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A bibliometric analysis of how cognitive technologies affects man-machine collaboration

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Abstract: Research addressing artificial intelligence (AI), and related topics, is rapidly increasing. However, despite this emerging interest, the current 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. 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. Our study contributes with the identification of four important dimensions of man-machine collaboration; Knowledge worker, Organization, Market, and Society. Moreover, our findings reveals that 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.

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 left 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 (e.g. Law- accounting- and engineering firms, architects and consultancies), 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

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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.

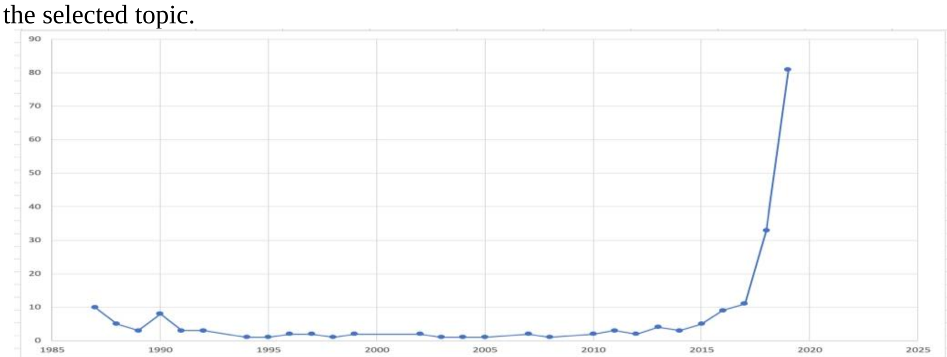

Figure 1: Development of publications per year, within the database consisting 202 papers

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.

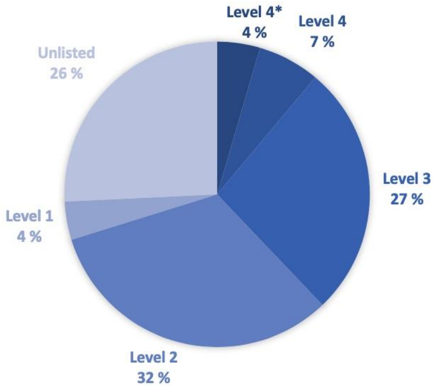

Figure 2: Percentage of journals within each AJG-list level.

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		

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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).

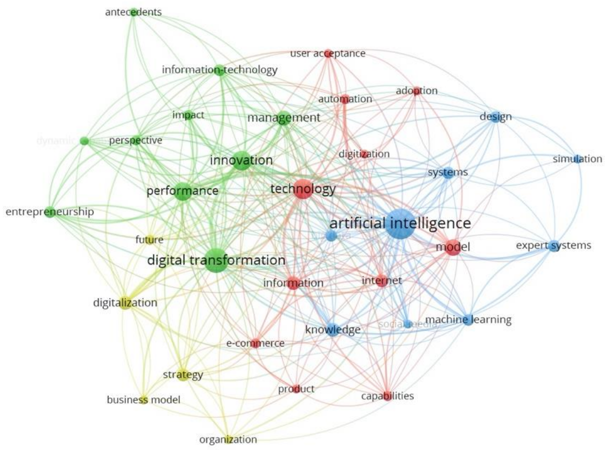

Figure 3: Keywords co-occurrence analysis

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*

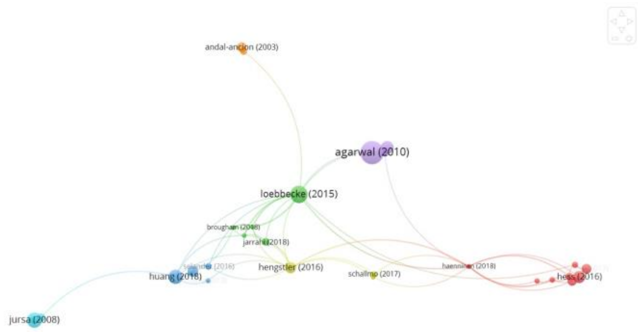

Figure 4: bibliographic coupling document analysis

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 worker

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

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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.

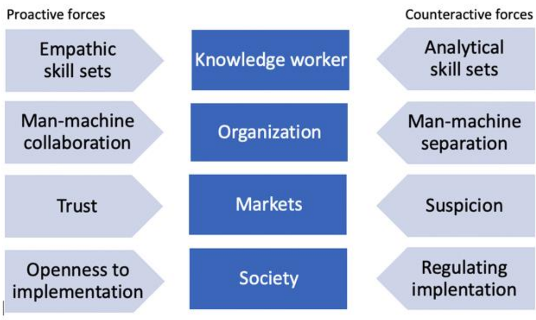

Figure 5: Four dimensions of man-machine collaboration with identified dilemmas

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6.

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.

7. 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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