orlikowski, 2011). In management and organization, a resource is often seen as a thing or quality that either is, by nature, a resource or has become a resource rather than the practices through which it is enacted as a resource: *"In the box-and-arrow figures so prevalent in organization theory, the boxes are always labelled, whereas the arrows are often unadorned by any text, as if they speak for themselves. Moreover, entities are often reified, considered sufficiently meaningful independent of their use or performance."* By contrast, practice theory focuses on theorizing the arrows to understand how actions produce outcomes. Based on that sociomateriality *"signals that technologies do not stand alone with certain inherent properties, but that their material characteristics and capabilities are relevant only in relation to specific situated practices"* (Scott and Orlikowski 2009, p. 1248-1249). Thus, particularly the future research on how the organizational processes change and are interacted between people and AI could benefit from the analytical lens of sociomateriality.

Sociomateriality also suits the study of potentially changing agency in these processes because in sociomateriality the capacity to act is discovered only when both human and material agencies are mangled. Work on posthumanism has also addressed different views on nonhuman agency relative to human agency, and articulated the consequential role played by nonhumans, such as natural objects and technological artifacts in producing social life. This has helped practice scholars to acknowledge the importance of materiality in the production of social life (Feldman & Orlikowski, 2011).

As in this doctoral dissertation the empirical focus is not on the actual users of the AI solutions, rather on the people developing the AI-based solutions for others, this posits a potential challenge between the planned and unanticipated (complementary) innovation effects and use purposes of the developed AI solutions. These findings could be complemented with the user perspective and comparisons could be made between the intended and actual AI solution innovation effects, when the human user's and AI's material agencies are mangled because, *"technology is not valuable, meaningful, or consequential by itself; it only becomes so when people actually engage with it in practice. The scope for human agency—in particular, the potential for humans to adapt technology (whether as developers or users) in multiple and contingent ways—was thus significantly understated in many theories of technology, as was the notion of technological construction, that technologies are artifacts whose operation and outcomes are neither fixed nor given a priori, but* *always temporally emergent through interaction with humans in practice."* (Feldman and Orlikowski, 2011, p. 1246).

A glimpse of these effects of AI might already be found in the findings related to sub-research questions four and five (see chapters 4.4, 4.5, 5.1.6-5.1.8) on measuring the empirical impacts as well as anticipated cumulative effects of AI on temporal dimensions. Yet, a longitudinal research could study the effects of AI further because the sociomaterial context *"shifts over time as interests, computers, networks, choices, algorithms, websites, preferences, links, identities, and capabilities change"* to better understand how the sociomaterial assemblage of humans and AI might produce both intended and unintended outcomes in the organizational life (Orlikowski, 2007, p. 1445).

Orlikowski's (2007) concrete example of the organizational complexity of sociomateriality and its mangled human and material agencies is the Google search algorithm. The search algorithm has been produced and maintained by software engineers, but the algorithm itself is executed on computers. Yet, both of their operation depends on the people who create and update content to the Internet and the people who enter search terms into the search engine. Similar multiple stakeholder logic and interdependence applies to the development of other AI/ML-using solutions, and their algorithms.

With the presented example of Google, the *"temporally emergent performance and results are multiple, shifting by time, by location, and political and institutional conditions"* (Orlikowski, 2007, p. 1445). Again, AI seems comparable. Thus, the same phenomenon could be studied also in the context of any technology-based company using AI. This might be particularly important in the strategic management of AI-based value creation and value capture (see more in chapter 5.3.5) because by managing the technological artifact rather than its use in practice, firms have been found to fail in achieving the benefits of the technology they had deployed (Feldman and Orlikowski, 2011, p. 1247).

This study has started to explore why the AI-based value creation might be challenging from the management and organization perspectives. To fully explore the complexity of this phenomenon, maybe the quantum mechanics logic and its learnings on organizational paradox in the sociomaterial context could be applied in future studies. Particularly interesting point of view for the future research on (human-centric) AI performance and its strategic alignment measuring might be the quantum mechanics view on the complexity of measuring not only the objective observation of a pre-existing reality but the potentialities of superposition: *"As soon as quantum objects become entangled, observing only parts of the system cannot reveal the full properties of the system"* (Hahn and Knight, 2021, p. 371). Ontologically, this *"entanglement implies that entangled systems constitute an inseparable whole where individual elements cannot be fully described in isolation* *without considering the state of other entangled elements… single elements of an entangled system cannot be fully described individually, but bear properties that depend on their interaction with other elements and the properties of the overall system."* (Hahn and Knight, 2021, p. 371).

From the organization perspective this might open new ways of measuring not only to the observable and easy-to-measure direct impacts but also to the more complex and delayed potentialities of enactment; and the (perceived and experienced) sociomaterial and even paradoxical impacts on different individuals, the whole organization, and its business environment when AI is increasingly taken into use as a resource. With the quantum approach the focus is put on distinguishing what can and cannot be known at once about the nature of organizational paradox (Hahn & Knight, 2021), but why not also about other impacts such as those of the impacts of implementing AI in an organization. This could open whole new avenues for organizational theory contribution. As with other innovations, also AI has potential for paradoxes that involve multiple tensions that are nested and interwoven.

I next move to applying and comparing my findings with the theory on organizational learning.

5.3.4 Organizational learning

When we talk about machine learning, it seems that comparing it to organizational learning might be interesting. Do they have any similarities? What are their main differences? How and what can organizations and people working in them learn with the help of AI? Organizational learning might also offer an interesting perspective to the study on AI-based value creation because *"(a)s researchers have considered the stability of differences in firm performance in the face of changing business environments, many have come to view the ability to learn as an important, indeed in some accounts a unique, source of sustainable competitive advantage"* (Burgelman, 1990; Senge, 1990, see Levinthal and March, 1993, p. 96).

The competitive advantage -perspective on organizational learning might also be one way how to approach AI productivity paradox -related studies in the future studies. Organizations can aim to produce competitive advantage through organizational arrangements that provide access to knowledge quickly and reliably. To achieve that, building skills and exercising routines in organizations may be required (W. W. Powell, Koput, & Smith-Doerr, 1996), and different models of organizing may be required such as tight coupling of linkages within an organization or to lean production or customers to enhance the kind of learning that is critical for each organization. Organizational learning on AI might also become critical for each organization at least in certain industries. How and why and when, and what does this organization learning related to AI entail remains for future studies to explore.

In the context of this doctoral dissertation that focuses purely on the empirical views of AI developers, organizational learning was mentioned multiple times, but extensive future studies are required to explore the AI related organizational learning further. In those future studies, more than one interviewee per organization should be included. Preferably the whole multi-disciplinary team collaborating with the whole AI solution lifecycle should be included to this kind of AI and organizational learning case studies. In this study the focus has been set to learn about AI as a general purpose technology and as a managerial and organizational phenomenon in multiple industry settings. Organizational learning is likely to be part of the studies of this phenomenon in the future, but it has been out of the scope of this study. However, in the future, if the learning can be on not only individual or team level, but on organizational level and combined to the learning ability of machines, AI might become a particularly interesting avenue for future contributions related to organizational learning.

In the future studies on AI and organizational learning, scholars could focus on the organizational learning history, and/or continuous learning processes, and/or the networks that the organizations have, and/or who have gained sustainable competitive advantage with the help of AI. How do they use AI and why? How has the organizational learning process been that enabled gaining AI-based sustainable competitive advantage? How have these organizations found a balance between the exploration efforts to develop new knowledge and exploitation of the current competencies?

Organizations should also learn from the mistakes made with AI: *"Tightly coupled systems are relatively good for system-wide error detection, but they are relatively poor for error diagnostics… The appropriate balance between investments in error detection and in diagnostics presumably depends on the frequency of errors and the difficulty of diagnosis."* (Levinthal and March, 1993, p. 98). With AI, not only completely new processes might be needed for developing AI solutions, but also for its use in the so-called maintenance phase, because we do not entirely know what is the spectrum of errors that AI agents can make, and why might they occur, and when. For that both organizational learning and further studies are required.

AI developers have also witnessed situations, where the development of AI solutions has surfaced a surprisingly huge number of mistakes made by people in the organization. And if the data is faulty with which the ML algorithm has been trained, also the machine's predictions and actions will be based on the faulty data. Thus, particularly relevant managerial implications and future theorizing opportunities might relate to the increased understanding and practical experiences on the impacts of misleading or wrong learning of either humans or machines, or both humans and machines. If the experiential record of the human or the machine, or that of both, is a biased representation of past reality, then through that it impacts also the estimated future likelihoods and decision-making based on it. Thus, future studies could focus also on the impacts of both human and machine biases, either separately, or together, in organizational learning.

An interesting aspect of this might be to also study the organizational unlearning of outdated or harmful things. A machine can forget everything it has learned by formatting its memory. A human is much slower in unlearning before being able to learn new. This potentially makes the learning and unlearning capabilities of both humans and AI in an organization an interesting avenue for future research. From previous studies we know that humans tend to overlook distant times, places, and failures: "*The first form of myopia is the tendency to ignore the long run. The short run is privileged by organizational learning. As a result, long run survival is sometimes endangered. The second form of myopia is the tendency to ignore the larger picture. The near neighborhood is privileged by organizational learning. As a result, survival of more encompassing systems is sometimes endangered. The third form of myopia is the tendency to overlook failures. The lessons gained from success are privileged by organizational learning. As a result, the risks of failure are likely to be underestimated."* (Levinthal and March, 1993, p. 101).

Knowing this, an interesting avenue for future research would be, could these identified organizational learning myopias be affected with hybrid intelligence, and if yes, how and to what extend? The research on the socio-technical mutual learning of hybrid intelligence and organizational learning could build on ambiguity, *"because actors who self-enhance seek ambiguity because ambiguity allows them to self-enhance"* (March et al. 1991, see Levinthal and Rerup, 2020, p. 534). *"(A)mbiguity is accepted or may even be sought and then later maintained to develop more complex understandings. As such, embracing ambiguity consists of two steps: (1) the extent to which organizational members perceive ambiguity in a positive or negative way and (2) the extent to which ambiguity is reduced, maintained, or even elaborated."* (Levinthal and Rerup, 2020, p. 537). Could the premise that the machine may always be wrong (because of multiple reasons) help in seeking ambiguity and thus enable to develop more complex understanding also on whole organization level?

As was in sociomateriality, also studying organizational learning related to AI might be challenging: *"Experience is clouded by the interactive complexity of history, particularly by the way experience is shaped by many actors simultaneously learning. If one's own actions are embedded in an ecology of the actions of many others (who are also simultaneously learning and changing), it is not easy to understand what is going on. The relationship between the actions of individuals in the organization and overall organizational performance is confounded by simultaneous learning of other actors."* (Levinthal and March, 1993 p. 97). This should be kept in mind by managers implementing AI solutions, particularly those of hybrid intelligence (Dellermann et al., 2019), and scholars alike.

Additionally, related to the sub-research question four of this study on measuring the impacts of AI (see chapters 4.4 and 5.1.6-5.1.7), also an organizational learning view on the importance of interpretations might have to be considered. Then organizational learning processes might need to highlight both the inputs and outputs while encoding conflicting or ambiguous performance outcomes as success or failure on a given outcome metric: *"a useful next frontier in research on performance feedback includes moving beyond the tacit assumption that for organizational members to take action they need to be able to encode outcomes into simple measures of success or failure"* (Levinthal and Rerup, 2020, p. 540).

Also studying the effects of AI to measuring how the complexity of multiple simultaneous goals is handled in an organization, and their effects to performance over time might require scholarly attention: *"When organizations pursue multiple goals, an important research question is how these goals interact with each other to inform organizational responses. Research on this question has so far relied mainly on the assumption of sequential attention to goals (Cyert and March 1963), and has produced evidence that low performance on a lower-priority goal spurs reactions only when performance on a higher-priority goal signals success."* (Greve 2008, Rowley et al. 2017, see Levinthal and Rerup, 2020, p. 528). Even then, the question remains what should define the referent point of success or failure in a multiple dimensional outcome space, in which there is not a single superordinate marker of performance but some set of indicators (Levinthal & Rerup, 2020). Yet the engineers designing e.g. autonomous robots, such as self-driving cars or autonomous drones, face similar challenges daily when the different sensor inputs need to be analyzed and action based on them needs to be prioritized. Is there something the whole organization as a complex entity with multiple simultaneous goals could learn from them? And how to take into consideration the human factors outside a closed and predictable technical system, when defining success or failure? For autonomous vehicles this might be a child kicking the ball in front of the car and running after it, and the car detecting the child in time to not run over him or her. In an organization, the less predictable human-factor may consist of the organizational politics and the problematic nature of the concept of an organizational goal (Levinthal & Rerup, 2020).

I next move to applying and comparing my findings with the theories on value creation and value capture.

5.3.5 Value creation and value capture

When looking for theory on value creation and value capture, the most cited papers focus on business models. Originally, based on the theories on virtual markets, value chain analysis, Schumpeterian innovation, RBV, strategic networks, transaction cost economics, and their application on value creation potential in e-business, the theory on business models was proposed (Amit & Zott, 2001). Business model is defined to depict the *”content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities”* (Amit and Zott, 2001, p. 511). In business model approach the focus is not at value appropriation but rather in the total value creation as a prerequisite for value appropriation. In other words, a business model focuses on how an enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit (Teece, 2010), so in emphasizing both the value creation and the value capture or value appropriation aspects: *“It thus reflects management’s hypothesis about what customers want, how they want it, and how the enterprise can organize to best meet those needs, get paid for doing so, and make a profit”* (Teece, 2010, p. 172).

This dissertation has started to explore elements related to the business model, but future studies could definitely make a deeper search for social facts (von Krogh, 2020) related to the AI-based value creation and value capture through business models. This is particularly important because AI requires developing *“waves of complementary innovation”* (Erik Brynjolfsson et al., 2017, p 1), and because business models are too often neglected in innovating: *“When executives think of innovation, they all too often neglect the proper analysis and development of business models which can translate technical success into commercial success. Good business model design and implementation, coupled with careful strategic analysis, are necessary for technological innovation to succeed commercially*” (Teece, 2010, p. 184). Novelty or a form of innovation can be the business model itself and it should be linked to the business strategy. Sometimes the creation of new business models even gives birth to new industries, or leads to competitive advantage, but a wrong business model may lead to a business failure: *“it is common to see great technological achievements fail commercially because little, if any, attention has been given to designing a business model to take them to market properly”* (Teece, 2010, p. 192).

The relationship between a business model and a business strategy is that the business model is more generic than the strategy, and strategy can be essential while designing a competitively sustainable business model: *“Coupling competitive strategy analysis to business model design requires segmenting the market, creating a value proposition for each segment, setting up the apparatus to deliver that value, and then figuring out various ‘isolating mechanisms’ that can be used to prevent the business model/strategy from being undermined through imitation by competitors or disintermediation by customers.”* These isolating mechanisms can be that 1) the implementation of the business model requires systems, processes and assets that are hard to replicate; 2) imitability can be made uncertain through opacity which makes it hard for outsiders to understand in detail which elements of the business model constitute the source of customer acceptability; and/or finally 3) transparently replicable business models cannibalize existing sales and profits or upset other important business relationships. (Teece, 2010, p. 180).

Yet, this study focused on the internal factors rather than the market analysis of AI, thus future studies and their empirical data would have to take business models into a specific research focus from the start to potentially offer interesting and valuable managerial insights, and potential theoretical contributions.

Internet-based e-business has enabled new ways of creating value and potential for innovative market mechanisms. The virtual markets have characteristics such as: ease of extending one's product range to include complementary products, improved access to complementary assets, new forms of collaboration among firms, the potential reduction of asymmetric information among economic agents through the Internet medium, and real-time customizability of products and services. All of these characteristics considered together have *"profound effect on how value-creating economic transactions are structured and conducted"* (Amit and Zott, 2001, p. 495).

With AI and other technologies, the effects of digital transformation and its effects on the microfoundations of dynamic capabilities of a firm have got even stronger and lead to increased need for agile strategic renewal related to business models, collaborative approach and culture in an organization (Warner & Wäger, 2019). From the organization perspective, digital transformation has also been found to move firms towards malleable organizational designs to enable the required continuous adaptation; and this move has been found to be embedded in and driven by digital business ecosystems (Hanelt, Bohnsack, Marz, & Antunes Marante, 2020). In general, the value creation and value capture seem to have become increasingly complex both on the micro and macro levels. This can be observed e.g. in the increasing research interest towards the delicate balance of creating and capturing value in platform ecosystems, where strategies reach from 1) winner-takes-all to 2) the vertical integration between platform competition and complements (Rietveld & Schilling, 2021). As the third theme in the value and platform literature has been 3) the heterogeneity and its effects to the categories of a platform, its complementors, and end users, and finally, 4) how platforms govern, or orchestrate the creation and capture of value in the ecosystem and its effects on control over the success or failure of different members of the ecosystem (Rietveld & Schilling, 2021). This fourth stream in the platform ecosystem literature on platform governance and orchestration, and the identified and suggested future research related to it, seems applicable also in the context of AI as organizations with AI-based competitive advantage are likely to share at least partly similar value creation and value capture ecosystem conditions as (dominant) platforms such as Google, Amazon and Facebook.

Thus, a logical continuation to the expected cumulative impacts of AI could be, how do the concerns on the delicate balancing acts on value creation and value capture change over time? Customers expect value, but at the same time the criticism towards the biggest free service providers is also growing. The market-leading platforms, such as Google, Amazon and Facebook that all use machine learning, have been *"accused of misusing their market power to stifle innovation and limit competitive entry; misappropriating end users' personal data, resulting in large-scale privacy scandals; and competing with complementors on the basis of unfair competitive advantage"* (Rietveld and Schilling, 2021, p. 1551). Thus, avenues for the future research could include e.g. studying the potential effects of the increasing scandals to the awareness and concerns related data privacy versus the data used to train ML models for better personalized service. Another avenue for future research might be whether the need for the ethical considerations of the use and (dis)adoption of AI might also start having measurable effects on the profits and losses of a firm. This might radically influence or disrupt the managerial implications on the socio-technical (Manz & Stewart, 1997; Pasmore, 1995) decision-making on when to use or not use AI as a resource in an organization.

In relation to AI, the value creation might become more complex. As we saw in findings related to sub-research questions two to four (see chapters 4.2-4.4 and 5.1.4-5.1.7) value capture might require careful and complex decision-making even at the expense of value capture. Even a paradigm shift in value creation has been expected, when AI is included in everything, including thinking work: then the conversation is no longer about productivity enhancement but the reordering of value creation and appropriation by human effort and the nature of work itself (Phan et al., 2017). Thus, the interlink between value creation and work seems to deserve further research attention in the future.

Particularly suitable future studies on the value creation of AI could start from the microfoundation movement in strategic management. There actor engagement is conceptualized as a microfoundation for value co-creation within the context of a service ecosystem, and actors are viewed as not only humans, but also as machines and various combinations of humans and machines, who are engaging in an interactive process of resource integration within a service ecosystem (Storbacka, Brodie, Böhmann, Maglio, & Nenonen, 2016). This might relate directly to AI scholars in management and organizing having started to question paradigms such as agency belonging only to humans (Raisch & Krakowski, 2021).

Other particularly interesting avenues for future research might include the focus on the perceived value of AI. A positive direct relationship between the AI capability of a platform and the value perceived in the platform by its users is found to be moderated by platform legitimation, data stewardship, and user-centric design (Gregory et al., 2021). Thus, interesting avenues for AI-related value creation might focus on the co-creation as enactment of interactional creation across interactive system-environments (Ramaswamy & Ozcan, 2018), or in the cocreation of value through markets and, more broadly, in society (Vargo & Lusch, 2016). When markets integrate AI technology into their offerings and services, a governing opportunity to better foster and encourage mutually beneficial co-creation in the AI innovation process has been found to emerge (Petrescu, Krishen, Kachen, & Gironda, 2022).

Maybe value co-creation would offer at least one solution in attempt to handle the paradoxical positive and negative (Gregory et al., 2021; Leonardi & Treem, 2020; Raisch & Krakowski, 2021) or unexpected (Wu & Kane, 2021) impacts on how AI is to shape our future.

5.3.6 Conclusions on AI as a case of future theorizing

In this chapter sub-section, I have offered an overview of AI as a phenomenon in relation to five management and organization theories: 1) resource-based view, 2) dynamic capabilities, 3) sociomateriality, 4) organizational learning, and 5) value creation and value capture. By contrasting the findings of this phenomenon-driven dissertation against these five theories, I intended to narrow the range of plausible explanations of my grounded observations for down-the-road theorizing (Bamberger, 2018).

However, based on this brief analysis, it seems that AI can be part of building many other theories, though other theories seem to have difficulty capturing the entire phenomenon of AI from the management and organization perspective.

Previous literature has had difficulty to fully explain AI through a single definition, and no definitions for AI as a managerial and/or organizational phenomenon was found. Thus I agree with Christianson and Whiteman (2018), who have stated that *“(m)anagement and organization scholars might have the opportunity surface AI as a new phenomenon, and through that make theoretical discoveries”*.

In this doctoral dissertation, each sub-study can be approached through the theoretical foundations of AI-related research in combination of a multitude of other theories. However, no other theory seems to fully capture the complexity and scope of AI related changes from the management and organization perspective. Yet, as identified in this chapter, AI opens countless new opportunities for new theory building in the future studies. In those future studies, AI might be a suitable option for challenging the boundaries of the existing management and organization theories either as a novel research method, subject of study, or both.

Finally, as the last concluding words in the next and final sub-section, I still want to summarize and tie all the above together to the title of this doctoral dissertation and aim to answer the burning question: in this study, what AI is as a managerial and organizational phenomenon a case of.

5.4 The strategic management of AI as a GPT

In this final sub-section of discussion and conclusions, I want to conclude the learnings of this doctoral dissertation titled strategically managing the value development and productivity paradox of artificial intelligence -the general purpose technology view. I close the circle from the end to the beginning by explaining how all the four key terms in the title relate to the main research question of this dissertation. I recap the learnings of this doctoral dissertation in relation to the title and argue that this dissertation offers a grounded and pre-theoretical (Bamberger, 2018; Van de Ven, 2015) step toward mapping future research directions related to the strategic management of AI, or more specifically to the strategically aligned (Park & Mithas, 2020; Peppard & Ward, 2004; Ravichandran, 2018) management of AI and business strategies.

Let me start with recapping the definition for AI. In this doctoral dissertation AI is understood as the multidisciplinary technology development continuum that started with the ‘Thinking machine’ in 1950’s (Turing, 1950). It consists of multiple different technologies that have developed into more sophisticated and contextually intelligent IT solutions over time due to increases in calculating power and algorithm development that allow machines to be trained with more heterogeneous structured and unstructured data (von Krogh, 2018). All this combined may create an illusion of more contextual or even seeming ‘human-like’ intelligence for the end user according to the experiences of industry AI developers (see chapters 2.1 and 4.1).

AI that uses machine learning has also been compared to other disruptive general purpose technologies (GPT) such as electricity and the combustion engine (Brynjolfsson & Mitchell, 2017), or information technology that have affected the whole economy (Jovanovic & Rousseau, 2005). Like other GPTs before it, also AI requires *“waves of complementary innovations”* (Erik Brynjolfsson et al., 2017, p 1) by different organizations and multi-disciplinary teams to create value and enable the full effects of AI in machines, business organizations, and the broader economy (Brynjolfsson & Mitchell, 2017). Up until now, AI and its algorithm development have required the cross-disciplinary collaboration from multiple disciplines such as mathematics and statistics to be combined to the development of IT, both hardware and software. Now the multi-disciplinary collaboration need seems to have grown even wider, as AI solutions are being developed to almost any industry, for different domains, and use purposes. Thus, GPTs could also be understood, or defined as enabling technologies (Rathje & Katila, 2020), and future research on GPTs could build on how to profit from their technical performance levels (weak, general superintelligence, see Bahoo, Cucculelli, & Qamar, 2023; Panda & Bhatia, 2018; Pennachin & Goertzel, 2007) through technological innovation (Teece, 1986, 2000a, 2006, 2018) as one way to respond to the productivity paradox of AI (Brynjolfsson et al., 2018, 2017).

The productivity paradox of AI refers to the clash of expectations and statistics when, simultaneously, systems using AI match or surpass human level performance in an increasing number of domains, leveraging rapid advances in other technologies and driving soaring stock prices, but the measured productivity growth still declines based on the statistics (Brynjolfsson et al., 2017). Thus, AI not only enhances employee productivity (Nauhaus et al., 2021); it may also harm employee productivity. Or what makes this challenging from the measuring point of view is that employee productivity has been found to both increase and decrease with AI as both effects have been found to co-exist (Tong et al., 2021). Despite all this, massive investments in AI (Tricot, 2021; Zhang et al., 2022, 2021) are made, yet their effect on the productivity statistics are found to be paradoxical (Brynjolfsson et al., 2017).

When studying the AI productivity paradox, Brynjolfsson et al. (2018, p 360) found that *"productivity is underestimated when the contribution of intangibles to outputs exceeds their contribution as inputs, and it is overestimated when the opposite holds"*. They propose that AI enables and requires significant complementary investments that are often intangible and poorly measured in national accounts, and this can lead to underestimation of productivity growth in the early years of AI and, later, when the benefits of intangible investments are harvested, productivity growth overestimation. These intangible investments often require a fundamental rethinking of the organization of production itself because in these firms new business processes need to be created, managerial experience needs to be developed, workers need to be trained, software needs to be patched, and other intangibles such as required skills and knowledge need to be built to put the GPT-related capital into use over a learning period (see Hornstein and Krusell, 1996 and Greenwood and Yorukoglu 1997 in Brynjolfsson et al., 2018).

To better understand these intangible investments required for AI-based productivity and value creation from the management and organization perspective, in this dissertation, I explored AI-based value creation based on the experiences of 34 AI developers working in 33 organizations and in 18 industries. This multiple-industry setting was required to empirically understand the GPT perspective or nature of AI. On top of that the first sub-research question aims to help with sensemaking of the GPT nature of AI as a managerial and organizational phenomenon both in the literature and in the multiple-industry settings (see chapters 2.1. and 5.1.1). As a key observation both in the literature and as a managerial implication, it seems that AI as a term always requires additional specification depending on the intended audience. This includes, but is not limited to, technically defining the actual algorithms used for a technical audience and/or practical examples of use cases or innovation effects (in a specific domain or expertise context) to help the non-technical audience understand what is it that AI means for them in practise, in their specific context and in their own non-technical language. Otherwise, they will not be able to understand AI and thus cannot contribute to the value creation attempts when developing complementary innovations based on AI in their specific domain area. (Note that the pure AI user perspective with no power position to impact the AI solution development itself has been excluded from this study.)

In this dissertation title, the term 'value creation' is used to include both use value and value exchange (Bowman & Ambrosini, 2000; Lepak et al., 2007). Exchange value, and its value capture, is realized when the product is sold, and it equals *"the amount paid by the buyer to the producer for the perceived use value"* (Bowman & Ambrosini, 2000, p 4). It differs from use value, because *"(u)se value refers to the specific quality of a new job, task, product, or service as perceived by users in relation to their needs, such as the speed or quality of performance on a new task or the aesthetics or performance features of a new product or service"* (Lepak et al., 2007, p 181). Use value depends on the perception of the user, because *"value is subjective, it is defined by customers, based on their perceptions of the usefulness of the product on offer",* and it does not necessarily equal the amount the customer is prepared to pay for the product because of a potential consumer surplus (Bowman & Ambrosini, 2000, p 3-4). Consumer surplus consists of the difference between the customer's valuation of the product, and the price paid. As part of the use value is included also the use value transformation by labour before new use value can be created (Bowman & Ambrosini, 2000). This value transformation and the new use value created might even turn into a dynamic capability, if the value transformation is used not only for altering the resource base of the firm to generate new value but also to drive *"the creation, evolution, and recombination of other resources into new sources of competitive advantage"* (Eisenhardt and Martin, 2000, p. 1107). Both in dynamic capabilities (Teece et al., 1997) and in value transformation as part of use value (Bowman & Ambrosini, 2000) the focus is set on processes inside the firm. Thus dynamic capabilities might offer an interesting avenue for future research of AI-based value creation when combined to the study of intangible investments required by GPTs to enable productivity growth (Brynjolfsson et al., 2018).

As a pre-theoretical contribution (Bamberger, 2018; Van de Ven, 2015), this doctoral dissertation offers a grounded step towards better understanding the intangible investment process related to AI-based value creation, and offers a first step toward starting to build the understanding of how AI might start to be transformed into a dynamic capability with an attempt to gain AI-based competitive advantage. The second through fifth research questions focus on exploring specific (non-consecutive) steps potentially required as part of the intangible investments required by AI as a GPT: rethinking of new business processes for them to be created, managerial experience to be developed, workers to be trained, software to be patched, and required skills and knowledge to be built to put the GPT-related capital into use during the learning period (see Hornstein and Krusell, 1996 and Greenwood and Yorukoglu 1997 in Brynjolfsson et al., 2018).

To do so, in this dissertation the second sub-research question explored the managerial decision-making when evaluating whether AI is a suitable solution or a resource to solve a specific business problem at hand. This AI investment decision-making was found to require evaluation both technically and from the socially constructed perspectives. The socially constructed perspective includes the expected value creation and value capture, human-centric approach, and potentially mitigating risks and ethical concerns in the short and/or long term (see chapters 4.2 and 5.1.4). This contributes a pre-theoretical (Bamberger, 2018; Van de Ven, 2015) step towards developing managerial experience, skills and knowledge related to AI-based investment decision-making to not only avoid investments in tasks impossible for AI technically, but also to realize the benefits of AI while aiming to mitigate its negative side effects (Raisch & Krakowski, 2021).

While the second sub-research question focused on a single AI investment decision-making level, the third sub-research question offers a pre-theoretical (Bamberger, 2018; Van de Ven, 2015) view to the actual use, or non-use, and portfolio management of multiple AI initiatives simultaneously. It focuses on differentiating the typology (Cornelissen, 2017) of different AI-initiatives based on their strategic alignment to the business strategy of the organization. The different types of AI use, or non-use, in the AI management portfolio are in different development phases of AI technically and commercially, inhouse and/or outside the organization (see chapters 4.3 and 5.1.5). Even though the empirical examples within this study are likely to get outdated, the typology proposed for management of multiple AI initiatives simultaneously within an organization is likely to hold time and help also practitioners tackle the need of continuous development of AI solutions at a great speed over time.

Yet, the portfolio management of AI opens ample opportunities for future studies. These future direction include, but are not limited to, further studies on the management of the portfolio consisting of multiple exploration projects simultaneously invested in (Vassolo et al., 2004); project, program and portfolio management as potential modes of organizing (Geraldi, Teerikangas, & Birollo, 2022) the AI-based value creation; the extent of synergies within a firm's resource portfolio (Adner & Zemsky, 2006) management related to AI; explorations on the portfolios of collaborative activities (W. W. Powell et al., 1996) related to AI use and development; and/or the studies the portfolios of idiosyncratic and difficult-to-trade assets and competencies and resources (Teece, 2007) related to AI as part of dynamic capabilities and (sustainable) enterprise performance development within an organization. A particularly relevant future direction to the AI development portfolio management seems to be how to assess and measure the value of AI as part of the overall IT investment portfolio (Seddon, Graeser, & Willcocks, 2002) in the short and the long term as part of the (sustainable) enterprise performance development.

Closely related to this is the fourth sub-research question that pre-theorizes (Bamberger, 2018; Van de Ven, 2015) empirically how the AI-based value creation has already been measured in organizations with different AI strategies. The grounded analysis phase also enabled the emergence (Glaser, 1992; Glaser & Strauss, 1967; Teerikangas, 2006) of a potential process (Cornelissen, 2017) model from the data for how the measuring of AI initiatives per initiative and/or per organization's AI maturity level might develop over time during the learning period of AI-based value creation (see chapters 4.4., 5.1.6 and 5.1.7). Based on the previous literature, there also seems to be a link between the AI use antecedents, the AI use, and the measurable empirical impacts (see chapters 2.5.3 and 2.5.5) which also paves the way for ample future research directions related to the strategic management of AI-based value creation, or even AI-based competitive advantage.

Thus finally, the strategic management of AI in this doctoral dissertation refers to strategically aligning (Park & Mithas, 2020; Peppard & Ward, 2004; Ravichandran, 2018) the management of AI and each organization's business strategy. This study focuses on AI-based value transformation (Bowman & Ambrosini, 2000) in an organization, and touches upon value creation and value capture perspectives (but not business models, see chapter 5.3.5) of this enabling (Quintas & Guy, 1995; Rathje & Katila, 2020; Teece, 2018; Zheng et al., 2017) or general purpose technology (Jovanovic & Rousseau, 2005; Tambe, Hitt, Rock, & Brynjolfsson, 2019; Yang, Chesbrough, & Hurmelinna-Laukkanen, 2022) and the complementary innovations (Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2017) developed on top of it. The economic value scope in this study includes the reduction of costs, enhancement of benefits (Becerra, 2009), and/or the hybrid approach that includes both (Leone, Schiavone, Appio, & Chiao, 2021) either for the organization itself or for that of the customer of the organization. The strategic management and the strategy to create and appropriate value in this study takes place in a business environment, where the resource management process of the organization is impacted both by 1) the competitive dynamics of competitors and 2) the market positioning in relation to the customers (Becerra, 2009, p 143). Finally, Helfat et al. (2023, p 1357) tie together the relationship between strategic management, value creation and value capture not only at a single point in time but as part of sustained firm performance: *"At its core, the strategic management field* *is devoted to building greater understanding of positive and sustained firm performance (Hoskisson & Harrison, 2021; Nag, Hambrick, & Chen, 2007) along with value creation and capture (Brandenburger & Stuart, 1996)."*

Thus, sub-research questions 2-4 have focused on the strategic management of value creation and value capture (and mitigation of the productivity paradox on an organizational level) in different AI use phases: in the AI investment decision-making phase before the AI is taken into use (antecedent, see chapters 2.4.1, 4.2, 5.1.4), the strategically aligned portfolio management of multiple AI agents and their development when AI has been taken into use in an organization (see chapters 2.4.2, 4.3, 5.1.5), and measuring the impacts of implemented AI-based complementary innovations (see chapters 2.4.3, 4.4, 5.1.6, 5.1.7).

In the premium literature on general management and organizational studies, however, also the fourth AI use phase (see chapters 2.4.4, 2.5.2) on the expected cumulative impacts of AI has gained a significant amount of research attention. With that and the strongly emerging (Glaser, 1992; Glaser & Strauss, 1967; Teerikangas, 2006) temporal dimensions related to AI, the expected cumulative impacts on the strategic management of time as a resource could not be ignored. Thus, the fifth and final sub-research question focused on the expected cumulative impacts of AI in temporal dimensions related to individuals, organizations, and their intersection (see chapters 4.5, 5.1.8). This study is to pave the way for down-the-road theorizing or pre-theorizing (Bamberger 2018) towards the strategic management of these three dimensions as part of the reduction of costs, or the enhancement of benefits (Becerra, 2009), and/or the hybrid approach that includes both (Leone et al., 2021) in a business environment impacted by competitors (Becerra, 2009).

Thus, despite the width of the main research question of this study 'What makes artificial intelligence -based value creation challenging from the management and organization perspective?', I argue to have explored this main research problem as widely as possible both theoretically and empirically (see chapters 2 and 3). This is also my main contribution. Through the abductive dialogue between the empirical observations and different theories, and with a special emphasis on the literature review on AI in the premium outlets on general management and organizational studies my main contribution is to provide a *"one-stop-shopping for someone who is looking for an overview of the AI in organizations literature, sprinkled with up-to-date, interesting examples"* (2023, pre-examination statement by Professor Katila).

That is not to say that this study is without limitations. Rather, this study offers and requires countless further studies by the research community to continue the theory-building further from the current pre-theoretical phase of AI as a managerial and organizational phenomenon. I hope to have inspired other scholars and industry managers to further analyze the implications of this general purpose technology from the strategic management perspective. To continue from this study, a special emphasis should be set not only on the different aspects of the value creation of AI but also on the mitigation of its negative side effects, and overocoming its productivity paradox at least on an organizational level.

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Appendices

Appendix 1. Basic information pre-survey questions

BASIC INFORMATION

1. Please shortly tell about your current job description:
2. How long have you been in the current position?
3. Do work in an expert, supervisor, senior manager role in your company? Or in some other role (please specify)?
4. How would you define "Artificial Intelligence"?
5. In relation to AI, are you a user, developer or supplier -or a combination of some of these?
6. How long is your history with AI?
7. How does your company use AI in your business?
8. What kind of AI solutions has your company offered or delivered to your clients?
9. Based on your view, what level AI strategy or vision does your company have on a scale from 1 to 5 (1=none, 5=excellent)? Please explain in 1 sentence.
10. What other company does your office consider your idol or benchmark in implementing AI? What is the name of that company? Please explain in 1 sentence.

Appendix 2. Semi-structured interview questions

1. In your own work, what do you use or would want to use AI for? What would you NOT want to use AI for?
2. How has your own job description changed after having AI as one of your ”colleagues”? How would your job description change, if you could use AI for what you would want to use it for?
3. To use AI in your work, what kind of skills are needed from you and from your colleagues?
4. What new job descriptions are or have been born, because of implementing AI?
5. In your opinion, what is the division of labor between a person and AI? E.g. in a new situation, who is responsible, and who ultimately decides what to do; a human being or AI?
6. How has the division of labor changed between employees and teams because of using AI? And/or how would you expect the division of labor to change when AI is used?
7. How has the relationship between your company and its clients changed because of using AI? And/or how would you expect this relationship to change when AI is used?
8. Based on your view, what use cases are applicable for AI? Why?
9. Based on your view, what use cases are NOT applicable for AI? Why?
10. Please name one application, where your company wants to apply AI.
11. What factors make it MORE attractive to start using AI in the application you mentioned above?
12. What factors make it LESS attractive to start using AI in the application you mentioned above?
13. Please name one AI application, that your company already uses.
14. Ultimately, what factors contributed to the decision that AI was taken into use in the application you mentioned above?
15. What factors make you continue using this AI application mentioned above?

16. What factors reduce the willingness to continue using this AI application mentioned above?
17. In some companies, the management or investors think it is important to use AI for the sake of using AI regardless of the application. What is the situation in your company?
18. What kind of measurable results has your company achieved by applying AI?
19. How has AI influenced the core business of your company?
20. Who in your company searches for AI use cases and develops AI solutions for them?How? (e.g. process)
21. Who in your company defines the data required for AI? How?
22. In your company, what sources are used to get the data for AI? How do you retrieve it?
23. In your company, what external data sources are used in applying AI?
24. Based on your view, what kind of management skills are needed to apply/implement AI?
25. Are some of these management skills new skill requirements?
26. What kind of technical skills managers need to have in order to apply/implement AI?
27. Are some of these technical skills new skill requirements?
28. Based on your experience, what company-related factors increase using AI?
29. Are some of these company-related factors new?
30. Based on your experience, what company-related factors hinder using AI?
31. Are some of these hindering company-related factors new?
32. What other AI related factors would you want to mention, that I did not ask for?
33. Who else should I interview for this research?

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