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Teaming man and machine?

A bibliometric analysis deconstructing research on how cognitive technologies affects man-machine collaboration

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Abstract

The field of research addressing artificial intelligence (AI), and related topics, is rapidly increasing. However, despite this emerging interest, the currently body of published research remains complex and unstructured. In particular, it remains to be understood how these technologies is implemented and cause changes in man-machine collaboration. In order to inform this issue, we conducted a bibliometric analysis of extant literature on AI and man-machine collaboration to take stock of extant published research in order to provide a foundation upon which both future theory and practice can be built. We based our analysis of an exhaustive structured literature search of published academic research in Web of Science (WoS) until 2019. Using the keywords digi* AND transform* OR artificial intelligence, 8 728 articles were identified. The bibliometric analysis enabled us first to identify 202 relevant articles published within the fields of business and management, and subsequently to further narrowing our scope to 25 core contributions using bibliometric coupling. A content analysis of these 25 articles revealed that whereas there is a lot of attention to the technological complexities related to the emerging cognitive technologies, there is to date limited empirical descriptions of the consequences for individuals, organizations or value creation of adopting these technologies. Our study identifies four important dimensions of man-machine collaboration; Knowledge worker, Organization, Market, and Society. Moreover, our findings reveal extant research is inconclusive with respect to the forces affecting these dimensions as different authors record both proactive forces and constraining forces associated with each of the four dimensions. Our contribution, as well as, the identification of a core canon of relevant research articles provides a foundation upon which future research and practice can be built by identifying core dimension and the forces acting upon them.

Preface

The dissertation you are about to read – “The future of man-machine collaboration – A bibliometric analysis deconstructing research on how cognitive technologies affects man-machine collaboration” – is a master thesis written to fulfill the graduation requirements of the study program Master of Science in Business Administration at Oslo Business School, Oslo Metropolitan University – OsloMet. The project dissertation constitutes was undertaken as I am interested in technology and what opportunities technological developments creates for people and organizations, which made the theme of my master thesis a natural choice. Further, by taking a major in strategy, organization and management the academic content has emphasized each subject area to influence on people, organization and society. Some subjects have in particular focused on today´s society, and especially gone in depth on how technological advancements affect people and organizations. Therefore, as technology and digitalization are hot topics undergoing rapid development, I found it exciting to contribute to the research area by conduction research on this topic.

The master thesis constitutes an experiment with a new article-based master dissertation performed by my supervisor Karl Joachim Breunig. The goal was to write an article with the potential to become published during our project engagement instead of a traditional research report format masters thesis. The experiment I have been part of has been incredibly fruitful and have broadened my academic horizon. I take with me valuable new knowledge about how research projects are conducted and completed to be shared with an academic audience. The final output of the experiment – this dissertation in a shorter articles format – has been submitted to the European Conference of the Impact of Artificial intelligence and Robotics (ECIAIR), and will be presented 22nd – 23rd of October in Portugal. The submitted dissertation you are about to read therefore includes, the entire research report version of our research project intended for submission as my master thesis with the finally submitted articles attached in appendix.

I was engaged in the research project from the fall of 2019 to May 2020. Leading up to the research project and throughout the process I have earned tremendous wisdom and support from my supervisor. For this I would like to thank my supervisor Karl Joachim Breunig for his continuous support and guidance.

Tina Alexandra Ngo

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1 Introduction

The Oxford Dictionary defines Artificial Intelligence (AI) as the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages[1]. Artificial intelligence has gained an enormous amount of attention during “the second wave of AI”. A recent search on google scholar indicate an astonishing 439 000 results on papers written only since 2016. Howard (2019) emphasize that AI is predicted to have a globally transformative influence on economic and social structures similar to the effect from other general-purpose technologies. In particular, the he recent development of cognitive technologies is predicted to cause fundamental changes in the way knowledge workers make their living (Chui et al. 2016) as AI is increasingly reshaping service by performing various tasks, constituting a major source of innovation (Huang & Rust, 2018).

Current and near future organizational strategies are placing great emphasis on machines, robots and AI (Holford, 2019). Automation to reduce menial or repetitive jobs, digitization of work to render remaining workers more efficient and AI to provide more reliable and productive top-end professional work are all interrelated initiatives enacted by current dominant imaginaries of efficiency and maximization. Holford (2019) states that such purely ‘efficient’ and analytical approaches fail to recognize the unique and inimitable characteristics of human creativity and its associated tacit knowledge. Interestingly, Hammershøj (2019) found that there is consensus in studies of future employment that creativity and innovation are among the most uniquely human capacities and therefore most resistant to automation, but there is no consensus as to if or when computers and robotics will be capable of creativity or innovation. What is more, this discussion tends to be vague and futile as it appears to be largely based on conjecture: either the opinion is expressed that it is simply a matter of computing power and, therefore, of time before computers become creative or there is a belief that creativity is something uniquely human in nature. Or are they?

Knowledge intensive firms have been described as insulated from technological automation (Løwendahl, 2005; von Nordenflycht, 2010). However, cognitive technologies incorporate advanced analytical methods to provide robust decision support. In light of recent technological

1 https://www.oxfordreference.com/view/10.1093/oi/authority.20110803095426960

advancements within cognitive technologies even knowledge intensive firms will need to address the fact that they need to undergo changes. Sawney (2016) states that technology offers professional service firms a way to raise productivity and efficiency. By leveraging the power of algorithm-driven automation and data analytics, nonlinear scale becomes feasible as productized services take over the high-volume tasks and aid judgement-driven processes. This frees up well-paid professionals to focus on jobs that require more sophistication and generate greater value for the company. However, productization is also a source of fear for many employees (Sawney, 2016). The flip side to the benefits of intelligent automation is that firms will need fewer people to manage a process. When robots take over manual tasks, companies generally move to a model in which they offer fewer, but more demanding jobs. Employees with the best skills and knowledge will keep their jobs, while those tied to repetitive manual tasks will find themselves at risk. In theory, you could even remove people altogether (Sawney, 2016). It's therefore easy to conclude that cognitive technologies pits humans against robots.

But is that really the future? Algorithms are created and improved by humans, and technology is nothing without people to guide it (Sawney, 2016). Thus, the future workplace will not be about you versus robot; it will be about you *and* robot – which we address as man-machine collaboration. It's also worth noting that cognitive technologies will ultimately leave employees with more-meaningful jobs and companies with more-profitable business models and innovative opportunities (Kakatkar, 2020; Sawney, 2016; Hammershøj, 2019; Kudyba et al. 2019).

Despite this rapidly increasing interest it remains to be understood how these cognitive technologies are implemented and how they cause changes in collaboration, structures, management and value creation in organizations. In particular it remains to be understood how these cognitive technologies affect man-machine collaboration beyond the anecdotal stories of application e.g. in oncology research[2] or as decision support for corporate boards, such as the AI VITAL (Validating Investment Tool for Advancing Life Sciences) as board member of Deep Knowledge Ventures[3]. The point is that some activities – such as cancer research or top management decision making have so far been conducted only by humans.

The gap in theory we address is that we bridge what is known about knowledge management (KM) with what extant research say about new types of activities that AI/cognitive technologies

[2] https://www.ibm.com/products/clinical-decision-support-oncology
[3] https://www.dkv.global/about

can solve. In extant KM literature there has been two main views: practice vs. objectivist view, where the objectivist view concentrate on databases for storage of knowledge. The databases however were constructed for human experts. But now, the cognitive technological advancements take usage of the information stored in the same databases. What happens then to the division of labour?

In light of these arguments, the attribution of this paper is to address the following research question:

> "*How does cognitive technologies affect man-machine collaboration in knowledge-intensive firms?"*

To explore the research question, we employed a structural literature search to extract a final search database that could be used for bibliometric analysis and to identify key articles for a content analysis. The search resulted in an initial sample of 8 728 articles which were reduced to 202 for our bibliometric analysis, resulting in a final sample of 25 articles upon which we conducted a content analysis.

The paper extends understanding of the AI implications for knowledge-intensive firms. Several papers explore technological advances of AI, leaving out implications for management covering AIs implementational effect on knowledge workers, business models and organizational structures. The study provides valuable insight to AI as a change agent in knowledge-intensive firms.

Because of the significant the amount of papers already published; we need to take stock of what the overwhelming amount of prior research have addressed about man-machine collaboration. The study contributes by identifying four core dimensions related to man-machine collaboration, starting at the individual level and progressing to the societal level. The identified dimensions are: Knowledge worker, Organization, Market, and Society. Moreover, existing research suggest different forces acting upon each of these dimensions. However, extant research is inconclusive with respect to the directionality, whether forces acting on a dimension is proactive or constrain. Our contribution is the synthetization of the insights provided by prior research and the subsequent conceptualization that explicate the counteracting forces for each of the four dimensions. The study thus has implications for theorization and practice alike, as it offers a vantage point for subsequent empirical and conceptual research to extend insight on related AI-implementation themes, especially related to innovation and strategy discussions, as well as to managerial decisions related to digital transformation and AI implementation.

The remainder of this paper is organized as follows. The next chapter provides a rather comprehensive review of the relevant literature. Research methodology is presented in chapter 3. Data analysis, results and their implications are provided in chapter 4. The paper concludes with chapter 5 where a summary of the findings, contribution, limitations of the study along with future research directions are given.

2 Theory

In this chapter we are going to focus on cognitive technologies, artificial intelligence and the debate about division of labor. Further we will present the value creation of professional service firms and the issue of trust in artificial intelligence. The chapter concludes with a theoretical summary.

2.1 Cognitive technologies

According to Kudyba, et al. (2019) cognitive technologies is a sector of emerging technologies in the digital era, which incorporates advanced analytic methods to provide robust decision support (Davenport, 2017; Kudyba, et al. 2019). Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing. Advancements in visualization, natural language processing, predictive modeling and search etc., have augmented the creation of and access to knowledge enhancing informational resources (Kudyba, 2014; Kudyba, et al. 2019). Other elements of the cognitive spectrum involve the utilization of artificial intelligence (AI) to perform an ever-increasing number of organizational processes (Westerman and Bonnet, 2015; Kudyba, et al. 2019).

2.2 Artificial intelligence

In recent years the knowledge management software market is exhibiting strong growth as more companies begin to understand how to apply knowledge management practices for the improvement of firm value. The technologies used to support knowledge management initiatives are evolving rapidly with new vendors entering. Of particular interest within the framework of technology's role in knowledge management is the role of artificial intelligence

(AI) in its various forms. AI has received considerable attention during the last two decades and has been widely applied in many business areas (Metaxiotis, 2003, pp. 216-221).

The term artificial intelligence was originally coined by John McCarthy in 1956 (McCarthy, 1959). However, Artificial intelligence (AI) is today considered an umbrella term. The term covers everything from dedicated tasks conducted by a computer (weak AI) e.g. identifying content in pictures or playing chess, to general AI (so-called general AI) which are systems which can be trained to do almost everything. AI is helping companies improve customer service, improve customer loyalty and brand reputation, and enable employees to focus on higher value tasks that provide greater returns. (Walch, 2019).

2.2.1 Automation vs. machine learning

Witz, et al. 2018 define service robots as system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customer. Robots are widely seen as machines capable of carrying out a complex series of actions. Based on the data they have received by various sensors and other sources; they are capable of autonomous decision making and adapt to the situation. Meaning that they can learn from previous episodes. In a frontline service setting they represent the interacting counterpart of a customer. Chatbots are more primitive and are virtually represented. But Witz, et al. (2018) argue that software that works autonomously and learns over time can also be categorized as service robots. In order to understand the machine learning process, we need to distinguish between supervised learning and unsupervised learning.

Supervised learning methods is based on computer vision applications. Training data are provided together with correct labels from which the computer learns the patterns and develops the rules to be applied to future instances of the same problem e.g. with objects- or speech recognition. Unsupervised learning methods aim at finding structure in high-dimensional data e.g. clustering and dimensionality reduction, to make it more accessible (Paschen et al. 2019) Chatbots like Aino (from DNB) uses the former method (Ripegutu, 2019), which means that the learning process and problem solving skills are still limited and needs training from other employees, for now.

2.3 The debate about division of labor

According to Fleming (2018) a number of high-profile studies of robotics and artificial intelligence (AI) in economics and sociology have predicted that many jobs will soon disappear, due to automation. The problems issued is that there are too few jobs created, compared to the ones disappeared. The anxiety about technological unemployment is not new (Fleming, 2018, p. 24). We find trace of the same phenomenon in the early days of industrialism. The 21st century will be marked by a "second machine age" where artificial intelligence (AI) absorbs not only manual work, but also cognitive and non-routine jobs, especially the jobs beyond the reach of mechanization (Brynjolfsson & McAfee, 2014; Fleming, 2018, p. 24).

Cost savings of moving service delivery from frontline employees to service robots can be assumed to be largely competed away and lead to lower prices, increased consumption and improved standards of living in a market economy (Witz, et al. 2018). In services like healthcare, education and public transportation robot-delivered services have the potential to dramatically improve the quality and availability of currently expensive and therefore scarce services that are increasingly important to society´s well-being.

Economists and sociologists leading the discussion about societal implications of the "second machine age" take either an optimistic view of the workforce future, more leisure time and employees' freedom away from the repetitive tasks. Or they have a pessimistic view envisaging levels of unemployment never before seen.

However, Fleming (2018) argues that the most likely jobs will not disappear. The main problem is organizations. Technological innovations do not simply unfurl according to their own endogenous potential, rather they are delimited by socio-organizational forces, which regulate why, how and whether a job or task is regulated. Fleming further states that the social consideration i.e. the price of labor, organizational power relations and the nature of the task, are more important drivers than the qualities of the technology itself. The robots will not steal your job, because "bounded automation" will results in jobs created in the "second machine age" that are considerable poorer in terms of skill, responsibility and pay (Fleming, 2018).

Fleming pointed out some general heuristics to help map out how computerization has reinforced paid employment. First are highly skilled and remunerated elite workers, which expertise that blends with managerial responsibilities. Second, was the semi-automated workers, which we can see are the former customer employees now training chatbot Aino. For those workers, automation will have a downward pressure on wages and conditions. And lastly, the jobs that are not worth automating.

2.4 The advantage of knowledge workers

Chatbots are more cost efficient, because they can work longer hours, do not need to sleep, have breaks or eat. They will behave identically across a service delivery system, providing highly predictable and homogenous service interactions and solutions (Wirtz et al., 2018)

Human error and fatigue are not a factor. Chatbots like Aino respond to their environment in a highly reliable manner. As chatbots are connected to the CRM system and can identify customers, they provide customized service on scale. Chatbots are also designed to have no biases, such as ethnic groups, gender, age and social status, unless programmed (Witz, et al. 2018)

Witz, et al. (2018) distinguishes between professional service roles (PSRs) and subordinate service roles (SSR) PSRs have complex cognitive tasks, which involves a high degree of flexibility, out-of-the box thinking and creative problem solution. Robots are flexible within the defined limits and out-of-box thinking seems unattainable for now. SSRs employers are often lowly paid, have low engagement and are often not motivated. In such positions they engage merely in surface acting. Here, robots may well provide better service compared to employees. They may in fact be even better at displaying surface-acted emotions. Due to their consistent pleasant surface acting robots may outperform people in routine service encounters. For low level, low pay SSRs, robots may become the preferred method of frontline service delivery.

In knowledge-intensive firms' employees are often viewed as an organization's most important asset. According to the current dominant service philosophy of the service-profit-chain (Witz, et al. 2018), competitive advantage is built through the painstakingly careful recruitment, training and innovation of employees. In service organizations high-performing human assets are harder to duplicate than any other corporate resource and are therefore frequently an important source of organizations sustainable competitive advantage.

On the other hand, Witz, et al. (2018) argue that service robots are unlikely to become a key source of competitive advantage, at least in the medium to long term. They illustrate this by drawing a comparison to ATM-machines which were supposed to replace human tellers, stating that hardly any bank position itself on better ATM-delivered service, as ATMs have become a commodity. Witz, et al. (2018) claims that the same is likely to happen regarding service robots, which will be developed and manufactured by organizations that sell frontlines service solutions to service organizations. Reduced importance of frontline employees and the economics of robot-delivered service means that economies of scale and scope (e.g. in data and knowledge bases and training of AIs) are likely to become important sources of competitive advantage with the risk of "winners take it all" markets.

2.5 Trust

Robots can become almost indistinguishable from humans, especially on phone and text interactions. A recent study found that 38 percent of chat users were uncertain whether they interacted with a human or chatbot. 18 percent guessed wrong (Wünderlich and Paluch, 2017; Witz, et al. 2018).

Trust in an organization can be defined as employee´s willingness to be vulnerable to the actions of the organization (Hughes et al. 2019). Based on this definition trust in AI management system as an employee´s willingness to be vulnerable to the actions of AI management system. Not only should the employees rely on their AI management system, but do so with a positive expectation about the outcome. The willingness to be vulnerable and the assumption of beneficial outcome explain why trust is a crucial component in the effectiveness of any AI management system (Hughes et al. 2019). Employees need to believe the AI management system will lead to a positive outcome and provide a satisfactory outcome.

Kolbjørnsrud et al. (2017) found that AI ability to facilitate cloud-based applications as advisors in contexts such as medical diagnosis, security analytics, drug discovery, financial advice, etc. may make some managers uncomfortable. When asked whether they would trust the advice of intelligent systems in making business decisions in the future, 46 percent of the top managers taking part in the survey strongly agreed with the statement. Only 24 percent of middle managers and 14 percent of front-line managers demonstrated the same level of agreement.

Witz, et al. (2018) states that the extent to which service robots can display the emotions, like empathy and compassion, and behavior that give the impression that they truly have the customers best interests at heart, may prove to be a challenge. It remains to see if the robot can provide the same emotional connection resulting in trust, while not be seen as an extension of the organization´s machinery.

People have a general aversion toward algorithms. Especially if the algorithm has made a mistake (Witz, et al. 2018). The aversion is prevalent even if the situations where evidence-based algorithms consistently outperform humans. People forgive other people, but quickly lose trust in AI.

2.5 Theoretical summary

Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing. Other elements of the cognitive spectrum involve the utilization of artificial intelligence (AI) to perform an ever-increasing number of organizational processes (Westerman and Bonnet, 2015; Kudyba, et al. 2019). It is clear that AI has a socio-economic impact in terms of labor division and how businesses will implement AI in knowledge-intensive firms in the near future. Fleming (2018) point out that all jobs probably will not be taken over by AI and contributed with some heuristics that help map out how computerization has reinforced paid employment: The Highly skilled and remunerated elite workers, semi-automated workers and lastly, the jobs that are not worth automating. Further Witz, et al. (2018) discuss the cost benefits of chatbots, but states that economies of scale and scope are likely to become important sources of competitive advantage with the risk of "winners take it all" markets. A future where man and machine work side by side seems to be inevitable, but the challenge of trust will have implications for organizational implementation of AI.

However, it remains to have a concise and unified understanding of how the current technological changes creates changes in the work practices and content of activities – what humans are best at, what can be let to technology – how to organize, create value considering these changes – and how to implement these new solutions and organizational structures in firms .- particularly knowledge intensive firms – where automation of activities are very new.

3 Methodology

In this chapter we start by defining bibliometrics and why we chose to use this method. Further we move on to describe the four-stage process was used to identify the papers for bibliometric analysis. Lastly, we describe how we conducted the descriptive-, bibliometric- and content analysis.

In this paper we employ science mapping from the discipline of bibliometrics with the aim to provide a systematic and thorough review of artificial intelligence research related to man-machine collaboration. Bibliometrics refer to "*the collection, the handling, and the analysis of quantitative bibliographic data, derived from scientific publications*" (Verbeek et al., 2002, p. 181). A systematic review adopts a replicable, scientific, and transparent process based on the theoretical synthesis of existing studies, thus differing from general reviews (Cook et al., 1997). In particular structural reviews that allows us to 1) examine relations between topic areas, and 2) use some form of quantification to shortly compile a large amount of literature (Porter, Kongthon, & Lu, 2002). While the common research paper cites around twenty references, providing an incomplete picture of the research context, a broad scan of a literature can, according to Porter, Kongthon, and Lu (2002, p. 351) "*extend the span of science by better linking efforts across research domains. Topical relationships, research trends, and complementary capabilities can be discovered, thereby facilitating research projects*." In addition, as structural reviews to some degree employ a form of quantification and objective analysis, such reviews "*improve the review process by synthesizing research in a systematic, transparent and reproducible manner*" (Tranfield, Denyer, & Smart, 2003, p. 207). Thus, structural reviews help overcome one of the traditional review papers limitations: their lack of rigor.

To provide a highly objective and systematic review of the literature containing keywords of both one or more of the digit* concepts in combination with either transform* and/or artificial intelligence we employ the VOSviewer science mapping framework (Van Eck et al., 2010; Van Eck & Waltman, 2014). By using VOSviewer science mapping, we are able to examine the intellectual content and structure of research on concepts of digitalization linked with transformation and/or artificial intelligence in rich detail. Further we employ content analysis to a selection of the papers in our final search database, selecting papers based on traditional- and bibliometric criteria. The content analysis allows us to make replicable and valid conjectures by interpreting the textual material.

3.1 Sample

A four-stage process was used to identify the papers for bibliometric analysis. First, we based our analysis of an exhaustive structured literature search of extant published academic research in Web of Science (WoS), 7th of March, 2020. Using the keywords digi* AND transform* OR artificial intelligence, 8 728 articles were identified. Second, we excluded only 2020 from publishing years, keeping all whole years to retain the opportunity to identify potential evolution of the field. Third, we included only articles, meaning we excluded all other document types. Fourth, in order to ensure that the search covered business-perspectives we systematically excluded non business-related categories in the search results under “Web of Science Categories”. The remaining categories were as follows: *Computer science artificial intelligence, law, management, business, communication, economics, international relations, ethics and psychology multidisciplinary.* Thus, systematically removing categories focusing on technology description and specifications (i.e. studies that take the perspective of emphasizing technological complexity). This resulted in 1 092 papers.

To assess categories relevant to answer our research question, we applied three selection methods based on the number of articles within each category.

Firstly, for categories with 50 or more papers we performed a bibliographic co-occurance analysis using a threshold of 5 to identify relevant keywords. Analyzing the clusters in each category revealed if articles focused on technological attributes or digitalization concepts. Secondly, to ensure that high-impact articles within categories that were discarded by the bibliometric analysis were not overlooked, we read the abstracts of the 25 most cited papers for each category, except for *management* and *business*, where we read all of the abstracts. And finally, for categories with less than 50 results, we read the abstract of all papers to assess their relevance.

The two most relevant categories were *business* and *management*. By reading through abstracts and keywords analysis we quickly realized that other categories/fields focused on different themes; i.e. categories like *law* contained a vast number of articles about ethics, and *computer science* mostly contained research articles of technical attributions and hardware descriptions. The bibliometric analysis enabled us first to narrow our search to 202 articles published within the categories of *business* and *management*.

We also performed the search using the Topic-search, following the same criteria as described above, but the resulting database was way to broad, including papers mainly related to hardware attributes to technology. Abstracts readings further confirmed that the papers in the database mainly described usage of different technologies. Thus, initial analysis suggested that the title search would make us much better equipped to answer our research question, we chose to build our paper on the title sample resulting in a final search database containing 202 papers.

3.2 Analysis

The analysis was threefold. First, we did a descriptive analysis consisting of our final search database to identify the evolution on the field and the development within highly ranked academic journals. The purpose was to ensure the validity of the database and to assess the distribution and impact of the various journals. Second, we did a bibliometric analysis based on the final search database to classify the relevant keyword clusters. The bibliometric analysis will enable us to pinpoint the most cited papers, thus helping us understand which main dimensions are referenced in the papers in our final search database. Finally, the bibliometric analysis is also conducted to contribute to the literature review as it is used to identify the most influential articles by analyzing the clusters, as we did a content analysis of the 25 most relevant papers in relation to our research to identify any conformity and contrasts of the man-machine collaboration.

3.2.1 Descriptive analysis

For the descriptive analysis we used the .txt file containing our final search, source title database exported from Web of Science and converted this to an Excel file. (See figure 1 for original distribution) We added a column for AJG-journal ranking. We defined the boundaries of our study to include academic articles published in top management and business journals globally as listed by the 2018 Academic Journal Guide (AJG-list). The AJG-list is the most comprehensive and frequently used ranking list among business scholars when choosing publication nutlets. It is the dominant source used to evaluate business research across Europe and the US. Thus, by limiting the scope of journals to the AJG-list suggests that the research included in the literature review is of high quality and liability. We sorted all the articles and cross referenced them to the rankings of the AJG-list, including only articles from journals at level 3, 4 and world-leading 4* articles at the AJG-list. Resulting in 75 articles in which we conducted a content analysis.

3.2.2 Bibliometric analysis

To obtain a better overview of the identified articles we saved all 202 articles in one file to permit a thorough bibliometric analysis (Markoulli et al., 2017). To conduct the analysis, we applied the VOSviewer software and identified clusters of interrelated articles. We have used the VOSviewer program to map and analyze our dataset. VOSviewer gives us the opportunity to visualize the dataset. The program generates a "map" where collections, or clusters, of articles are characterized by color. Equal colors indicate that they include the same theme.

Within bibliometric analysis there are several methods to find literary correlations. The methods include Co-Citation, Co-Occurrence, Bibliographic Coupling, Citation and Co-Authorship (Van Eck and Waltman 2014). The co-citation method shows which authors are often referred to in a dataset. The method also provides an insight into the relationships between authors or between articles (Small 1973). Bibliographic coupling is a method that can be used to see which authors in a dataset have overlapping literature lists, this can give us an indication of which articles deal with the same themes or refer to the same sources (Boyack and Klavans 2010). Co-occurrence is a method that draws keywords from Abstract, Title and Keywords in publishing. Co-occurrence thus gives an indication of how often two keywords are used together in the articles in a data set (Van Eck and Waltman 2014).

VOSviewer contains several key metrics to help identify the most influential articles or authors. These include links, total link strength and citations. Links say something about how many times an event has happened between two articles or two authors. For example, how many times two articles have cited each other. Total link strength indicates the total number of links one article or author has. Citations simply shows how many times an article has been cited by other articles (Van Eck and Waltman 2019).

Several analyses were conducted in VOSviewer to receive relevant maps to answer our research question. Co-citation and Co-occurrence analysis were conducted to compute relevance of keywords and citations between them, and bibliographic coupling was conducted to find the most influential articles within the final search database.

3.2.3 Content analysis

To ensure relevance and identify the unit for further literature review we made a selection from the 75 articles. First, we read the abstract of all 75 articles to ensure thematic relevance and selected the ones that informed or defined the phenomenon of man-machine collaboration and related terms. During the reading every article was scored on relevance related to the research question on the following scale: (A) Relevant; (B) Borderline relevant; and (C) Irrelevant. During this process the papers that did not contain concepts of man-machine collaboration was discarded, e.g. papers with a core focus on hardware and technological attributes. The selection result included 25 out of 202 papers.

The content analysis was conducted by reading and assessing the 25 papers identified through the three selection criteria. We read all papers and coded them in Excel to provide an overview of how each paper described the respective artificial intelligence concept and how they defined the effect of it. Further, the content analysis was split by collecting the information from the papers in separate tables to easier identify the content and common features of each concept.

4 Findings

4.1 Descriptive

The quantity of the publications is an important indicator that reveals the development trends of a scientific research. Figure 1 depicts a chronological view on volume of articles published.

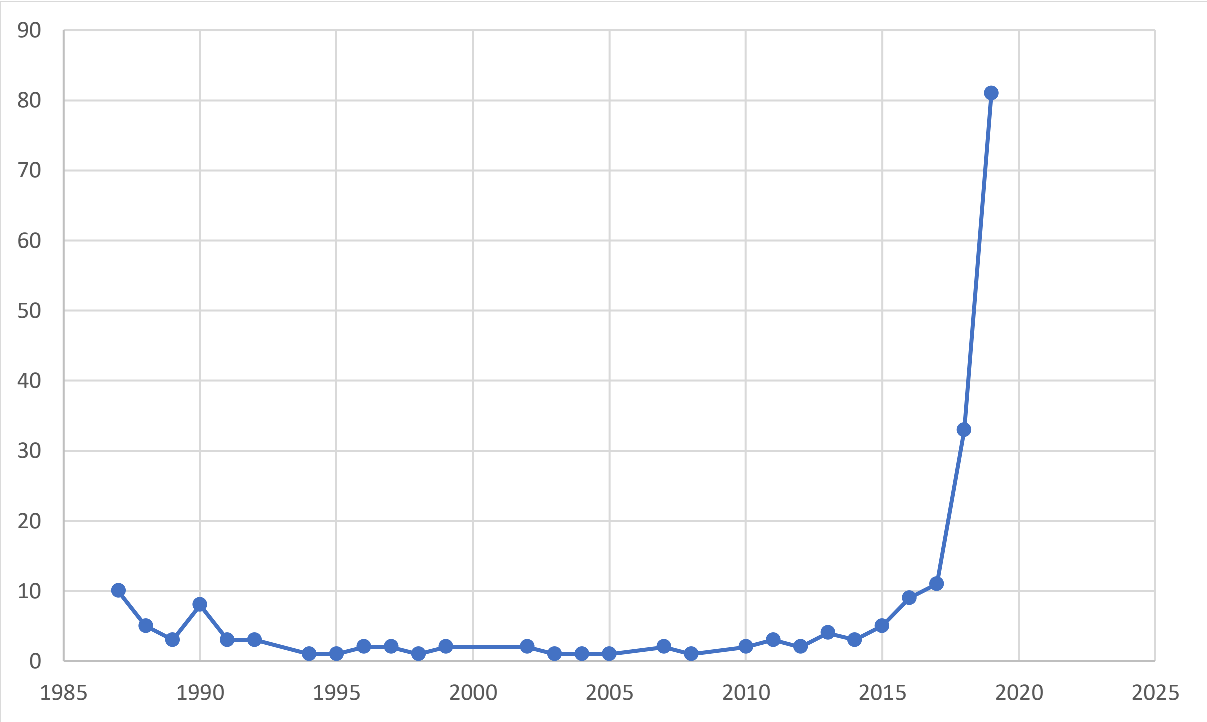

Figure 1: Development of publications per year, within the database consisting 202 papers

To identify overall trends and key figures in our database we employed Microsoft Excel. First, by looking at the publishing year for our database we identified an upward trend in the number of publications per year. The development in number of publications was stable between 1994 and 2012, but from 2013 there has been an exponential growth in published research with a drastic increase in number of annual published research between the years 2013 and 2019, going from 4 to 82 publications. 40 per cent of the publications appeared in 2019. It can be argued that the development from 2013 can be explained by the emergence of technology and IT solutions, creating new business- and social opportunities. The development indicates that the interest among researchers for the different digi* terms and/or artificial intelligence is increasing and based on this trend and the current developments in technology, it is safe to assume that the quantitiy of scientific papers will increase in the years to come.

The 202 papers in our sample are published in 100 different journals. This gives an average of 2.02 paper per journal in our database. Figure 2 illustrates the distribution of papers amongst journals.

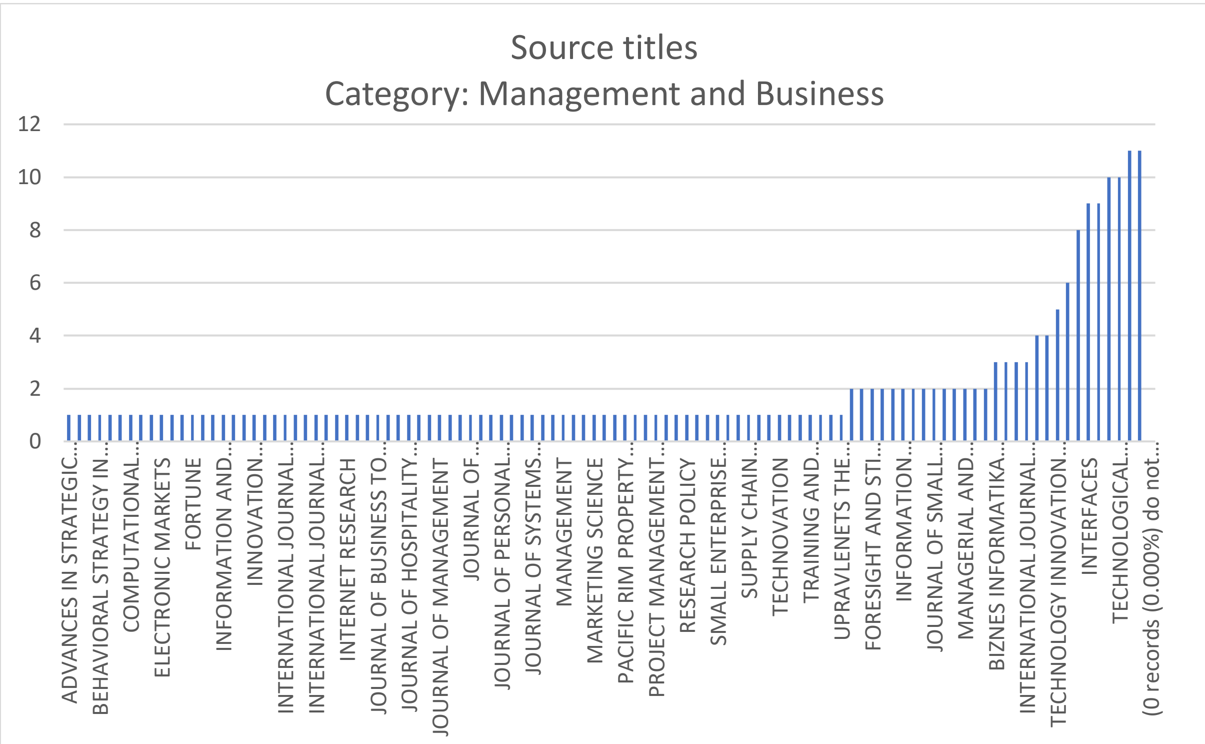

Figure 2: Source title distribution of 202 articles from Web of Science

Based on the large number of journals represented, we found it beneficial to use the AJG-list as a guideline to make further selection, as described in chapter 3. Figure 3 presents an overview of the distribution of AJG-list levels for the database.

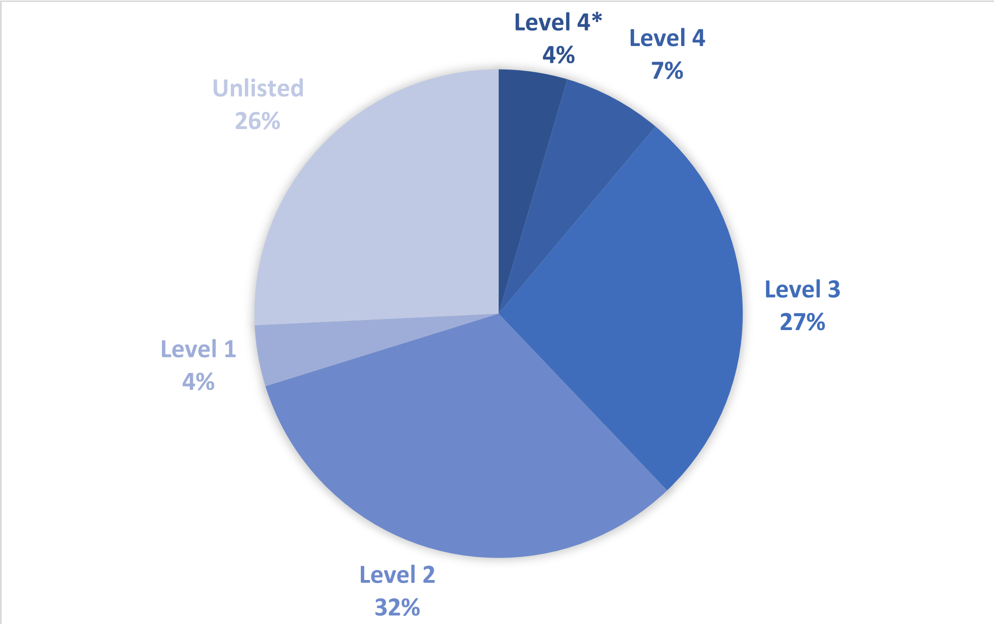

Figure 3: Percentage of journals within each AJG-list level.

Given the overwhelming number of identified articles published in top ranking journals for business and management related fields, we found it necessary to limit the number of articles to consists of articles from level 4*, level 4 and level 3. As we can observe from figure 3, 11 percent of the articles are published at level 4 and 4*. The sample we chose for our content analysis consists of level 4*, level 4 and level 3, which gives the total of 38 percent. Thus, ensuring the validity of the database and to assess the distribution and impact of the various journals.

Table 1 gives an overview of level 4* and level 4 journals and number of publications we included before conducting our content analysis.

Level 4	**Nr. of publications**
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	10
INFORMATION SYSTEMS RESEARCH (4*)	1
INTERNATIONAL JOURNAL OF RESEARCH IN MARKETING	1
JOURNAL OF CONSUMER RESEARCH (4*)	1
JOURNAL OF MANAGEMENT (4*)	1
JOURNAL OF MANAGEMENT INFORMATION SYSTEMS	1
JOURNAL OF SERVICE RESEARCH	1
MANAGEMENT SCIENCE (4*)	1

MARKETING SCIENCE (4*)	1
MIS QUARTERLY (4*)	1
RESEARCH POLICY (4*)	1
STRATEGIC MANAGEMENT JOURNAL (4*)	2

Table 1: Level 4 and 4* journals and number of publications

Figure 4 illustrates publications within journals at the AJG-list level 4 and 4*.

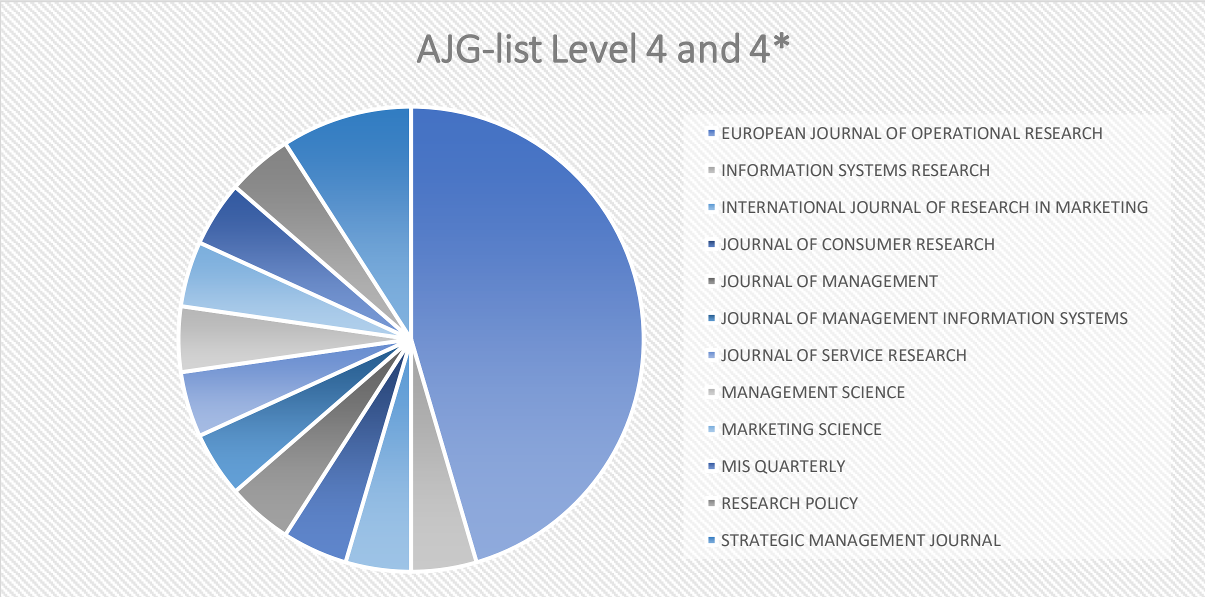

Figure 4: Publications within AJG-list level 4 and 4* journals.

Level 4* and level 4 consists of 22 papers in total. An immediate observation is the high number of publications within operational research journal at level 4, since 10 publications out of 13 publication from level 4 are from *European Journal of Operational Research*. Since *European Journal of Operational Research (EJOR)* publishes high quality, original papers that contribute to methodology of operational research (OR) and to practice of decision making, we were assured that the sample was contributing to our research question.

9 papers out of 22 papers at level 4* are also very assuring. At the AJG-website it states

> *"Within the business and management field, including economics, there are a small number of grade 4 journals that are recognized world-wide as exemplars of excellence. As the world leading journals in the field, they would be ranked among the highest in terms of impact factor. The initial paper selection and review process would be rigorous*

and demanding, accepted papers would typically not only bring to bear large scale data and/or rigour in theory, but also extremely finely crafted and provide major advances to their field." (AJG-homepage)

The remaining 13 papers are at level 4. All journals rated at level 4 publish the most original and best-executed research. As top journals in their field, these journals typically have high submission and low acceptance rate. Papers are heavily referred. These top journals generally have among the highest citation impact factors within their field. This finding again validates the method used in this paper.

Level 3	**Nr. Of publications**
CALIFORNIA MANAGEMENT REVIEW	8
DECISION SCIENCES	3
EUROPEAN JOURNAL OF MARKETING	1
EUROPEAN JOURNAL OF WORK AND ORGANIZATIONAL PSYCHOLOGY	1
HARVARD BUSINESS REVIEW	3
INDUSTRIAL MARKETING MANAGEMENT	2
INFORMATION AND ORGANIZATION	1
INTERNATIONAL JOURNAL OF FORECASTING	1
JOURNAL OF BUSINESS ETHICS	1
JOURNAL OF BUSINESS RESEARCH	2
JOURNAL OF INFORMATION TECHNOLOGY	1
JOURNAL OF STRATEGIC INFORMATION SYSTEMS	2
JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY	9
LONG RANGE PLANNING	1
MIT SLOAN MANAGEMENT REVIEW	4
ORGANIZATION	1
PUBLIC MANAGEMENT REVIEW	1
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	10
TECHNOVATION	1

Table 2: Level 3 journals and number of publications

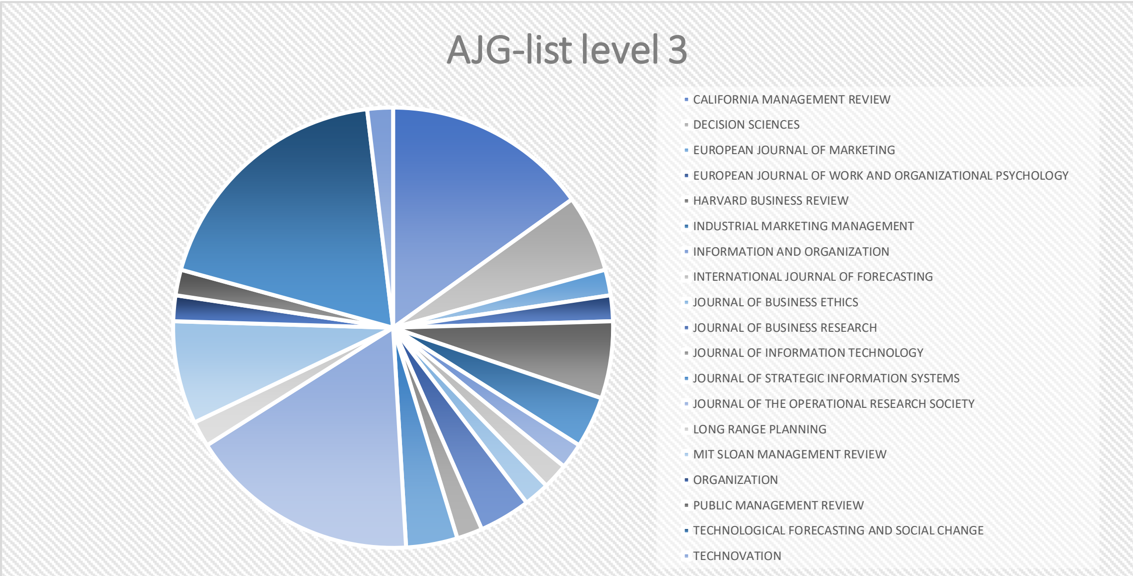

Figure 5: Publications within AJG-list level 3.

Table 2 gives an overview of level 3 journals and respective publications we included before conducting our content analysis. Figure 5 is sector diagram illustrating publications wihin AJG-list level 3. Level 3 consists of 53 papers. Level 3 journals publish original and well executed research papers and are highly regarded. The journals typically have good submission rates and are very selective in what they publish. Papers are heavily referred. These journals generally have good to excellent journal metrics relative to others in their field.

At level 3, 10 out of 53 papers are from the *Techological Forecasting and Social Change* journal, which is an international journal – a major forum for those wishing to deal with methodology and practice of technological forecasting and future studies as planning tools as they interrelate social, environmental and technological factors. 9 out of 53 publications are from *Journal of the Operational Research Society* and 8 out of 53 publications are from *California Management Review*. The chosen sample gives us a total of 46 papers, which will be our database for the content analysis. The fact that the majority of the papers in this sample, comes from journals within operational research, management and technological forecasting makes us very assured about our research methodology and clearly indicate that this sample will enlighten our research question.

4.2 Bibliometric analysis

4.2.1 Co-keywords analysis

Keywords are nouns or phrases that reflect the core content of a publication. The bibliometric data show 986 keywords involved in this research. Co-keyword network visualization was based on occurrences. The co-occurrence threshold was set as 5 and 35 items where brought into visualization (Figure 6a).

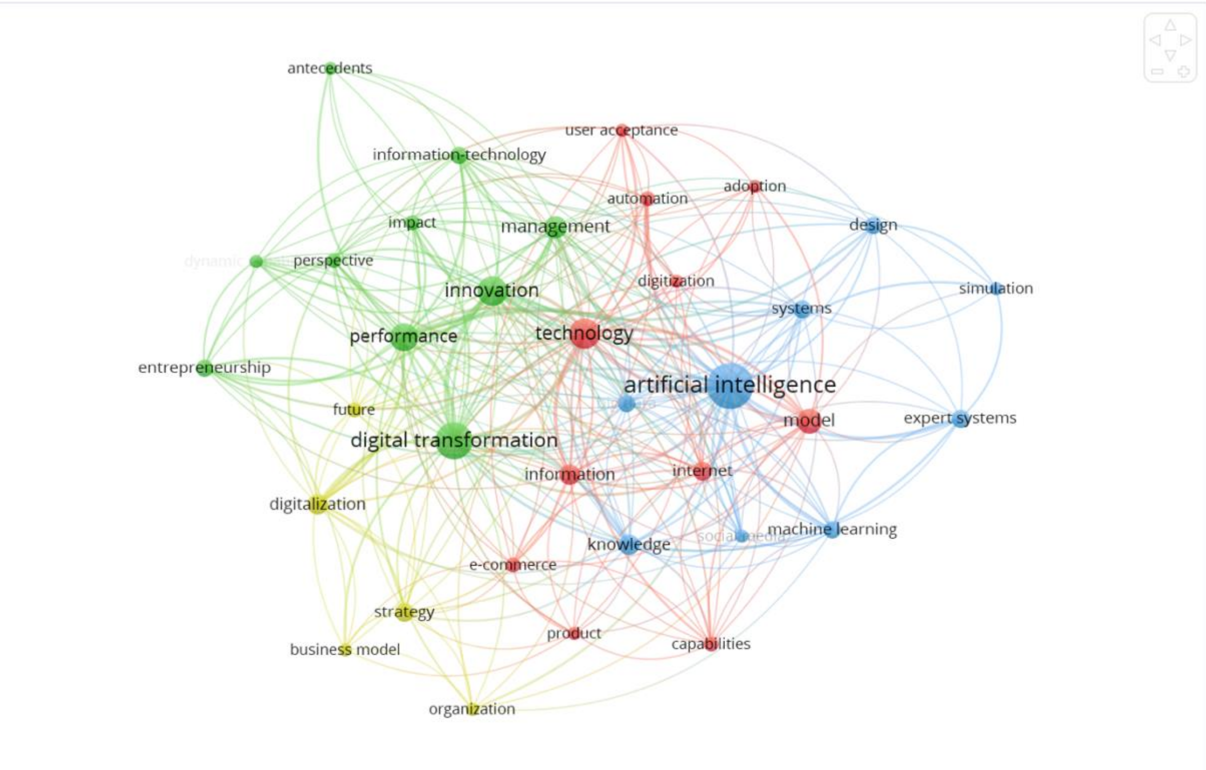

Figure 6a: Keywords co-occurrence analysis

In figure 6a, the size of the circles represents the occurrences of keywords. The larger the circle the more a keyword has been co-selected in the digi* transform* and/or artificial intelligence publications. The keyword "artificial intelligence" and "digital transformation" and "technology" had the strongest strength. The distance between the keywords are demonstrated relative strength and topic similarity. Circles in the same color cluster suggested a similar topic among these publications. The co-keyword network in Figure 6 clearly illustrated four distinct clusters. Each represented a subfield or a field of technological development. Appropriate labels of the four main clusters could be allocated to each of them by analysing the main node circles. The cluster number derive from the VOSviewer software.

Especially, as was shown in the red cluster (Figure 6a, cluster 1, center, 11 items) overlap with both the blue and green cluster. Containing keywords such as digitization, automation, user acceptance, adoption, internet, e-commerce etc., apparently related to the topic of “techonology”. The green cluster (Figure 6a, cluster 2, upper left corner, 10 items) gives us the keywords such as performance, innovation, management, informational technology, dynamic capabilities, entrepreneurship etc. focused on the main domain “digital transformation”.

In The blue cluster (Figure 6a, cluster 3, upper right, 9 items), keywords such as knowledge, machine learning, expert systems, big data, simulations etc., apparently related to the topic of “artificial intelligence”. From the green cluster branches out the yellow cluster (figure 6a, cluster 4, bottom left corner, 5 items) containing keywords such as digitalization, future, strategy, business model and organization.

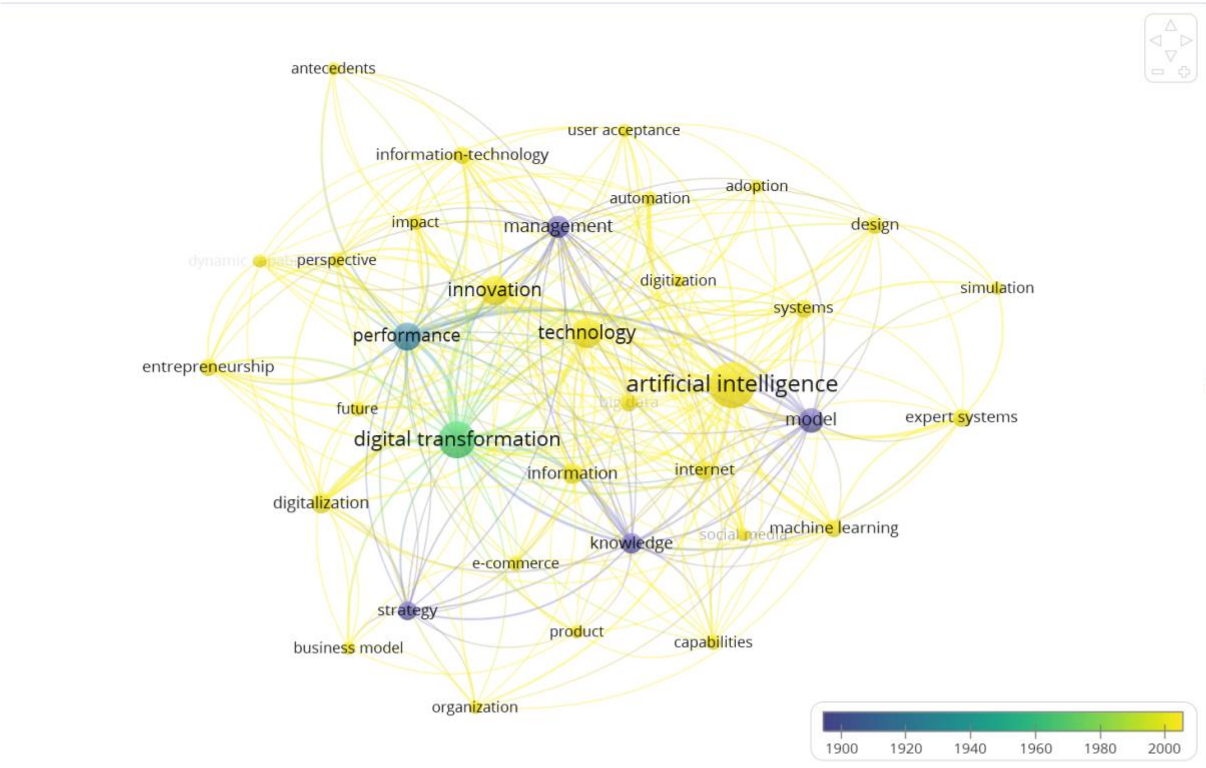

Figure 6b: Co-keyword network visualization of the database of 202 papers

Co-keyword overlay visualization was based on the occurrences and average publication per year scores. As shown in Figure 6b, the colors were used to represent the time-varying keyword occurrences from 1816 (in dark purple) to 2019 (bright yellow). Figure 6 might be confusing. We here include the total link strength information and top 10 occurrences keywords to be listed in Table 3. Note that APY = Average publication years in Figure 6b.

Ranking Number	Keyword	Cluster number	Links	Total Link Strength	Occurances	APY*
1	artificial intelligence	3	31	104	57	2015.88
2	digital tranformation	2	30	85	38	1965.39
3	technology	1	10	82	26	2017.00
4	innovation	2	25	73	24	2018.12
5	performance	2	25	69	21	1921.19
6	model	1	22	42	17	1897.35
7	knowledge	3	21	40	12	1846.17
8	digitalization	4	18	36	12	2018.33
9	Information	1	21	17	12	2018.67
10	internet	1	18	26	10	2013.90

Table 3: The link and total link strength of the top 10 occurnces keywords.

In table 3 a link means a co-occurrence connection between two keywords. According to the VOSviewer manual, each link has a strength, represented by a positive numerical value. The higher this value, the stronger the link. The total link strength indicates the number of publications in which two keywords occur together. By the view of the table in Table 3, it can be seen that the new research hotspot mainly concentrated on the artificial intelligence, technology and innovation.

4.2.2 Co-authorship visualization analysis

The function module of the co-authorship visualization of VOSviewer was applied to analyse the cooperation patterns of the authors, organizations and countries publishing research papers in our database. Based on the 202 publications that were contributed by 482 authors, the cooperation network of the authors was visually mapped in Figure 7.

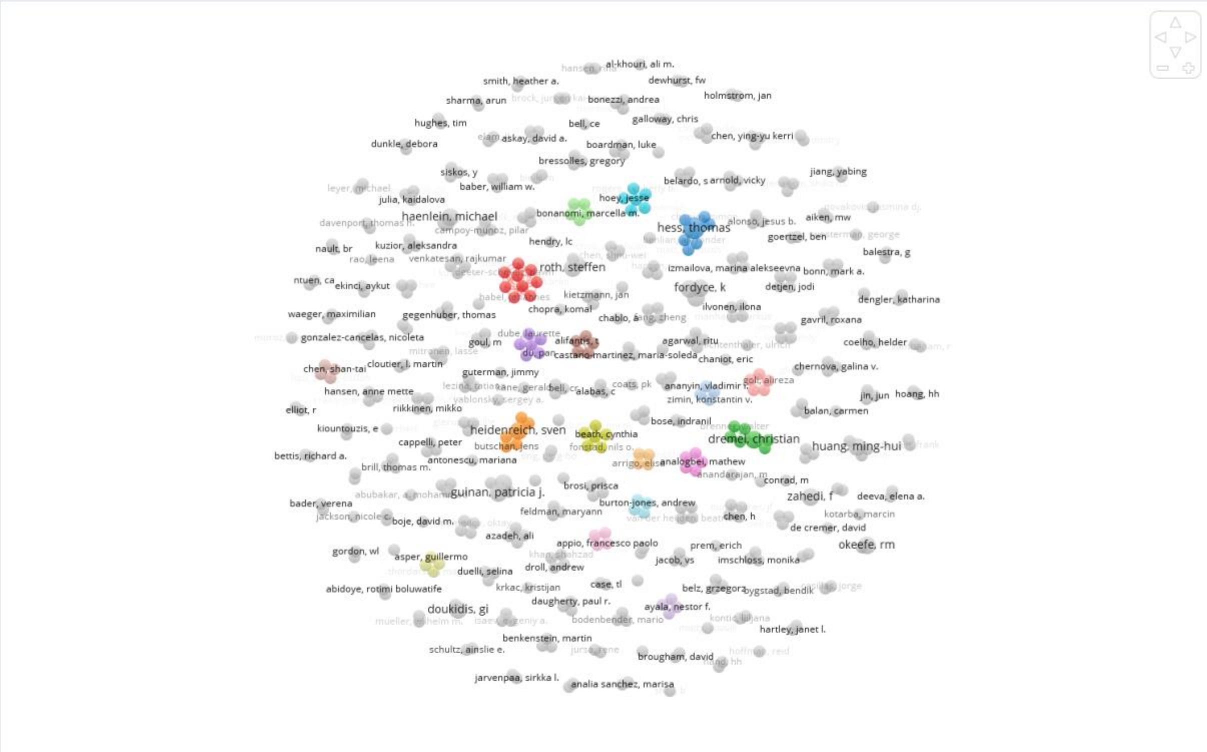

Figure 7 co-authorship visualization from the database of 202 papers

From Figure 7 we find it safe to assume that not many of the authors in our database collaborated on their research papers. We can observe some clusters of collaboration which are visible in Figure 7, represented in various colors. But we found the need to investigate even further.

Statistically, 3 percent out of the authors were credited in two publications in this database. When creating author data based on co-authorship map, the threshold value was set to 2 in order to find the prominent authors. Note that network visualization was based on author link weights (a) and overlay visualisation was based on document weights and average publication years scores (b).

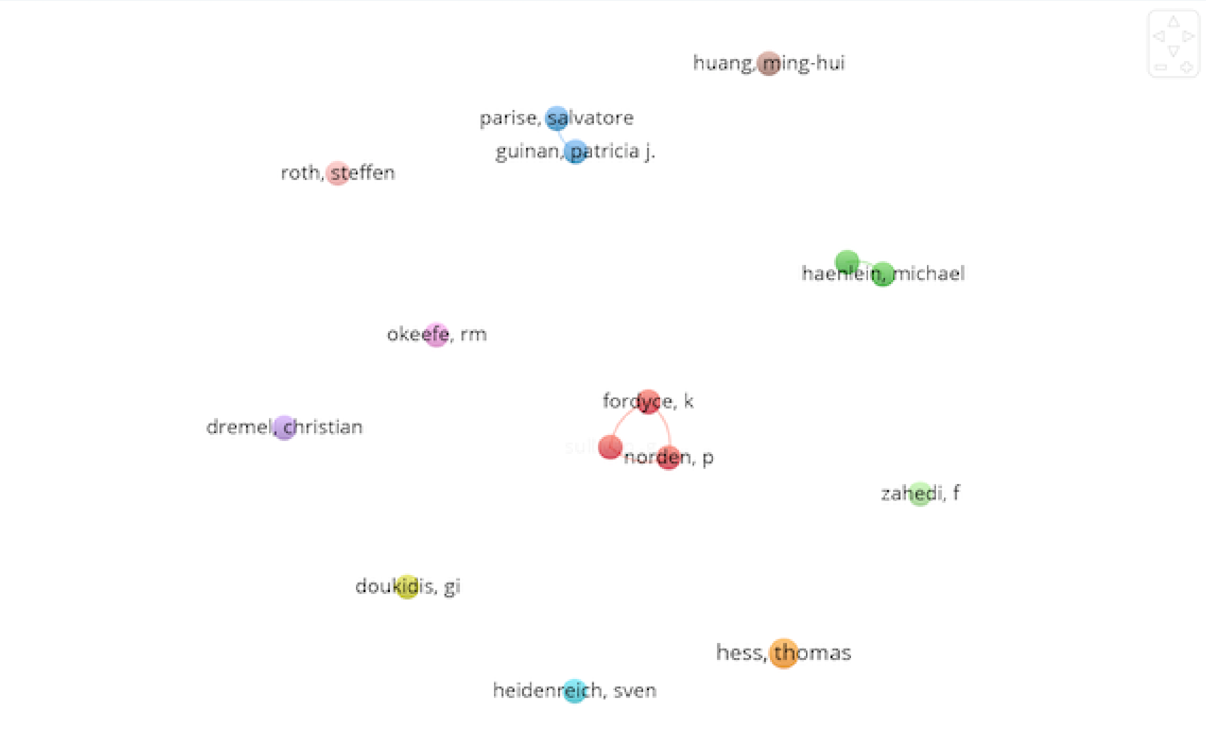

Figure 8a: Authors cooperation network in the database of 202 papers

In Figure 8, lines among the authors represent their cooperation links, while 11 different colors seen in Figure 8a represent the collaboration cluster of the authors. Among these clusters, main academic relations and excellent researcher could be uncovered in the network. But there was very few of such clusters observed in this overlay visualization.

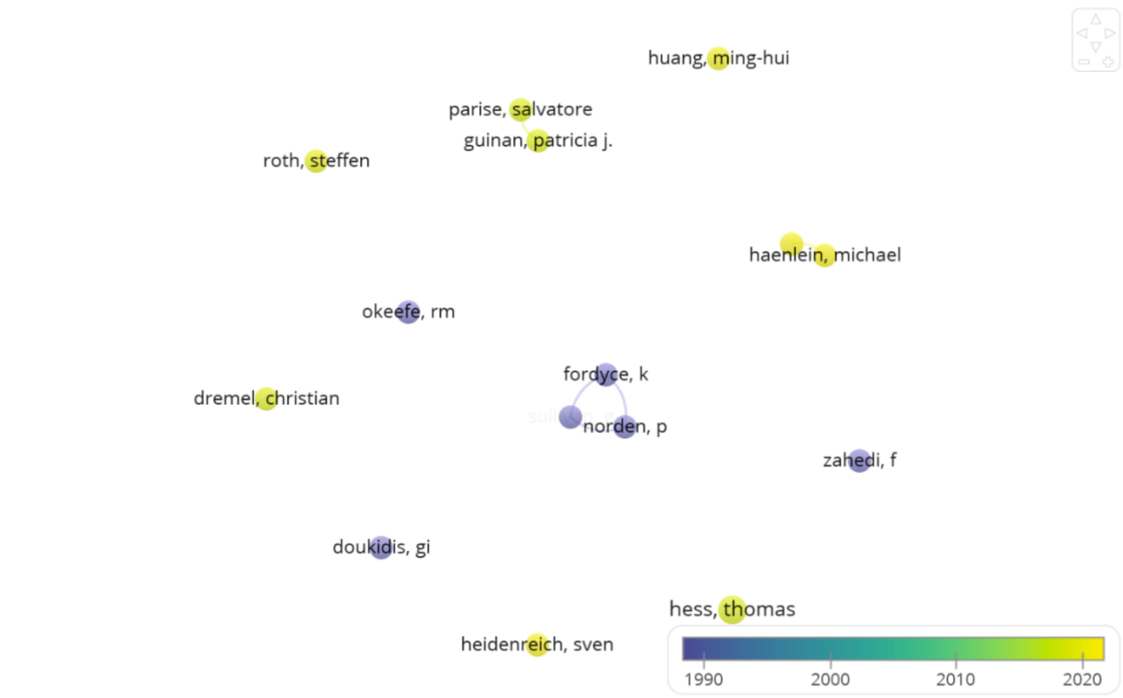

Figure 8b: Authors cooperation overlay in the database of 202 papers

In Figure 8b, the size of the circles represents the average publication of an author and the gradient color from blue to yellow demonstrates the freshness of articles. The productive author, strong linked author and the pioneer in the field were often the same person. However, because of the spread in this visualization the data is inconclusive.

4.2.3 Bibliographic coupling document analysis

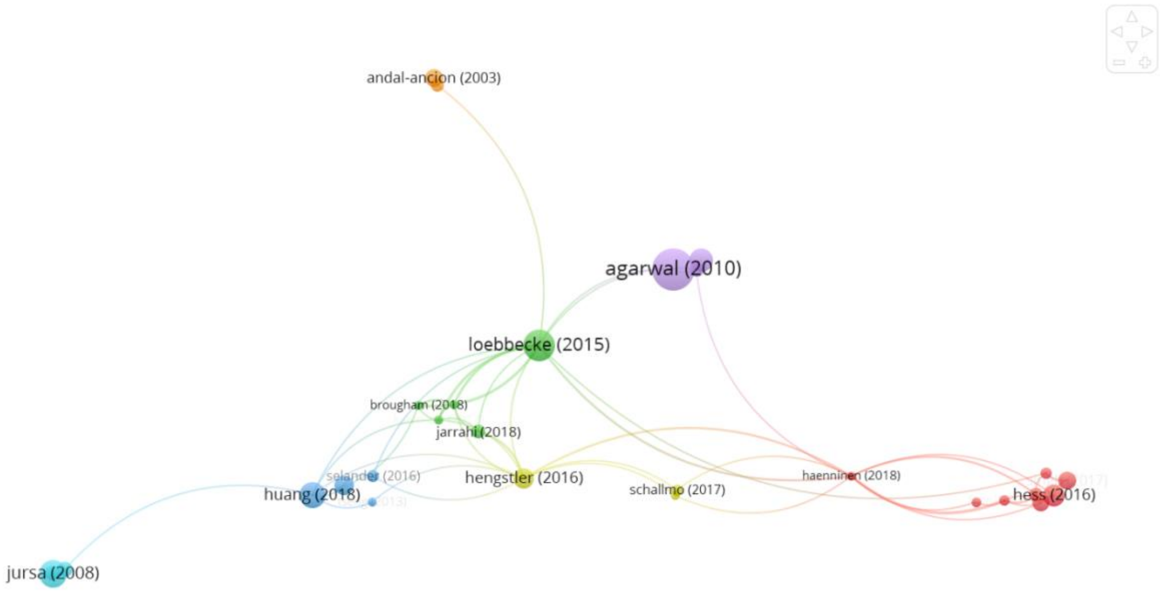

Figure 9: bibliographic coupling document analysis

Figure 9 shows VOSviewers clusters based on the bibliographic coupling method. Here we conducted a full counting and the unit of analysis were documents. The minimum number of citations of a document was 10. Of the 202 documents, 55 meet the threshold. The size of the circles represents the number of citations for each document. In Figure 9 lines among the documents represent their co-citation links, while 7 different colors seen in Figure 9 represent the co-citation cluster of the documents.

For each of the 154 documents, the top 10 most cited documents of the bibliographic coupling links with other documents are presented in Table 4.

Ranking	Document	Cluster	Links	Total link strength	Citation
1	Agarawal (2010)	5	2	2	219
2	Loebbecke (2015)	2	12	19	125
3	Jursa (2008)	6	1	1	98
4	Huang (2018)	3	7	7	84
5	Holmstrom (2014)	5	1	1	70
6	Hess (2016)	1	5	5	60
7	Hengstler (2016)	4	10	12	53
8	Kaplan (2019)	3	2	2	47
9	Andal-ancion (2003)	7	1	1	41
10	Singh (2017)	1	2	3	40

Table 4: The links and total link strength of the top 10 most cited documents

In Table 4 a link means a co-citation connection between two documents. According to the VOSviewer manual, each link has a strength, represented by a positive numerical value. The higher this value, the stronger the link. The total link strength indicates the number of publications in which two documents occur together.

Our research question revolves around man-machine collaboration in the context of knowledge intensive firms. after conducting three bibliometric methods we did not find any direct contribution to man-machine collaboration. However, in the keyword analysis we did find a lot of keywords which gives an indication of the content within this database. The different themes in the literature can be associated with and might inform our research question. It was good a clear visualization of the content within the chosen database. The co-author analysis gave an indication of minor collaboration structures and the bibliographic coupling of documents gave an indication of how documents were connected to each other and which papers that were most influential. Nevertheless, we found the need to conduct a thorough content analysis, based on insights from both the descriptive analysis of journals and the bibliometric analysis.

4.3 Content analysis

Previously in this paper we have described the process of our selection of the 25 articles to conduct our content analysis. After a thorough reading of the documents we identified four dimensions which are used to give a comprehensive presentation of the findings in this chapter. The dimensions are: Knowledge worker, Organization, Market and Society.

Referance	Knowledge worker	Organization	Market	Society
Bader & Kaiser (2019)			x	
Brock & von Wangenheimz (2019)	x	x		
Chablo (1994)			x	
Davenport & Ronanki (2018).	x	x		
Doukidis & Paul (1990)		x		
Garbuio & Lin (2019)	x	x		
Haenlein & Kaplan (2019)				x
Hall (1999)		x		
Hengstler et al. (2016)			x	
Huang & Rust (2018)	x			
Huang et al. (2019)	x	x	x	
Kumar et al. (2019)				x
Loebbecke & Picot (2015)	x	x		
Longoni et al. (2019)			x	
Luo et al. (2019)			x	
Martinez-Lopez & Casillas (2013)		x		
Metcalf et al. (2019)	x			
Montes & Goertzel (2019)				x
Quinn et al. (2016)		x		
Robinson et al. (2005)	x			
Shrestha et al. (2019)		x		
Syam & Sharma (2018)			x	
Tambe et al. (2019)	x			
Warner & Wager (2019)				x
Wilson et al. (2017)	x			

Table 4: Content analysis of 25 core articles revealing four dimensions of man-machine collaboration

4.3.1 Knowledge worker

The great fear about cognitive technologies is that they will put masses of people out of work. Of course, some job loss is likely as smart machines take over certain tasks traditionally done by humans. But at what pace and which stages the job replacement or potential collaboration will take place are yet inconclusive.

Davenport & Ronanki (2018) believe that most workers have little to fear at this point. Cognitive systems perform tasks, not entire jobs. The human job losses we've seen were primarily due to attrition of workers who were not replaced or through automation of outsourced work. Most cognitive tasks currently being performed augment human activity, perform a narrow task within a much broader job, or do work that wasn't done by humans in the first place, such as big-data analytics (Davenport & Ronanki, 2018).

Additionally, Huang & Rust (2018) further states that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI) intelligence tasks first. AI first replaces some of a service job's tasks, a transition stage seen as augmentation, and then progresses to replace human labor entirely when it has the ability to take over all of a job's tasks. The progression of AI task replacement from lower to higher intelligences results in predictable shifts over time in the relative importance of the intelligences for service employees. The authors states that analytical skills will become less important, as AI takes over more analytical tasks, giving the "softer" intuitive and empathetic skills even more importance for service employees. Eventually, AI will be capable of performing even the intuitive and empathetic tasks, which enables innovative ways of human-machine integration for providing service but also results in a fundamental threat for human employment. (Huang & Rust, 2018)

Loebbecke & Picot (2015) further state that due to the nature of knowledge work and cognitive processes, they expect digitization and big data analytics to hit knowledge-based business models and cognitive workers as hard as – and perhaps even faster – than non-knowledge business models and manual workers. Digitization and big data analytics are associated with the autonomous information processing tasks typically performed by firms and knowledge workers – whose high profits and wages provide economic incentives to even speed up substitution (Loebbecke & Picot, 2015).

But is there hope for man-machine collaboration? Brock & von Wangeheim (2019) identified lack of skilled staff and knowledge in digital technologies as the top AI implementation challenge and engaged skilled staff as one of the key AI implementation success factors. Therefore, managers need to develop digital intelligence in the form of suitable human skills within their organization. This intelligence extends beyond the necessary data-related data science skills to include the strategic-, technological-, and security-related capabilities. In fact, AI requires organizations to develop *human* intelligence (Brock & von Wangeheimz, 2019).

Huang, et al. (2019) further urges managers to think of AI and human workers as a team. Managers need to transform jobs to be more people oriented and shift emphasis in hiring from analytical ability to people skills. For the employees the advice is to increase emphasis on feeling intelligence and people skills and learn to work with AI.

We found a study based on this premise. In Accenture PLC's global study of more than 1,000 large companies already using or testing AI and machine-learning systems, Wilson et al. (2017) identified the emergence of entire categories of new, uniquely human jobs. These roles are not replacing old ones. They are novel, requiring skills and training that have no precedents. Companies that deploy advanced AI systems will need a cadre of employees who can explain the inner workings of complex algorithms to nontechnical professionals. More specifically, the research reveals three new categories of AI-driven business and technology jobs. We label them trainers, explainers, and sustainers. Humans in these roles will complement the tasks performed by cognitive technology, ensuring that the work of machines is both effective and responsible — that it is fair, transparent, and auditable (Wilson et al. 2017).

At the same time this discussion opens up for another concern. Bader & Kaisers (2019) study show that humans are increasingly detached from decision-making spatially as well as temporally and in terms of rational distancing and cognitive displacement. At the same time, they remain attached to decision-making because of accidental and infrastructural proximity, imposed engagement, and affective adhesion. When human and algorithmic intelligence become unbalanced in regard to humans' attachment to decision-making, three performative effects result: deferred decisions, workarounds, and (data) manipulations.

4.3.2 Organization

Already in 1990, Doukidis and Paul reported the enthusiasm of practitioners and clients trying AI. But the benefits have yet to be demonstrated (Doukidis & Paul, 1990). Their findings indicated that there were growing confidence that there are benefits to be gained from AI, and an increased anticipation of greater participation. However, how AI are to be implemented and which positive organizational effects AI will bring, is yet inconclusive even after additional 30 years of research.

Brock & von Wangeheimz (2019) stated that at this stage, managers are left with little empirical advice on how to prepare and use AI in their firm's operations. Based on case studies and the results of two global surveys among senior managers across industries, this article shows that AI is typically implemented and used with other advanced digital technologies in firms' digital transformation projects. The digital transformation projects in which AI is deployed are mostly in support of firms' existing businesses, thereby demystifying some of the transformative claims made about AI (Brock & von Wangeheimz, 2019). The results of this study imply that, in many ways, AI is similar to other technologies companies adopt and implement. It certainly is typically deployed in digital transformation projects, and, as such, shares many similarities with other digital projects. At the same time, the focus on self-learning projects and long-run scaling comes with several interesting findings, such as the focus being integral, teaming, and agile.

When considering the questions of how AI implementation can enhance decision making and corporate governance there are reported some concerns. Shrestha, et al. 2019 stated that adding to the more familiar limitations of human decision makers, practitioners and scholars need to advance understanding of the implications of AI's limitations for organizational decision making. First, there is a risk that AI is "fooled" into altering decision outcomes—either through the manipulation of the data it uses as input or through its design (e.g., by changing weights of predictors). These issues can be difficult to discover due to algorithms' inherent opacity. Thus, inviting algorithmic decision making into organizations will require new regulation and procedures for auditing AI algorithms. Encouraging developments in the AI community will conceivably deliver new techniques for enhancing the robustness and defenses of neural networks against biases and adversarial attacks. Second, there is by now a vast body of evidence that AI-based decisions amplify human biases in available data. Bias and unfairness embedded in AI decisions are particularly detrimental to vulnerable groups in our society. Countering these grave concerns requires a stronger emphasis on the development of algorithms that can expose biases in data and human decision making, as well as collaboration between the AI community, legal practitioners, policy makers, corporates, and scientists to develop new measures for fair, accountable, and transparent applications of AI in organizations. Third, introducing AI-based decisions into organizations becomes relatively effective when some level of transparency or interpretability of decisions can be achieved. Managers need to keep abreast of the developments in interpretable and explainable AI. Finally, algorithmic decision-making skills remain highly specialized such that decision outcomes are often difficult to interpret. In introducing AI to organizational decision making, managers must build internal capabilities to decide on the inputs to the algorithm, the algorithms themselves, and the interpretation of predictions. Because AI technologies advance rapidly, organizations must remain vigilant to the strengths and limitations of AI in fully delegated and hybrid human–AI decision-making structures (Shrestha, et al. 2019).

On the other hand, Davenport & Ronanki (2018) reported that managers experienced with cognitive technology are bullish on its prospects. Although the early successes are relatively modest, they anticipate that these technologies will eventually transform work. They believe that companies that are adopting AI in moderation now— and have aggressive implementation plans for the future—will find themselves as well positioned to reap benefits as those that embraced analytics early on. Through the application of AI, information-intensive domains such as marketing, health care, financial services, education, and professional services could become simultaneously more valuable and less expensive to society. The authors further states that business drudgery in every industry and function—overseeing routine transactions, repeatedly answering the same questions, and extracting data from endless documents—could become the province of machines, freeing up human workers to be more productive and creative (Davenport & Ronaki, 2018). Cognitive technologies are also a catalyst for making other data-intensive technologies succeed, including autonomous vehicles, the Internet of Things, and mobile and multichannel consumer technologies. (Davenport & Ronanki, 2018). The authors believe that every large company should be exploring cognitive technologies. There will be some bumps in the road, and there is no room for complacency on issues of workforce displacement and the ethics of smart machines. But with the right planning and development, cognitive technology could usher in a golden age of productivity, work satisfaction, and prosperity.

4.3.3 Markets

In the consumers dimension there are more prominent differences regarding different sector as to how AI effect the man-machine collaboration.

Longoni et al, (2019) report that consumers are reluctant to utilize healthcare provided by AI in real and hypothetical choices, separate and joint evaluations. Consumers are less likely to utilize healthcare (study 1), exhibit lower reservation prices for healthcare (study 2), are less sensitive to differences in provider performance (studies 3A-3C), and derive negative utility if a provider is automated rather than human (study 4). Uniqueness neglect, a concern that AI providers are less able than human providers to account for consumers' unique characteristics and circumstances, drives consumer resistance to medical AI. Indeed, resistance to medical AI is stronger for consumers who perceive themselves to be more unique (study 5). Uniqueness neglect mediates resistance to medical AI (study 6), and is eliminated when AI provides care (a) that is framed as personalized (study 7), (b) to consumers other than the self (study 8), or (c) that only supports, rather than replaces, a decision made by a human healthcare provider (study 9). (Longoni et. al, 2019)

In sales, as early as 1994 Cahblo reported that expert systems will be of use in advising sales staff on the most appropriate telecommunications system that can meet a customer's needs. These can help to structure the interview between sales staff and customer and ensure accuracy and consistency of information provided to customers (Chablo, 1994).

Going forward, perhaps the greatest impact of digitalization in sales will be in all the activities and efforts that go into understanding customer behavior in order to design and deliver highly customized offerings (Syam, N., & Sharma, A. 2018). Thus, in the future, technology will act as an active decision-facilitator, maybe even a decision maker in some cases, that can act in close collaboration with the salesperson to enhance the latter's effectiveness. Some examples of customer behavior are development of consideration sets, development of preferences and utilities from consumption, social influence, and, buying patterns. This understanding is critical to the success of sales strategies (Syam, N., & Sharma, A. 2018).

However, Luo et al. (2019) reported negative effect if usage of chatbots where incorporated. Luo et al. (2019) reported that as long as the chatbot identity is disclosed, regardless of before or after the conversation, customer purchase rates are negatively affected. However, disclosing the bot identity after the conversation helps mitigate such negative impact. This is reasonable because the customer might form a good impression in the first one-minute interaction with the AI chatbot, which can help reduce the distrust of the chatbot. The findings are also suggesting that prior AI experience is helpful in reducing the negative disclosure effect (Luo et. al, 2019).

Further Hengstler, et al (2016) did a study which findings revealed that operational security and data security are decisive factors promoting the performance dimension of trust in a technology. Operational safety is a fundamental determinant of trust in the technology. A technology based on the delegation of control will not be trusted if it is flawed. Their findings also revealed cognitive compatibility, trialability, and usability as the main factors related to the process dimension of trust in a technology. The results show that in the context of applied AI technologies, usability is influenced by both the intuitiveness and mediation effect of the human–machine interface. Ultimately, they determined contextualization of an application and its design as decisive factors regarding the purpose dimension of trust in a technology. The cases show that visibility of a technology has an effect on trust in the technology. Accordingly, high visibility of a technology (e.g., in the transportation industry through autonomous cars or in the medical technology industry through the medical adherence app by AiCure and Care-O-bot by Fraunhofer IPA) requires more intensive efforts to foster trust in the technology in the three dimensions. Regarding trust in the innovating firm, the findings suggest that stakeholder alignment, transparency of the development process, and gradual introduction of the technology are crucial strategies. Stakeholder alignment and transparency of the development process are means to increase the credibility of the innovating firm (Hengstler, et al. 2016).

4.3.4 Society

As AI will be more and more part of the organizational, employee and consumer dimension there are also studies which address the societal effect of AI implementation. Kumar, et al. (2019) claims:

> "*This time, the focus has moved toward how we manage information. We are in a knowledge economy, its currency is information, and the performance indicator is increasing returns to knowledge. This shift has risen, in particular, due to the role of technology. We are now able to collect, store, process, and (re)use information through technology. This has given us further thrust in exploring new frontiers, and AI is part of that new frontier*".

On the other hand, Haenlein & Kaplan (2019) points out that regulation might again be a way to avoid such an evolution. For example, firms could be required to spend a certain percentage of the money saved through automation into training employees for new jobs that cannot be automated. States may also decide to limit the use of automation. In France, self-service systems used by public administration bodies can only be accessed during regular working hours. Or firms might restrict the number of hours worked per day to distribute the remaining work more evenly across the workforce. All of these may be easier to implement, at least in the short term, than the idea of a Universal Basic Income that is usually proposed as a solution in this case (Haenlein & Kaplan, 2019).

Lastly, Montes, G. A., & Goertzel, B. (2019) propose a new technology development to prevent "the winner takes all" markets. The authors explain that decentralized AI affords functions that could transform the AI landscape with positive ethical effects. AI can be unsiloed and made to coordinate and cooperate with other AIs, breeding an economy of AI-as- a-service. Discovery mechanisms increase visibility of otherwise also siloed independent developers and small businesses. AI developer talent can be incentivized to earn financial reward for their work more quickly without necessarily going through the startup ecosystem or into elite academia. Access to powerful AI tools and datasets earlier in a developer's career path affords an opportunity to bolster the professional development of each developer more than if they had to wait for a long time with little to no reward, then settling when they get hired by a well-paying company with its own scope of interest, which may not necessarily align with the developer's. In this point, we can envision an alignment between values and work earlier on in a personal/career path, something that is arguably not uncommonly compromised as an individual sublimates into the corporatist system conveyor belt, as many developers might forgo adhering to their positive value structures in order to gain income. Through a coalescence of political, benefit, and research-oriented motives, a decentralized AI platform such as SingularityNET can serve as a benevolent steward for humanity, with the more of the human race as a whole participating in the growth of AGI. While there have been many all-too-optimistic propositions of technology improving ethics, the present case study demonstrates how a combination of features baked into the technology positions it to become a diverse and flexible decentralized breeding ground of intelligence (Montes, G. A., & Goertzel, B. 2019).

5 Discussion

In this paper our aim was to get a deeper understanding of the effect by cognitive technologies on man-machine collaboration in the context of knowledge intensive firms. As a result of our content analysis, we have mapped out four dimensions: Knowledge worker, Organization, Market and Society. Based on the findings we want to find what it means in relation to our problem statement and how our core articles look at man-machine collaboration in relations to the views we presented in our theory section. Figure.5 illustrates cognitive technologies affect on the different dimensions, further we discuss the findings from each dimension in the following sections.

5.1 Knowledge worker

The great fear about cognitive technologies is that they will put masses of people out of work. Of course, some job loss is likely as smart machines take over certain tasks traditionally done by humans. But at what pace and which stages the job replacement or potential collaboration will take place are yet inconclusive.

In knowledge-intensive firms' employees are often viewed as an organization's most important asset. According to the current dominant service philosophy of the service-profit-chain (Witz, et al. 2018), competitive advantage is built through the painstakingly careful recruitment, training and innovation of employees. In service organizations high-performing human assets are harder to duplicate than any other corporate resource and are therefore frequently an important source of organizations sustainable competitive advantage.

Interestingly, we found that Loebbecke & Picot (2015) state that due to the nature of knowledge work and cognitive processes, they expect digitization and big data analytics to hit knowledge-based business models and cognitive workers as hard as – and perhaps even faster – than non-knowledge business models and manual workers. Digitization and big data analytics are associated with the autonomous information processing tasks typically performed by firms and knowledge workers – whose high profits and wages provide economic incentives to even speed up substitution (Loebbecke & Picot, 2015).

Chatbots are more cost efficient, because they can work longer hours, do not need to sleep, have breaks or eat. They will behave identically across a service delivery system, providing highly predictable and homogenous service interactions and solutions (Wirtz et al., 2018) Human error and fatigue are not a factor. Chatbots like Aino respond to their environment in a highly reliable manner. As chatbots are connected to the CRM system and can identify customers, they provide customized service on scale. Chatbots are also designed to have no biases, such as ethnic groups, gender, age and social status, unless programmed (Witz, et al. 2018)

Fleming (2018) point out that all jobs probably will not be taken over by AI and contributed with some heuristics that help map out how computerization has reinforced paid employment: The Highly skilled and remunerated elite workers, semi-automated workers and lastly, the jobs that are not worth automating. Additionally, Davenport & Ronanki (2018) believe that most workers have little to fear at this point. Cognitive systems perform tasks, not entire jobs. The human job losses we've seen were primarily due to attrition of workers who were not replaced or through automation of outsourced work. Most cognitive tasks currently being performed augment human activity, perform a narrow task within a much broader job, or do work that wasn't done by humans in the first place, such as big-data analytics (Davenport & Ronanki, 2018).

Additionally, Huang & Rust (2018) further states that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI) intelligence tasks first. AI first replaces some of a service job's tasks, a transition stage seen as augmentation, and then progresses to replace human labor entirely when it has the ability to take over all of a job's tasks. The progression of AI task replacement from lower to higher intelligences results in predictable shifts over time in the relative importance of the intelligences for service employees. The authors states that analytical skills will become less important, as AI takes over more analytical tasks, giving the "softer" intuitive and empathetic skills even more importance for service employees. Eventually, AI will be capable of performing even the intuitive and empathetic tasks, which enables innovative ways of human-machine integration for providing service but also results in a fundamental threat for human employment (Huang & Rust, 2018).

Witz, et al. (2018) states that the extent to which service robots can display the emotions, like empathy and compassion, and behavior that give the impression that they truly have the customers best interests at heart, may prove to be a challenge. It remains to see if the robot can provide the same emotional connection resulting in trust, while not be seen as an extension of the organization´s machinery.

Brock & von Wangeheim (2019) identified lack of skilled staff and knowledge in digital technologies as the top AI implementation challenge and engaged skilled staff as one of the key AI implementation success factors. Therefore, managers need to develop digital intelligence in the form of suitable human skills within their organization. This intelligence extends beyond the necessary data-related data science skills to include the strategic-, technological-, and security-related capabilities. In fact, AI requires organizations to develop *human* intelligence (Brock & von Wangeheimz, 2019).

Huang, et al. (2019) further urges managers to think of AI and human workers as a team. Managers need to transform jobs to be more people oriented and shift emphasis in hiring from analytical ability to people skills. For the employees the advice is to increase emphasis on feeling intelligence and people skills and learn to work with AI.

Man-machine collaboration in the employee dimension seems applicable. Our recommendations for management urge the development of human intelligence, and to think of AI and humans as a team. As we have identified here the skills and knowledge in digital technologies are of grave importance in order to implement a successful AI system. Employees should focus on the empathic skills, as the cognitive technologies have an advantage in analytical skills. By usage of man-machine collaboration employees will gain the newfound capabilities will ultimately leave employees with more-meaningful jobs and companies with more-profitable business models and innovative opportunities.

5.1 Organization

There seems to be an overall consensus about the strengths of cognitive technologies and how they excel in efficiency and outperform in analytical tasks. Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing and to provide robust decision support (Davenport, 2017; Kudyba, et al. 2019). AI has received considerable attention during the last two decades and has been widely applied in many business areas (Metaxiotis, 2003, pp. 216-221). AI is helping companies improve customer service, improve customer loyalty and brand reputation, and enable employees to focus on higher value tasks that provide greater returns (Walch, 2019).

In our findings we found that already in 1990, Doukidis and Paul reported the enthusiasm of practitioners and clients trying AI. Brock and von Wangeheimz (2019) also reported on two global surveys among senior managers across industries and shows that AI is typically implemented and used with other advanced digital technologies in the firm’s digital transformation projects. However, the digital information projects in which AI is deployed are mostly in support of firm´s existing businesses. The consensus around usage and implementation of cognitive technologies validates the need to consider man-machine collaboration in the near future.

However, when implementing new technology there are always concerns about trust. Kolbjørnsrud et al. (2017) found that AI ability to facilitate cloud-based applications as advisors in contexts such as medical diagnosis, security analytics, drug discovery, financial advice, etc. may make some managers uncomfortable. When asked whether they would trust the advice of intelligent systems in making business decisions in the future, 46 percent of the top managers taking part in the survey strongly agreed with the statement. Only 24 percent of middle managers and 14 percent of front-line managers demonstrated the same level of agreement.

Shrestha, et al. 2019 addresses that human decision makers, practitioners and scholars need to advance understanding of the implications of AI's limitations for organizational decision making. First, there is a risk that AI is "fooled" into altering decision outcomes—either through the manipulation of the data it uses as input or through its design (e.g., by changing weights of predictors). These issues can be difficult to discover due to algorithms' inherent opacity. Thus, inviting algorithmic decision making into organizations will require new regulation and procedures for auditing AI algorithms. Encouraging developments in the AI community will conceivably deliver new techniques for enhancing the robustness and defenses of neural networks against biases and adversarial attacks.

Second, there is by now a vast body of evidence that AI-based decisions amplify human biases in available data. Bias and unfairness embedded in AI decisions are particularly detrimental to vulnerable groups in our society. Countering these grave concerns requires a stronger emphasis on the development of algorithms that can expose biases in data and human decision making, as well as collaboration between the AI community, legal practitioners, policy makers, corporates, and scientists to develop new measures for fair, accountable, and transparent applications of AI in organizations.

Third, introducing AI-based decisions into organizations becomes relatively effective when some level of transparency or interpretability of decisions can be achieved. Managers need to keep abreast of the developments in interpretable and explainable AI. Finally, algorithmic decision-making skills remain highly specialized such that decision outcomes are often difficult to interpret. In introducing AI to organizational decision making, managers must build internal capabilities to decide on the inputs to the algorithm, the algorithms themselves, and the interpretation of predictions. Because AI technologies advance rapidly, organizations must remain vigilant to the strengths and limitations of AI in fully delegated and hybrid human–AI decision-making structures (Shrestha, et al. 2019).

In the discussion implementing AI and man-machine collaboration at the organizational dimension, there are many factors which need taken into consideration. Man-machine collaboration seems to be inevitable in the future, as the popularity of implementing AI into the organization are rapidly increasing. Man-machine collaboration seems to increase value and give way to new business models as well. But as Shrenstha, et al. (2019) pointed out there are several risks to be aware of. Although the research only covers a brief number of papers in the literature there are clear differences in each field on how to implement cognitive technologies and how man-machine collaboration are to be achieved in the near future.

5.3 Markets

Robots can become almost indistinguishable from humans, especially on phone and text interactions. A recent study found that 38 percent of chat users were uncertain whether they interacted with a human or chatbot. 18 percent guessed wrong (Wünderlich and Paluch, 2017; Witz, et al. 2018).

However, Luo et al. (2019) reported negative effect if usage of chatbots where incorporated. Luo et al. (2019) reported that as long as the chatbot identity is disclosed, regardless of before or after the conversation, customer purchase rates are negatively affected. However, disclosing the bot identity after the conversation helps mitigate such negative impact. This is reasonable because the customer might form a good impression in the first one-minute interaction with the AI chatbot, which can help reduce the distrust of the chatbot. The findings are also suggesting that prior AI experience is helpful in reducing the negative disclosure effect (Luo et. al, 2019).

Longoni et al, (2019) report that consumers are reluctant to utilize healthcare provided by AI in real and hypothetical choices, separate and joint evaluations. Consumers are less likely to utilize healthcare (study 1), exhibit lower reservation prices for healthcare (study 2), are less sensitive to differences in provider performance (studies 3A-3C), and derive negative utility if a provider is automated rather than human (study 4). Uniqueness neglect, a concern that AI providers are less able than human providers to account for consumers' unique characteristics and circumstances, drives consumer resistance to medical AI. Indeed, resistance to medical AI is stronger for consumers who perceive themselves to be more unique (study 5). Uniqueness neglect mediates resistance to medical AI (study 6), and is eliminated when AI provides care (a) that is framed as personalized (study 7), (b) to consumers other than the self (study 8), or (c) that only supports, rather than replaces, a decision made by a human healthcare provider (study 9) (Longoni et. al, 2019). In the words of Witz, et al. (2018): "*People have a general aversion toward algorithms. Especially if the algorithm has made a mistake,"*. The aversion is prevalent even if the situations where evidence-based algorithms consistently outperform humans. "*People forgive other people, but quickly lose trust in AI*."

In order for successful communication with the consumers of the organization it is important that the firm are transparent about their usage of AI in their consumer interaction. Educational approaches to consumers will be beneficial in the long run, as consumers with prior AI experience prevents aversion and distrust. It is also important that man-machine collaboration is communicated and visible as utility of the services will increase and resistance will decrease if the decision is made in a man-machine collaborative environment.

5.4 Society

In the theory chapter we found that economists and sociologists leading the discussion about societal implications of the “second machine age” take either an optimistic view of the workforce future, more leisure time and employees’ freedom away from the repetitive tasks. Or they have a pessimistic view envisaging levels of unemployment never before seen.

In our findings we first found the optimism of AI in Kumar, et al. (2019) statement about that the focus have shifted to information management. The shift has risen, in particular, due to the role of technology. The ability to collect, store, process and reuse information through technology has given us further thrust in exploring the new frontier of AI.

On the other hand, Haenlein & Kaplan (2019) point out that governmental regulation might again be a way to prevent such an evolution. They point at some examples of firms required to spend a certain percentage of the money saved through automation into training employees for new jobs, that cannot be automated. States may also decide to limit the use of automation. Or they might restrict the number of hours worked per day to distribute the ramining work more evenly across the workforce. These restrictions could prevent or at least delay the evolution of cognitive technologies, and the reluctance of the state will potentially stagnate the prosperity of man-machine collaboration in the future.

Yet the findings also reveal the development of new technology to prevent “the winner takes all” markets. Montes & Goertzel (2019) describes how decentralization of AI affords functions that could transform the AI landscape with positive ethical effects, by unsiloing AI making it coordinate and cooperate with other AIs.

The AI evolution in our society and the effect of it, will remain to be inconclusive at this point. There are indeed optimistic and pessimistic views on cognitive technologies and the possibility of man-machine collaboration. Even so, the man-machine collaboration are yet an important part of the societal debate. As the machines are made in the reflections of humans, when constructing new cognitive technologies there will no doubt be necessary for a close man-machine collaboration in the development-, implementation- and monitoring phase. The fear is that we as a society will not be able to base the AI-data on unbiased foundations and that it will be difficult to address accountability of the decision or fault of man and machine. The society must also see the opportunities rather than the treats of the technological advancements; thus, the man-machine collaboration will be possible at a societal level.

6 Concluding comments

6.1 Contribution

By conducting a rigorous assessment of extant published research to address: How does cognitive technologies affect man-machine collaboration in knowledge-intensive firms, this study provides a foundation for researching the currently hyped phenomenon of artificial intelligence and related topics such as cognitive technologies and man-machine collaboration. The study confirms that the field remains immature and fragmented, and despite revealing that all identified articles in our content analysis sample address artificial intelligence and cognitive technologies as an important aspect of changes in organizations and related strategy development, few journals deals with the man-machine collaboration in particular. Indeed, there exist no comprehensive description on how strategy should be adapted to technological developments. There is also a limited published quantitative research relating to the limited understanding of how different man-machine collaborations relates to different organizational outcomes.

We have found that cognitive technologies affect man-machine collaboration in knowledge intensive firms in different ways. In order to provide a vantagepoint upon which research efforts could be based, we have identified four dimensions that experience different effects on man-machine collaboration. We contribute with a figure which map out cognitive technologies affect on man-machine collaboration within the four dimensions (figure 9).

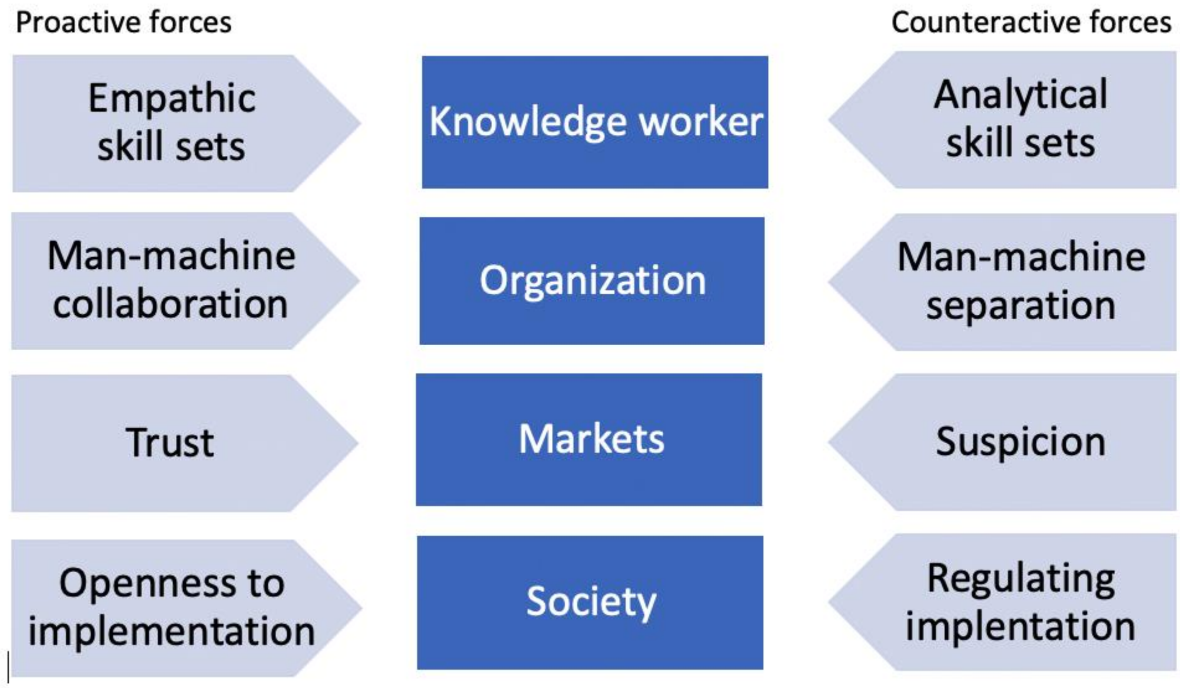

Figure 9: Four dimensions of man-machine collaboration with identified dilemmas

Our findings and the above discussion reveal how prior research addressing man-machine collaboration in the context of digital transformation of knowledge intensive firms is inconclusive with respect to the forces acting upon the four dimensions identified in this study. Literature depicts both proactive and counteractive forces for each of the dimensions. Figure 5 is an attempt to illustrate the dilemmas for each of the four dimensions Based on the above discussion of the dilemmas, or counteracting forces, associated with each of the four dimensions. Knowledge workers face the dilemma of relevant skill sets, either continue with analytical skill sets or pursue more empathic skill sets. Organizations considers whether they want the workforce to be separated from the machines or pursue man-machine collaboration. At the market level, consumers are suspicious towards cognitive technology and thus face the dilemma of how to trust communication with knowledge intensive firms. Consequently, society as a whole need to consider if regelation or openness to implementation of cognitive technology will benefit the current and next generation facing man-machine collaboration. To date there exist limited empirical research that can establish the directionality of these counteracting forces.

Key findings in this study are that the influence on man-machine collaboration is largely dependent on individual factors, such as attitudes to technology and change, as well as societal attitudes towards the AI-evolution. Man-machine collaboration is a tool for business model innovation as it can contribute to the shift from product to service-based businesses. Man-machine collaboration relates to both intra-organizational levels and external environments with implications for all four dimensions, therefore these dimensions offers a vantage point for subsequent empirical and conceptual research to extend insight on related AI-implementation themes, especially related to innovation and strategy discussion of scalability, automation, channel selection and connectivity.

6.2 Practical implications

Deciding on implementing artificial intelligence and cognitive technologies is currently of primary concern to practitioners when navigation of an increasingly disruptive environment. Our study condensed an overwhelmingly amount of digitalization research into a digestible 25 papers spanning across different disciplines. Moreover, we proposed four dimensions that can be utilized to inform the innovation and strategy discussions within firms when deciding on future directions for their digitalization efforts. We suggest that managerial teams discussing the selection and implementation of cognitive technologies to consider the different possibilities for man-machine collaboration underpinning our suggested dimensions, when addressing their digital innovation strategy in general and in particular when deciding on business model innovation, digital disruption, digital transformation, artificial intelligence implementation, disruptive innovation and Industry 4.0.

Furthermore, this research has implications for managers who want to utilize cognitive technologies while balancing the consideration of employee engagement. Our findings thus indicate that man-machine collaboration is to a greater extent something that cannot be seen from the outside, which means that interpersonal relationships between managers and employees are essential to reduce resistance to change and succeed with technological implementations.

6.4 Limitations

The set of papers identified for this sample may differ from those one might identify using other search strings and/or sampling strategies. For example, an alternative search string could be a title search of digi* exclusively or using the same search string for topic search. Further the boundaries set by only including AJG-list journals at level 3 and up, may possibly exclude papers published in less recognized journals. An alternative research strategy could have been to include all journals, regardless of ranking and manually review all articles in the initial database and identify every single paper touching upon man-machine collaboration. Although this manual process also would have significant limitations (e.g. introducing considerable subjectivity into the paper selection process, time intensiveness), such a process could capture papers on cognitive technology that did not meet any of our sampling parameters (e.g. not mentioning man-machine collaboration or artificial intelligence in their title or abstract, not being on the AJG-list at all). However, we believe that the systematic criteria we applied are reasonable for identifying relevant articles to better understanding of cognitive technologies effect on man-machine collaboration in a business context. Based on the findings of this study and the associated limitations, we will make recommendations for future research.

6.5 Further research

Our study reveals how extant research have recorded how cognitive technologies affect man-machine collaboration in different ways and have identified four dimensions that experience different effects on man-machine collaboration. The influence on man-machine collaboration is largely dependent on individual factors, such as attitudes to technology and change, as well as societal attitudes towards the AI-evolution. Moreover, extant research is inconclusive with respect to the forces affecting these dimensions, depicting the forces almost as dilemmas. Future research can build on this insight to further knowledge of the vast potential of AI application and digital transformation by empirically seeking answers to the directionality of forces at each dimension level. Moreover, the study can be utilized to inform the innovation and strategy discussions when implementing cognitive technologies. We found little empiricism about the effects cognitive technologies have in the workplace, as well as empirics from only one industry. The reason for this may be that this type of technology is still in the growth phase and thus has little basis for researching the implications. Therefore, we look at what interesting research continues on the effects cognitive technologies have on knowledge-intensive professions. In our assignment, we did not focus significantly on what man-machine collaboration is, but it emerged from our findings that this is very individual. It is different from the traditional definitions of collaboration. It would therefore have been interesting to research more on what defines the man-machine collaboration of knowledge workers. In order to investigate the individual circumstances that determine perceived autonomy more closely, it may be beneficial to research further with a qualitative approach. It would also be interesting to do a longitudinal study of man-machine collaboration within each knowledge intensive industry (e.g. education, finance, audit, etc.).

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Appendix I

A bibliometric analysis deconstructing research on how cognitive technologies affects man-machine collaboration

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Abstract: The field of research addressing artificial intelligence (AI), and related topics, is rapidly increasing. However, despite this emerging interest, the currently body of published research remains complex and unstructured. In particular, it remains to be understood how these technologies is implemented and cause changes in man-machine collaboration. In order to inform this issue, we conducted a bibliometric analysis of extant literature on AI and man-machine collaboration to take stock of extant published research in order to provide a foundation upon which both future theory and practice can be built. We based our analysis of an exhaustive structured literature search of published academic research in Web of Science (WoS) until 2019. Using the keywords digi* AND transform* OR artificial intelligence, 8 728 articles were identified. The bibliometric analysis enabled us first to identify 202 relevant articles published within the fields of business and management, and subsequently to further narrowing our scope to 25 core contributions using bibliometric coupling. A content analysis of these 25 articles revealed that whereas there is a lot of attention to the technological complexities related to the emerging cognitive technologies, there is to date limited empirical descriptions of the consequences for individuals, organizations or value creation of adopting these technologies. Our study identifies four important dimensions of man-machine collaboration; Knowledge worker, Organization, Market, and Society. Moreover, our findings reveal extant research is inconclusive with respect to the forces affecting these dimensions as different authors record both proactive forces and constraining forces associated with each of the four dimensions. Our contribution, as well as, the identification of a core canon of relevant research articles provides a foundation upon which future research and practice can be built by identifying core dimension and the forces acting upon them.

Keywords: Artificial intelligence, bibliometric analysis, digital transformation, cognitive technology, man-machine collaboration.

1. Introduction

Artificial intelligence (AI) is about imbuing machines with a kind of intelligence that is mainly attributed to humans (Kakatkar et al. 2020), such as visual perception, speech recognition, decision-making, and translation between languages. Artificial intelligence has gained an enormous amount of attention during “the second wave of AI”. A recent search on google scholar indicate an astonishing 439 000 results on papers written only since 2016. Current and near future organizational strategies are placing great emphasis on machines, robots and AI (Holford 2019). Automation to reduce menial or repetitive jobs, digitization of work to render remaining workers more efficient and AI to provide more reliable and productive top-end professional work are all interrelated initiatives enacted by current dominant imaginaries of efficiency and maximization. Hammershøj (2019) found that creativity and innovation are among the most uniquely human capacities and therefore most resistant to automation, but there is no consensus as to if or when computers and robotics will be capable of creativity or innovation.

In light of recent cognitive technology developments, even knowledge intensive firms (e.g. Løwendahl 2005; von Nordenflycht 2010) might not be as insulated towards automation of core task as anticipated in extant theory. Sawney (2016) states that technology offers professional service firms a way to raise productivity and efficiency. By leveraging the power of algorithm-driven automation and data analytics, nonlinear scale becomes feasible as productized services take over the high-volume tasks and aid judgement-driven processes. This frees up well-paid professionals to focus on jobs that require more sophistication and generate greater value for the company, as well as employees with more-meaningful jobs and companies with more-profitable business models and innovative opportunities (Kakatkar 2020; Sawney 2016; Hammershøj 2019; Kudyba et al. 2019).. However, these predictions necessitate organizational changes based on a sensible division of labor between man-machine.

To date, we lack knowledge about this division of labor and the opportunities and best practices of AI implementation across different organizational and industry contexts. Moreover, it remains to be understood how these cognitive technologies are implemented and how they cause changes in collaboration, structures, management and value creation in organizations. To enlighten these issues, our study addresses the following research question: "*How does cognitive technologies affect man-machine collaboration in knowledge-intensive firms?"*

To explore the research question, we employed a structural literature search to extract a final search database that could be used for bibliometric analysis and to identify key articles for a content analysis. The search resulted in an initial sample of 8 728 articles which were reduced to 202 for our bibliometric analysis, resulting in a final sample of 25 articles upon which we conducted a content analysis. Our findings suggest that man-machine collaboration is dependent on individual factors, such as attitudes to technology and change, as well as societal attitudes towards the AI-evolution. The study contributes by identifying four core dimensions related to man-machine collaboration, starting at the individual level and progressing to the societal level. The identified dimensions are: Knowledge worker, Organization, Market, and Society. Moreover, existing research suggest different forces acting upon each of these dimensions. However, extant research is inconclusive with respect to the directionality, whether forces acting on a dimension is proactive or constrain. Our contribution is the synthetization of the insights provided by prior research and the subsequent conceptualization that explicate the counteracting forces for each of the four dimensions. The study thus has implications for theorization and practice alike, as it offers a vantage point for subsequent empirical and conceptual research to extend insight on related AI-implementation themes, especially related to innovation and strategy discussions, as well as to managerial decisions related to digital transformation and AI implementation.

2. Theory

According to Kudyba et al. (2019) cognitive technologies is a sector of emerging technologies in the digital era, which incorporates advanced analytic methods to provide robust decision support (Kudyba et al. 2019).

Artificial intelligence (AI) has received considerable attention during the last two decades and has been widely applied in many business areas (Metaxiotis 2003, pp. 216-221).The term artificial intelligence was originally coined by John McCarthy in 1956 (McCarthy 1959). However, Artificial intelligence (AI) is today considered an umbrella term. The term covers everything from dedicated tasks conducted by a computer (weak AI) e.g. identifying content in pictures or playing chess, to general AI (so-called general AI) which are systems which can be trained to do almost everything. AI is helping companies improve customer service, improve customer loyalty and brand reputation, and enable employees to focus on higher value tasks that provide greater returns. (Walch 2019). According to Davenport (2017) AI can be considered a cognitive technology that emulates activities traditionally associated with the human brain. Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing. Advancements in visualization, natural language processing, predictive modeling and search etc., have augmented the creation of and access to knowledge enhancing informational resources (Kudyba 2014; Kudyba et al. 2019). Other elements of the cognitive spectrum involve the utilization of artificial intelligence (AI) to perform an ever-increasing number of organizational processes (Westerman and Bonnet 2015; Kudyba et al. 2019).

Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing. Other elements of the cognitive spectrum involve the utilization of artificial intelligence (AI) to perform an ever-increasing number of organizational processes (Westerman and Bonnet 2015; Kudyba et al. 2019). It is clear that AI has a socio-economic impact in terms of labor division and how businesses will implement AI in knowledge-intensive firms in the near future. Fleming (2018) point out that all jobs probably will not be taken over by AI and contributed with some heuristics that help map out how computerization has reinforced paid employment: The Highly skilled and remunerated elite workers, semi-automated workers and lastly, the jobs that are not worth automating. Further Witz et al. (2018) discuss the cost benefits of chatbots, but states that economies of scale and scope are likely to become important sources of competitive advantage with the risk of "winners take it all" markets. A future where man and machine work side by side seems to be inevitable, but the challenge of trust will have implications for organizational implementation of AI. However, it remains to have a concise and unified understanding of how the current technological changes creates changes in the work practices and content of activities – what humans are best at, what can be let to technology – how to organize, create value considering these changes – and how to implement these new solutions and organizational structures in firms.- particularly knowledge intensive firms – where automation of activities traditionally have been perceived as very difficult.

3. Methodology

We employ science mapping from the discipline of bibliometrics with the aim to provide a systematic and thorough review of artificial intelligence research related to man-machine collaboration. Bibliometrics refer to "*the collection, the handling, and the analysis of quantitative bibliographic data, derived from scientific publications*" (Verbeek et al. 2002, p. 181). A systematic review adopts a replicable, scientific, and transparent process based on the theoretical synthesis of existing studies, thus differing from general reviews (Cook et al. 1997). We based our analysis of an exhaustive structured literature search of extant published academic research in Web of Science (WoS) (Van Eck & Waltman 2014), 7th of March, 2020. Using the keywords digi* AND transform* OR artificial intelligence, 8 728 articles were identified. Subsequently we reduced the sample to 1092 papers by only selecting the Web of Science Categories: *Computer science artificial intelligence, law, management, business, communication, economics, international relations, ethics and psychology multidisciplinary.* For categories with 50 or more papers we performed a bibliographic co-occurrence analysis using a threshold of 5 to identify relevant keywords. We also read the abstract of all papers to assess their relevance for categories with less than 50 results. To ensure that high-impact articles within categories that were discarded by the bibliometric analysis were not overlooked, we read the abstracts of the 25 most cited papers for each category, except for *management* and *business*, where we read all of the abstracts. Experimentation with different search function (e.g topic-, key word- or title-search) , and subsequent reading of abstracts, suggested that the title search would make us best equipped to answer our research question, we chose to build our paper on the title sample resulting in a final search database condensed down to 202 relevant papers.

The analysis commenced in three stages. First, we did a descriptive analysis consisting of our final search database to identify the evolution on the field and the development within highly ranked academic journals (2018 Academic Journal Guide (AJG guide). The purpose was to ensure the validity of the database and to assess the distribution and impact of the various journals. Subsequently, we sorted all the articles and cross referenced them including only articles from journals at level 3, 4 and world-leading 4* articles at the AJG-list. Resulting in 75 potential articles for a content analysis. Second, we deployed the VOSviewer software to map and analyze our dataset, enabling us to visualize the dataset through a bibliometric analysis cluster visualizationa (Markoulli et al. 2017). VOSviewer contains several key metrics to help identify the most influential articles or authors e.g. links, total link strength and citations). We experimented with several different analysis provided by the software (e.g. Co-Citation, Co-Occurrence, Bibliographic Coupling, Citation and Co-Authorship (Van Eck and Waltman 2014)). Co-citation and Co-occurrence analysis were conducted to compute relevance of keywords and citations between them, and bibliographic coupling was conducted to find the most influential articles within the final search database. The bibliometric analysis enabled us to identify the most cited papers, thus helping us understand which main dimensions are referenced in the selected papers. Finally, the bibliometric analysis was utilized to identify the most influential articles by analyzing the clusters, and performed a content analysis of these papers identifying how issues pertaining to man-machine collaboration was treated. First, we read the abstract of all 75 articles and excluded the papers that did not contain concepts of man-machine collaboration, resulting in a final sample of 25 out of 202 papers. We thoroughly read all papers and coded them in Excel. Further, the data from the initial coding was further compiled in separate tables to identify the content and common features of each concept.

4. Findings

4.1 Descriptive analysis

The quantity of the publications is an important indicator that reveals the development trends of a scientific research. Figure 1 depicts a chronological view on volume of articles published, and the current exponential growth in published research addressing the selected topic.

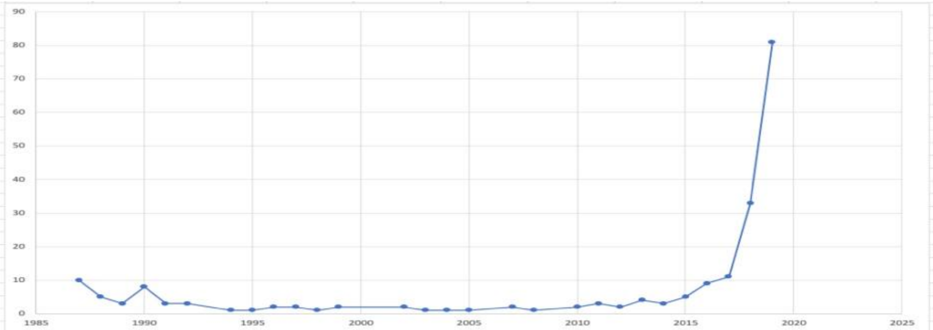

Figure 1: Development of publications per year, within the database consisting 202 papers

Based on the large number of journals represented, we found it beneficial to use the AJG-list as a guideline to make further selection. Figure 2 presents an overview of the distribution of AJG-list levels for the database.

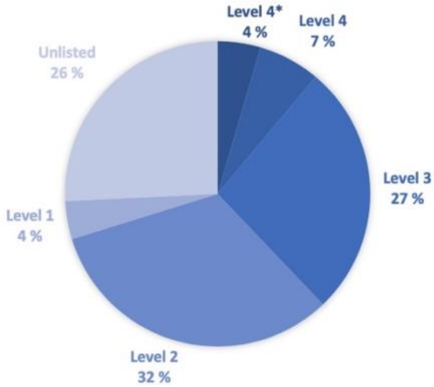

Figure 2: Percentage of journals within each AJG-list level.

Given the overwhelming number of identified articles published in top ranking journals for business and management related fields, we found it necessary to limit the number of articles to consists of articles from level 4*, level 4 and level 3. As we can observe from figure 3, 11 percent of the articles are published at level 4 and 4*. The sample we chose for our content analysis consists of level 4*, level 4 and level 3, which gives the total of 38 percent. Thus, ensuring the validity of the database and to assess the distribution and impact of the various journals. Table 1 gives an overview of level 3, 4 and 4* ranked journals by AJG, and number of publications we included before conducting our content analysis.

Table 1: Level 3, 4 and 4* journals and number of publications

Level 4*, 4 and 3 rated journals by AJG	#	**Level 4*, 4 and 3 rated journals by AJG cont.**	#
Information systems research (4*)	1	Harvard Business Review (3)	3
Journal of Consumer Research (4*)	1	Industrial Marketing Management (3)	2
Journal of Management (4*)	1	Information and Organization (3)	1
Management Science (4*)	1	International Journal of Forecasting (3)	1
Marketing Science (4*)	1	Journal of Business Ethics (3)	1
Mis Quarterly (4*)	1	Journal of Business Research (3)	2
Research Policy (4*)	1	Journal of Information Technology (3)	1
Strategic Management Journal (4*)	2	Journal of Strategic Information Systems (3)	2
European Journal of Operational Research (4)	10	Journal of the Operational Research Society	9
International Journal of Research in Markt. (4)	1	Long Range Planning (3)	1
Journal of Management Information Systems (4)	1	MIT Sloan Management Review (3)	4
Journal of Service Research (4)	1	Organization (3)	1
California Management Review (3)	8	Public Management Review (3)	1
Decision Sciences (3)	3	Technological Forecasting And Social Change (3)	10
European Journal of Marketing (3)	1	Technovation (3)	1
European Journal of Work and Organizational Psych. (3)	1		

4.2 Bibliometric Analysis

4.2.1 Co-Keywords analysis

Keywords are nouns or phrases that reflect the core content of a publication. The bibliometric data show 986 keywords involved in this research. Co-keyword network visualization was based on occurrences. The co-occurrence threshold was set as 5 and 35 items where brought into visualization (Figure 3).

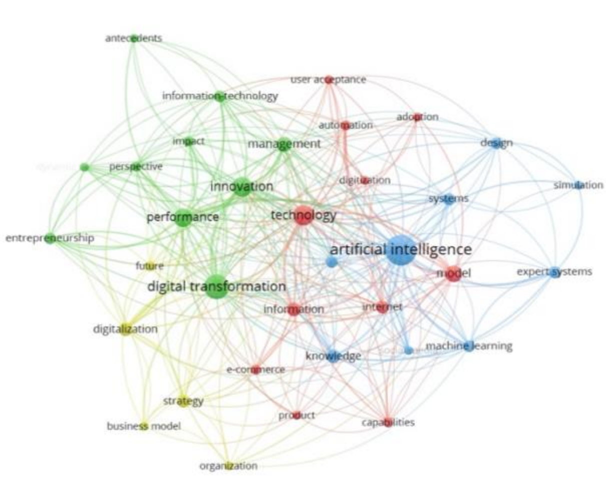

Figure 3: Keywords co-occurrence analysis

In figure 3, the size of the circles represents the occurrences of keywords. The larger the circle the more a keyword has been co-selected in the digi* transform* and/or artificial intelligence publications. The keyword "artificial intelligence" and "digital transformation" and "technology" had the strongest strength. The distance between the keywords are demonstrated relative strength and topic similarity. Circles in the same color cluster suggested a similar topic among these publications. The co-keyword network in Figure 6 clearly illustrated four distinct clusters. Each represented a subfield or a field of technological development. Appropriate labels of the four main clusters could be allocated to each of them by analysing the main node circles. The cluster number derive from the VOSviewer software. Especially, as was shown in the red cluster (Figure 2, cluster 1, center, 11 items) overlap with both the blue and green cluster. Containing keywords such as digitization, automation, user acceptance, adoption, internet, e-commerce etc., apparently related to the topic of "techonology". The green cluster (Figure 6a, cluster 2, upper left corner, 10 items) gives us the keywords such as performance, innovation, management, informational technology, dynamic capabilities, entrepreneurship etc. focused on the main domain "digital transformation". In The blue cluster (Figure 2, cluster 3, upper right, 9 items), keywords such as knowledge, machine learning, expert systems, big data, simulations etc., apparently related to the topic of "artificial intelligence". From the green cluster branches out the yellow cluster (figure 2, cluster 4, bottom left corner, 5 items) containing keywords such as digitalization, future, strategy, business model and organization.

4.2.2 Bibliographic coupling analysis

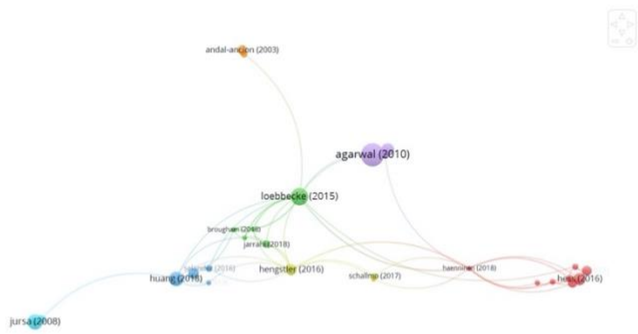

Figure 4: bibliographic coupling document analysis

Figure 4 shows VOSviewers clusters based on the bibliographic coupling method. Here we conducted a full counting and the unit of analysis were documents. The minimum number of citations of a document was 10. Of the 202 documents, 55 meet the threshold. The size of the circles represents the number of citations for each document. In Figure 4 lines among the documents represent their co-citation links, while 7 different colours seen in Figure 4 represent the co-citation cluster of the documents.

After conducting three bibliometric methods we did not find any direct contribution to man-machine collaboration. However, in the keyword analysis we did find a lot of keywords which gives an indication of the content within this database. The different themes in the literature can be associated with and might inform our research question. It was good a clear visualization of the content within the chosen database. The co-author analysis gave an indication of minor collaboration structures and the bibliographic coupling of documents gave an indication of how documents were connected to each other and which papers that were most influential. Nevertheless, we found the need to conduct a thorough content analysis, based on insights from both the descriptive analysis of journals and the bibliometric analysis.

4.3 Content analysis

Previously in this paper we have described the process of our selection of the 25 articles to conduct our content analysis. After a thorough reading of the documents we identified four dimensions which are used to give a comprehensive presentation of the findings in this chapter. The dimensions are: Knowledge worker, Organization, Market and Society.

Table 2: Content analysis of 25 core articles revealing four dimensions of man-machine collaboration

Referance	Knowledge worker	Organization	Market	Society
Bader & Kaiser (2019)			x	
Brock & von Wangenheimz (2019)	x	x		
Chablo (1994)			x	
Davenport & Ronanki (2018).	x	x		
Doukidis & Paul (1990)		x		
Garbuio & Lin (2019)	x	x		
Haenlein & Kaplan (2019)				x
Hall (1999)		x		
Hengstler et al. (2016)			x	
Huang & Rust (2018)	x			
Huang et al. (2019)	x	x	x	
Kumar et al. (2019)				x
Loebbecke & Picot (2015)	x	x		
Longoni et al. (2019)			x	
Luo et al. (2019)			x	
Martinez-Lopez & Casillas (2013)		x		
Metcalf et al. (2019)	x			
Montes & Goertzel (2019)				x
Quinn et al. (2016)		x		
Robinson et al. (2005)	x			
Shrestha et al. (2019)		x		
Syam & Sharma (2018)			x	
Tambe et al. (2019)	x			
Warner & Wager (2019)				x
Wilson et al. (2017)	x			

5. Discussion

In this paper our aim was to get a deeper understanding of how cognitive technologies affect man-machine collaboration in the context of knowledge intensive firms. Our content analysis revealed four dimensions of this man-machine collaboration addressed in extant published research; Knowledge worker, Organization, Market and Society. The study further identified important dilemmas associated with each of the dimensions.

5.1 Knowledge workers

In knowledge-intensive firms' employees are often viewed as the most important asset, and competitive advantage is built through careful recruitment and training of employees. In service organizations, high-performing human assets are harder to duplicate than any other corporate resource. According to Loebbecke and Picot (2015) the nature of knowledge work and cognitive processes, digitization and big data analytics expect to hit knowledge-based business models and cognitive workers as hard as – and perhaps even faster – than non-knowledge business models and manual workers. Digitization and big data analytics are associated with the autonomous information processing tasks typically performed by firms and knowledge workers – whose high profits and wages provide economic incentives to even speed up substitution (Loebbecke & Picot 2015). An illustrative example is Chatbots. They will behave identically across a service delivery system, providing highly predictable and homogenous service interactions and solutions (Wirtz et al., 2018) Human error and fatigue are not a factor. As chatbots are connected to the CRM- system connection, and can identify customers, they provide customized service on scale and they are also designed to have no biases, such as ethnic groups, gender, age and social status, unless programmed (Witz et al. 2018). Fleming (2018) point out that all jobs probably will not be taken over by AI and described three types of work: The Highly skilled and remunerated elite workers, semi-automated workers and the jobs that are not worth automating. Additionally, Davenport and Ronanki (2018) believe that most workers have little to fear at this point. Cognitive systems perform tasks, not entire jobs. Most cognitive tasks currently being performed augment human activity, perform a narrow task within a much broader job, or do work that wasn't done by humans in the first place, such as big-data analytics (Davenport & Ronanki, 2018).

Huang and Rust (2018) further states that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI) intelligence tasks first. The progression of AI task replacement from lower to higher intelligences results in predictable shifts over time in the relative importance of the intelligences for service employees. The authors states that analytical skills will become less important, as AI takes over more analytical tasks, giving the "softer" intuitive and empathetic skills even more importance for service employees. Witz et al. (2018) states that the extent to which service robots can display the emotions, like empathy and compassion, and behavior that give the impression that they truly have the customers best interests at heart, may prove to be a challenge. It remains to see if the robot can provide the same emotional connection resulting in trust. Brock and von Wangeheimz (2019) identified lack of skilled staff and knowledge in digital technologies as the top AI implementation challenge and engaged skilled staff as one of the key AI implementation success factors. Therefore, managers need to develop digital intelligence in the form of suitable human skills within their organization. In fact, AI requires organizations to develop *human* intelligence (Brock & von Wangeheimz 2019).

Man-machine collaboration in the employee dimension seems applicable. Our recommendations for management urge the development of human intelligence, and to think of AI and humans as a team. As we have identified here the skills and knowledge in digital technologies are of grave importance in order to implement a successful AI system. Employees should focus on the empathic skills, as the cognitive technologies have an advantage in analytical skills. By usage of man-machine collaboration employees will gain the newfound capabilities will ultimately leave employees with more-meaningful jobs and companies with more-profitable business models and innovative opportunities.

5.2 Organization

There seems to be an overall consensus about the strengths of cognitive technologies and how they excel in efficiency and outperform in analytical tasks. Cognitive technologies leverage significant enhancements in data availability and processing that have augmented information and knowledge creation capabilities to enhance operational strategizing and to provide robust decision support (Davenport 2017; Kudyba et al. 2019). AI is helping companies improve customer service, customer loyalty, brand reputation, and enable employees to focus on higher value tasks that provide greater returns (Walch 2019). We found that already in 1990, Doukidis and Paul reported the enthusiasm of practitioners and clients trying AI. Brock and von Wangeheimz (2019) also reported two global surveys among senior managers across industries that AI is typically implemented and used with other advanced digital technologies in the firm's digital transformation projects. However, the digital information projects in which AI is deployed are mostly in support of firm´s existing businesses. Kolbjørnsrud et al. (2017) found that AI ability to facilitate cloud-based applications as advisors in contexts such as medical diagnosis, security analytics, drug discovery, financial advice, etc. may make some managers uncomfortable. 46 percent of the top managers taking part in the survey stated that they would trust advice of intelligent systems. Only 24 percent of middle managers and 14 percent of front-line managers demonstrated the same level of agreement.

Shrestha et al. 2019 addresses that human decision makers, practitioners and scholars need to advance understanding of the implications of AI's limitations for organizational decision making. First, there is a risk that AI is "fooled" into altering decision outcomes—either through the manipulation of the data it uses as input or through its design (e.g., by changing weights of predictors). Thus, inviting algorithmic decision making into organizations will require new regulation and procedures for auditing AI algorithms. Secondly, AI-based decisions amplify human biases in available data. Bias and unfairness embedded in AI decisions are particularly detrimental to vulnerable groups in our society. Countering these grave concerns requires a stronger emphasis on the development of algorithms that can expose biases in data and human decision making, as well as collaboration between the AI community, legal practitioners, policy makers, corporates, and scientists to develop new measures for fair, accountable, and transparent applications of AI in organizations. Furthermore, introducing AI-based decisions into organizations becomes relatively effective when some level of transparency or interpretability of decisions can be achieved. Managers need to keep abreast of the developments in interpretable and explainable AI. Finally, algorithmic decision-making skills remain highly specialized such that decision outcomes are often difficult to interpret. In introducing AI to organizational decision making, managers must build internal capabilities to decide on the inputs to the algorithm, the algorithms themselves, and the interpretation of predictions. Because AI technologies advance rapidly, organizations must remain vigilant to the strengths and limitations of AI in fully delegated and hybrid human–AI decision-making structures (Shrestha et al. 2019). In the discussion implementing AI and man-machine collaboration at the organizational dimension, there are many factors which need taken into consideration. Man-machine collaboration seems to be inevitable in the future. Man-machine collaboration increase value and give way to new business models as well. But as Shrenstha et al. (2019) pointed out there are several risks to be aware of. Although the research only covers a brief number of papers in the literature there are clear differences in each field on how to implement cognitive technologies and how man-machine collaboration are to be achieved within each organization.

5.3 Markets

Robots can become almost indistinguishable from humans, especially on phone and text interactions. A recent study found that 38 percent of chat users were uncertain whether they interacted with a human or chatbot. 18 percent guessed wrong (Wünderlich and Paluch 2017; Witz et al. 2018). However, Luo et al. (2019) reported negative effect if usage of chatbots where incorporated. Luo et al. (2019) reported that as long as the chatbot identity is disclosed, regardless of before or after the conversation, customer purchase rates are negatively affected. However, disclosing the bot identity after the conversation helps mitigate such negative impact. The findings are also suggesting that prior AI experience is helpful in reducing the negative disclosure effect (Luo et al. 2019). Longoni et al. (2019) report that consumers are reluctant to utilize healthcare provided by AI in real and hypothetical choices, separate and joint evaluations. Consumers are less likely to utilize healthcare (study 1), exhibit lower reservation prices for healthcare (study 2), are less sensitive to differences in provider performance (studies 3A-3C), and derive negative utility if a provider is automated rather than human (study 4). Uniqueness neglect, a concern that AI providers are less able than human providers to account for consumers' unique characteristics and circumstances, drives consumer resistance to medical AI. Indeed, resistance to medical AI is stronger for consumers who perceive themselves to be more unique (study 5). Uniqueness neglect mediates resistance to medical AI (study 6), and is eliminated when AI provides care (a) that is framed as personalized (study 7), (b) to consumers other than the self (study 8), or (c) that only supports, rather than replaces, a decision made by a human healthcare provider (study 9) (Longoni et al. 2019). In the words of Witz et al. (2018): "*People have a general aversion toward algorithms. Especially if the algorithm has made a mistake,".* The aversion is prevalent even if the situations where evidence-based algorithms consistently outperform humans. Educational approaches to consumers will be beneficial in the long run, as consumers with prior AI experience prevents aversion and distrust. Man-machine collaboration should be communicated to gain trust.

5.4 Society

Economists and sociologists leading the discussion about societal implications of the "second machine age" take either an optimistic view of the workforce future or they have a pessimistic view envisaging levels of unemployment never before seen. In our findings we first found the optimism of AI in Kumar et al. (2019) statement about that the focus have shifted to information management. The shift has risen, in particular, due to the role of technology. The ability to collect, store, process and reuse information through technology has given us further thrust in exploring the new frontier of AI. On the other hand, Haenlein and Kaplan (2019) point out that governmental regulation might again be a way to prevent such an evolution. They point at some examples of firms required to spend a certain percentage of the money saved through automation into training employees for new jobs, that cannot be automated. States may also decide to limit the use of automation. Or they might restrict the number of hours worked per day to distribute the remaining work more evenly across the workforce. These restrictions could prevent or at least delay the evolution of cognitive technologies, and the reluctance of the state will potentially stagnate the prosperity of man-machine collaboration in the future. Yet the findings also reveal the development of new technology to prevent "the winner takes all" markets. Montes and Goertzel (2019) describes how decentralization of AI affords functions that could transform the AI landscape with positive ethical effects, by unsiloing AI making it coordinate and cooperate with other AIs. The AI evolution in our society and the effect of it will remain to be inconclusive at this point. There are indeed optimistic and pessimistic views on cognitive technologies and the possibility of man-machine collaboration. Even so, the man-machine collaboration is yet an important part of the societal debate. As the machines are made in the reflections of humans, when constructing new cognitive technologies there will no doubt be necessary for a close man-machine collaboration in the development-, implementation- and monitoring phase. The fear is that we as a society will not be able to base the AI-data on unbiased foundations and that it will be difficult to address accountability of the decision or fault of man and machine. The society must also see the opportunities rather than the treats of the technological advancements; thus, the man-machine collaboration will be possible at a societal level.

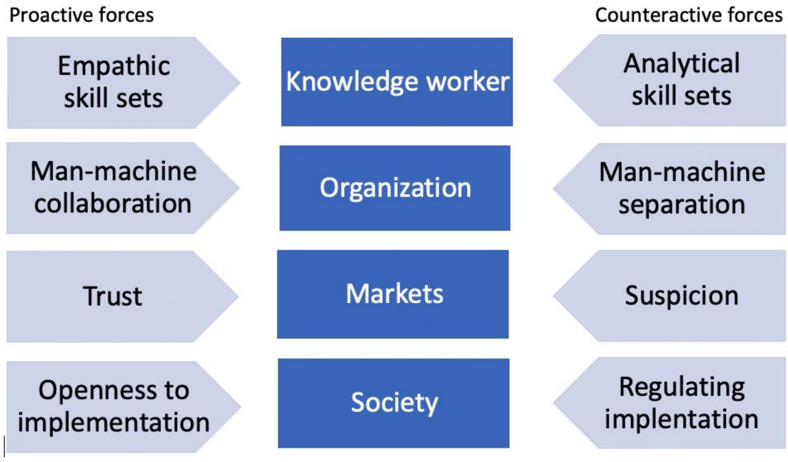

Figure 5: Four dimensions of man-machine collaboration with identified dilemmas

Our findings and the above discussion reveal how prior research addressing man-machine collaboration in the context of digital transformation of knowledge intensive firms is inconclusive with respect to the forces acting upon the four dimensions identified in this study. Literature depicts both proactive and counteractive forces for each of the dimensions. Figure 5 is an attempt to illustrate the dilemmas for each of the four dimensions based on the above discussion of the dilemmas, or counteracting forces, associated with each of the four dimensions. Knowledge workers face the dilemma of relevant skill sets, either continue with analytical skill sets or pursue more empathic skill sets. Organizations considers whether they want the workforce to be separated from the machines or pursue man-machine collaboration. At the market level, consumers are suspicious towards cognitive technology and thus face the dilemma of how to trust communication with knowledge intensive firms. Consequently, society as a whole need to consider if regelation or openness to implementation of cognitive technology will benefit the current and next generation facing man-machine collaboration. To date there exist limited empirical research that can establish the directionality of these counteracting forces.

6. Conclusion

The study confirms that the field remains immature and fragmented, and despite revealing that all identified articles in our content analysis sample address artificial intelligence and cognitive technologies as an important aspect of changes in organizations and related strategy development, few journals deals with the man-machine collaboration in particular. Indeed, there exist no comprehensive description on how strategy should be adapted to technological developments. Our study condensed an overwhelmingly amount of digitalization research into a digestible 25 papers spanning across different disciplines. Our study reveal how extant research have recorded how cognitive technologies affect man-machine collaboration in different ways, and have identified four dimensions that experience different effects on man-machine collaboration. The influence on man-machine collaboration is largely dependent on individual factors, such as attitudes to technology and change, as well as societal attitudes towards the AI-evolution. Moreover, extant research is inconclusive with respect to the forces affecting these dimensions, depicting the forces almost as dilemmas. Future research can build on this insight to further knowledge of the vast potential of AI application and digital transformation by empirically seeking answers to the directionality of forces at each dimension level. Moreover, the study can be utilized to inform the innovation and strategy discussions when implementing cognitive technologies. Our study also has clear limitations. Whereas we based the study on an exhaustive search, and experimented with different search phrase combinations, we still were neither able to identify a large number of articles addressing the effects cognitive technologies have in the workplace, nor empirical data describing contingencies within one industry. The reason for this may be that this type of technology is still in the growth phase and thus has little basis for researching the implications. Further research should therefore continue the investigation of what defines the man-machine collaboration of knowledge workers, both conceptually and empirically.

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Appendix 2

25 core articles:

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