Business Impacts of Technology Disruption - A Design Science Approach to Cognitive Systems' Adoption Within Collaborative Networks

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Abstract. Digitalisation and data are stated to be significant drivers of change, technology disruption, and new business. The purpose of this study is to explore the business impacts of technology disruption, more specifically the adoption of cognitive systems within collaborative networks through a design science approach. In accordance with design studies, the relevance of the research results and the research quality are evaluated against the practices of seven companies that participated in the research process. At the crossroads of technology and business disruption the two main dimensions illustrate: (1) the technical complexity of cognitive systems adapted from conventional data utilisation to learning cognitive systems and (2) the broadness of business impacts from a company's internal processes to changes in ecosystems.

Keywords: Technology diffusion · Collaborative networks · Design science Cognitive systems · Big data analytics · Business ecosystems

1 Introduction

Disruptive technologies not only enhance technological possibilities, but they also allow and force actors to experiment with alternative innovative processes and arrangements at several levels from societal changes at macro level to human behaviour at micro level [1, 2]. The new generation of data-driven business and cognitive systems are changing the way companies manage and operate their business processes [3], but the impact is not equal in all phases and levels of value chains. The advancements in cognitive systems create new business opportunities for some companies while others suffer from losing current traditional business opportunities. In this networked business setting of our study, collaborative cognitive systems have a broad meaning of an interconnected system of humans, data processes and artificial intelligence agents across company borders. For example, cognitive systems are replacing manual work processes through artificial intelligence applications, but they also open new markets

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for data integration and data-enabled novel services. Although the potential business impacts of cognitive systems are surrounded by tremendous hype emphasizing the vast opportunities, empirical research is scarce. Design science was, therefore, a natural choice for the research approach of our study, to bridge the gap between theoretical discussion and practical challenges related to technology disruption and systemic change. Furthermore, the area of collaborative networks is by nature multi-disciplinary as well as interdisciplinary, it can enhance a more holistic understanding of the technology diffusion at stake, as has been pointed out regarding the similar hype around the concept of Industry 4.0 [4].

Understanding the systemic change required for technology diffusion is simultaneously an engrossing academic research question and a practical challenge for all actors involved in data-driven business and cognitive systems. The technology disruption in this study is examined especially from the perspective of new business creation through data utilization/data-driven business. In this study, we recognized four categories that illustrate the impact of cognitive systems adoption based two main dimensions of technology and business disruption: (1) the technical complexity of the cognitive system adopted and (2) business impacts from companies' internal processes to changes at ecosystems.

2 Design Science Approach

In management studies, a design science approach is often linked to other qualitative approaches, such as action research, participatory case studies, academia–industry partnership, and constructive approaches. They all share the aim of joint problem solving and bridging between theory and practice. In this study, the research process was based on the design science framework (see Fig. 1). According to it, *build and evaluate* are the key research activities in design science. In this joint problem solving process between the practitioners and the researchers, constructs (or concepts) form a vocabulary for the problem solving and a model presents relationships among constructs. The challenge of construction building in this study was the need to combine a variety of theories and concepts from business management and information technology.

	Build	Evaluate	Theorize	Justify
Constructs				
Model				
Method				
Instantiation				

Fig. 1. Design science research process in this study introduced by March and Smith 1995 [5].

This kind of approach also suggests that research is not just about understanding and explaining issues and phenomena but also about changing them [6] and affecting creation of new ideas and innovation. Therefore, a joint project (or process) of researchers and practitioners – companies or other organisations – and close cooperation throughout the problem solving are necessary in such a research setting. In the other words, through the practical case studies, the practitioners and the researchers strove to jointly build and evaluate the design science research artefact, a framework for business impacts of cognitive systems (Fig. 2). The methods in design science refer to a set of steps and an instantiation operationalizes these constructs, models and methods, i.e. they are the realization of the jointly built artefact in its environment.

In Table 1, we present the research process covered in this paper. The build column includes exploration of discussion related to technology and business disruptions – and more specifically the literature on cognitive systems and collaborative networks (Sect. 3 of this paper). The evaluation column covers the methods by which the constructs and models have been evaluated with the practitioners through an iterative process (Sect. 4).

As Table 1 indicates, our study is in the early phases of theorizing and justifying the research outcomes, although the joint problem solving process started a year and half ago. This is mainly due to the challenging research setting at the crossroads of several theoretical concepts, i.e. multi-disciplinary and interdisciplinary approaches have been needed. Therefore, both practitioners and researchers participating in the research process have different backgrounds from business development to data analytics. And time is needed to find key concepts, shared language and make sense of meanings of the concepts, i.e. making the vocabulary together.

3 Constructs: Making the Vocabulary for Practical Problem Solving

3.1 Technology Diffusion and the Challenge of Systemic Change

By far one of the greatest disruptions seems to be digitalization and the Internet. And this transformation is driven by two major forces: the new technological possibilities and the fast changing market demands [4]. Such disruptive technologies, by definition, disrupt existing social institutional arrangements as they challenge and revolutionize the way business is conducted, competition in the market place as well as human interaction in a society. In other words, their diffusion requires a systemic change from macro to micro level [1, 2]. Companies have had to particularly tackle the question of what they can do to avoid displacement brought on by technological disruption [8], as new technologies demand new kinds of business capabilities and often businesses may even have to learn to move away from the logic of action which they are used to. The question is multifaceted. First, new technologies and the accompanied new business models utilizing them require that companies have the kind of competencies they do not yet have. Secondly, companies must learn away from the present industry paradigms, i.e. logic of action, within their business environment. And thirdly, the radical change in business operations requires interlinked changes of companies' customers and partners' businesses. In other words, collaborative or networked innovations are needed.

Table 1. Summary of the key research activities of the design science process in this study.

	Build	Evaluate	Theorize/Justify
Constructs	Find key concepts for cognitive systems and business impact in ecosystems through	Investigating the practical challenges in business development	Barriers – the challenge and opportunity taxonomy ([7]: ISPIM conference paper)
Model	Define the factors for technology and business disruption (Workshop)	Framing for business impacts of cognitive systems' adoption	A framework presented in this paper
Method	Interviews (22), literature review, and one workshop	Two workshops	

3.2 Big Data, Artificial Intelligence and Cognitive Systems

Big data has various definitions, because research in the big data area is quite novel [9, 10] and academic research focuses on data analytic tools rather than business impacts. Big data can be described, for example, as "a collection of large and complex data sets, which are difficult to process using common database management tools or traditional data processing applications." [11]. There are typically three features – volume, variety and velocity – that characterize big data [12]. Thus, business data is typically consisting from both big and non-big data. Furthermore, it is often exclusive in containing non-disclosure agreements, but firms are realizing the strategic importance of investing in insight based decision-making and value co-creation [3].

The ability to capture, store, aggregate and analyse data for extracting intelligence is vital for strategic decisions [13] and there is a variety of different means for data processing. Similarly to big data, artificial intelligence (AI) also has several definitions. AI can be defined, for example, as an ability that a digital computer or computer-controlled robot can use to complete tasks that are commonly associated with intelligent beings. Thus, the scenarios of the future impact of AI technologies and their potential vary from a utopian to dystopian world [14], which is typically in case of broader disruptions causing significant uncertainty.

Cognition, both natural and artificial, is about anticipating the need for action and developing the capacity to predict the outcome of those actions. *Collaborative cognitive systems* have been defined as systems where there are intelligent agents that assist humans in their cognition [15]. In this networked business setting collaborative cognitive systems have the broader meaning of an interconnected system of humans, data processes and artificial intelligence agents across company borders. Regarding the technology disruption, we have positioned these three concepts – big data, artificial intelligence and cognitive systems – in a continuum describing the intensity of technology change in this study. This is in-line with the well-known continuum presented in the DIKW (data, information knowledge, wisdom) - model (for a summary of the DIKW - concept see, for instance [16]).

3.3 Business Ecosystems/Collaborative Networks

In the current networked business environment cooperative actions and decisions are not made in a centralized way [17]. Therefore, the full potential of a data-rich world can be captured in collaboration with a variety of external actors, i.e. collaborative networks (CN), as access to and integration of third-party big data sources is required to explore changes in this business environment [18].

Our study approached "collaborative cognitive systems" from the meso (organisational) level. The concept of collaborative network organisations (CNOs) highlights that there is an organisation encompassing shared governance rules as well as the participants' activities, and roles, whereas the concept of virtual organisation breeding environment (VBE) represents the more loosely coupled co-operation setting found with a bundle of organisations. Thus, long-term co-operation agreements and interoperable infrastructure are also mentioned as a 'base' for breeding environments [12].

Anyhow, the practitioners were more familiar with the concept of business ecosystems. Therefore, in order to help the joint sense making we preferred to use the concept of *business ecosystems* to capture a dynamic, temporary, continuously changing, hyperconnected, and networked assemblage that emphasize the need for collaborative system level choice. Through the ecosystem approach, collaborative networks are defined as autonomous, geographically distributed, and heterogeneous [19]. It highlights that even in collaborative networks each network member has its own reasons to collaborate.

4 Practical Evaluation of Constructs and Models - Methods for Joint Problem Solving

Through a design science approach, we explored the business impacts expected from the adoption of cognitive systems within collaborative networks, i.e. business ecosystems. First, to set the scene and understand the practical problems the researchers conducted semi-structured interviews (typically more like discussions) with the key persons of the seven companies participating in the process (Table 2). Five of the companies (A - D and G) have a main business model linked to traditional domains (healthcare, manufacturing, automation and recruitment), whereas three (E, F and H) focus on services related to data processing through Big Data analytics and AI technologies. The role of these three firms was to support the others in envisioning the change and opportunities arising. Thus, company H only took part in the workshop phase of the process.

These discussions highlighted that the companies are actively considering how to benefit from technology disruption and grab the opportunities enabled by new technologies. Or on the other hand, they have to think of what they can do to avoid displacement brought on by technological disruption. The interviewees stated that the

Table 2. Case companies and interviews.

Case company	Industry	Size	Experience in big data utilization	Number of interviewees
A	Healthcare	Large	Experienced	6
B	Manufacturing	Medium-sized	Beginner	3
C	Automation	Large	Experienced	2
D	Manufacturing	Large	Beginner	6
E	Data processing	Start-up	Advanced	2
F	Data processing	Large	Advanced	1
G	Recruiting & staffing (services)	Large	Experienced	2
H	IT consulting and services	Small	Experienced	–

question of technology disruption is multifaceted. First, utilizing new technologies and the accompanying new business models require that companies have the kinds of competencies they do not yet have. Secondly, companies must learn away from the present industry paradigms, i.e. logic of action within their business environment. And thirdly, the radical change in business operations requires interlinked changes of companies' customers and partners' businesses. In other words, collaborative or networked innovations are needed to grasp the emerging opportunities.

This kind of approach also proposes that research is not just about understanding and explaining the phenomena but also about changing them [6] and participating in the creation of new ideas and innovation. Therefore, a joint project (and process) of researchers and practitioners – companies or other organisations – and close cooperation throughout the problem solving are necessary in such a research setting. Therefore, at the first workshop (see Table 3) – concurrently with one-to-one discussions – researchers and practitioners set the scene together, i.e. a joint understanding of the state-of-the-art and *build* together the constructs and models for making sense and understanding the key factors of this technology and business disruption. The second workshop went deeper in understanding the challenges of the creation of new data-driven business and discusses on different constructs (i.e. variety of data sources and analytics tools) and the taxonomy created [7]. This resulted in the grounding for the third workshop, where researchers and practitioners utilized the business impacts framework (presented in the next section) in order to *evaluate* the systemic changes related to technology disruption.

Table 3. Workshops.

Workshops	Actors	Participants	Discussion topics	Content	Date
1. Set the scene (vocabulary and constructs)	5 companies (A, B, D, E, H) and 3 research organizations	14	The content of each case, feedback and finding synergies	Case presentations and joint discussion	7.6.2017
2. Understanding challenges of new business creation through big data utilization	4 companies (A, D, E, H) and 3 research organizations	12	Challenges of new business creation through big data utilization and achieving feedback for presented categorization	Presentation of interview results, individual assignment, joint discussion based on individual assignments	21.11.2017
3. Business impacts and roles in data-driven business	2 companies (D, E) and 3 research organizations	8	The business impacts of big data utilization and the different roles for creating business from it	Presentation of research findings, joint discussion (individual assignments …)	8.2.2018

5 Business Impacts Framework - Illustrating the Four Categories

At the crossroads of technology and business disruption the two main dimensions illustrate changes in: (1) the technical complexity of cognitive systems adopted as a continuum from big data, artificial intelligence and collaborative cognitive systems (Sect. 3.2) and (2) business impacts from companies' incremental improvement of internal processes to systemic changes at ecosystems (Sect. 3.3).

The framework (Fig. 2) contains four categories. The first two categories, the process change and the role change in the value chain, describe the more company specific impact of data utilization. Therefore, a company may accelerate its own performance through traditional data mining or even change its role in the value chain, when utilizing more intelligent data systems. The last two categories, the competition environment change and the significant turning point of the market and emerging ecosystems, describe the more ecosystem specific impact of data utilization. Therefore, the data utilization may have an influence on the competition environment or even disrupt the market and enable new ecosystem emergence.

The framework was utilized to identify the level of cognitive systems adaptation and to demonstrate its impacts on a company's internal processes and the surrounding ecosystems through two dimensions (vertical and horizontal). In the following four sub-sections typical company perspectives related to these categories are highlighted through quotations. Most of the quotations are from the five companies currently operating in traditional sectors, as they perceived the change to be more concrete. The two companies, who had their competence in data processing, supported others in foreseeing the in-coming changes and opportunities provided by technology.

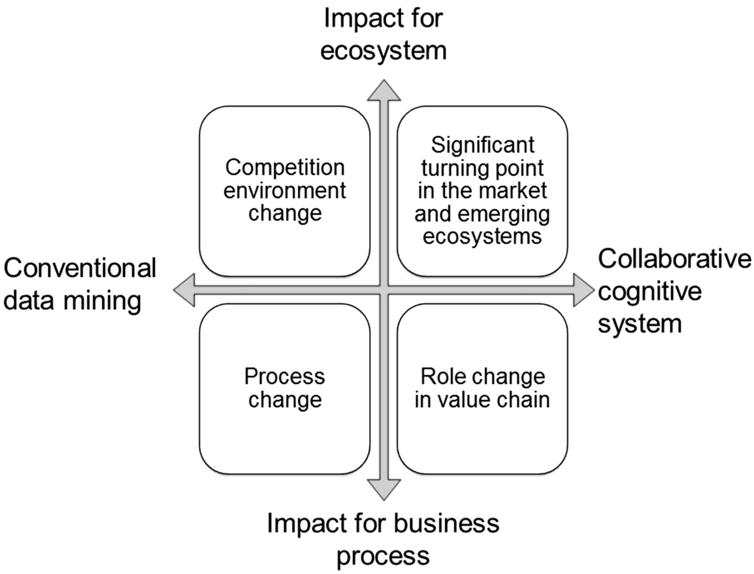

Fig. 2. Business impacts framework.

The following quotation from the entrepreneur of company E illustrates how he was challenging the other companies to start with analysis of the strategic importance of knowledge and data processing tools: "*from the company perspective, the management group or on the management level, they should be capable of formulating what is wanted out of data. ... it's a combination of many kinds of know-how. But nothing happens unless the management group has an understanding of what is wanted out of the data.*"

5.1 Process Change

In the first of the identified categories, the impact of big data affects the business processes within the organization. Apart from the two data processing companies (E and F), the other five companies (A - D and G) recognized that the process change is a typical impact from utilizing big data in business development. The following quotation from the customer service, communications and marketing manager of company B represents a typical example: "*With data, you are able to understand the customer better. It also helps the way we develop our processes, so that we concentrate on the right things. So, it guides our own development measures….We can automatize the way we work, and then also create savings, and thus offer more competitive pricing.*"

5.2 Role Change

In the second of the identified categories, the impact of big data or artificial intelligence on the business processes within the organization, only a few of the participating companies had actively been processing the possibilities to change their role in value chains, i.e. both B and D are transforming from product-based businesses to services, while the others already had more service-oriented business models. One example of such consideration is provided by corporate social responsibility director of company B: *"We have analysed the news feed, and recognized trends such as where we are going, what is happening beneath, and this is something that customers see a remarkable added value in. The comments we have received is that we are the first component manufacturer that talks about future… it's not like we have all the answers about the future, but we are starting the discussion. And this gives an impression to customers that this is something that we manage… and we have translated it to "common language" so that everyone can seize on it… So, analysing and data and trying to think how you can serve customers with it, that alone can add competitiveness."*

5.3 Competition Environment Change

In the third of the categories, the impact of big data on the business ecosystem level, all of the companies have recognized that these digital technologies have caused or will cause significant changes in their business environment. The following quotation from the business development manager of company D states that decision-makers need new tools for understanding the turbulent business environment: "*I think it gives an opportunity to recognize new things, which is important because being aware is essential to the management. Decision-makers need to understand how the world is changing and why it is so."* Thus, not all of them had an active or reactive perspective on these in-coming changes. In the following quotation a business intelligence manager from company C highlights how they are looking for external data sources and analytics to gain a better understanding of the business environment: "*A part of the data that we buy are analyses on the future development of the business field. We aim to buy these from many providers. We don't really make this kind scenario work by ourselves. We also follow and analyse our competitors, and if we see that a competitor is making a new move and there is something happening, we try to figure out what it means for us. For example, if a competitor is being sold, we try to figure out what it means for us, in the short-term and in the long-term."*

5.4 Ecosystem Change

Finally, in the fourth category, the impact of cognitive systems on the business ecosystem level, one of the companies stated that they have a clear vision of how to make new business enabled by AI technologies, as the following quotation from the research and clinic director of company A presents: "*In the future we can sell these insights [that we get from data]. And we can also use this data as a tool in political discussions… From data, we can see what will happen and we can quantify it, which makes observations a political argument in these discussions."*

Similarly, the business intelligence manager of company C described how technology development opens possibilities to renew both processes and thinking, at ecosystem level: *"The reality is that, like I said, decisions are made intuitively, but utilising data may bring out and verify things that have been assumed… so with data we can break those harmful, intuitive beliefs so changes can be made to the established practices… a machine could present us the fresh, unlocked way of thinking."*

To sum up, the practitioners had a strong belief that the business ecosystems were changing significantly. The following quotation from the service director of company G highlights this well: "*I believe that when we catch data and knowledge flows, and are able to manipulate the data with powerful tools such as AI solutions, we can make really big changes and make an impact."*

6 Discussion About Making Sense of the Business Implications of Cognitive Systems

Disruptive technologies may propel the emergence of and experimentation with new and alternative innovation paradigms [3], and collaboration networks [4, 18]. However, their business impacts are complex and multi-faceted and seldom simply positive or negative. Furthermore, the sense-making process within these dimensions seems to be broken up to technology- and business-oriented tracks, both in practice and at academic discussions.

Also, it was quite typical in the participating companies that big data utilisation or the possibilities of Artificial Intelligence had been considered by persons responsible for IT systems, AI technologies or business intelligence. In other words, the clear connection to business development was still limited and or focused on collecting and analysing customer data. The quotation of the entrepreneur from company F highlights how a joint understanding and continuous discussion is needed for success: "*this is not an IT project, this is not an HR project, this is a management group's project*."

The framework (Fig. 2) also supported the shared sense-making between the technology- and business-oriented persons (both researchers and practitioners) as it helped to build a joint vocabulary for the level of changes. For example, as the DIKW (data, information knowledge, wisdom)-model was well known it also supported understanding of the impact of different technologies from big data on cognitive systems. Thus, the practical examples show that the new way to manage and operate business processes through and with data-driven cognitive systems disrupts existing markets, change value chains or only affects the operative capability of companies. For example, adopting gene data in the healthcare services opens new bio-banking markets whereas improving analyses of customer behaviour through big data impacts the internal operative effectiveness only at the level of the marketing department.

In some business areas, cognitive systems are creating new business opportunities or even new markets for technology and service providers. The companies need new technological applications and services when adopting cognitive systems. The way in which companies adopt new cognitive systems impacts either their business processes or entire ecosystems. For example, companies may adopt the cognitive systems by improving quality control or customer satisfaction through deploying advanced data analytics instead of manual excel sheets. In this way, the adaptation of cognitive systems is changing the existing business processes within the organization, but its impact on the entire ecosystem is low. The use of cognitive systems is not reshaping new markets but it is only improving the way in which companies operate business processes. The adoption of cognitive systems in creating new business has an effect at the level of ecosystems as we have seen in the gene data-based biobank business or in marketing, where cognitive systems predict consumer behaviour in e-commerce.

To sum up, the level of impact on the business ecosystem mainly depends on the business needs that the companies are solving, ranging from the effects on emerging ecosystems to the effects for conventional process improvement. Additionally, the impact is not similar for all players in the same business ecosystem, which reveals changes in the roles of service and technology providers.

7 Conclusions

The managerial implications of this study consist of clarifying the scattered concepts around cognitive systems and a framework for understanding the business impacts. Theoretical contributions indicate how the design science approach is a suitable method for addressing ill-structured managerial problems of technology and business disruption. Regarding joint problem solving, the specific challenge in this study was the need to combine a variety of theoretical concepts – as well as the practical know-how – from the business management and information technology areas.

Design science is more traditionally utilized in information systems fields [20] and therefore, also the practitioners with Information technology background were more familiar with the approach. In management and business studies, design science holds a steady but minor position on the side lines of mainstream descriptive studies – there are some examples in operations management [21] and on-going discussion also within the collaborative networks research community. Thus, a design science approach can also be linked to several other qualitative approaches, which all share the aim of joint problem solving and bridging between theory and practice. These kinds of needs are definitely increasing in the area of business research as the business environment is highly turbulent and technological hype is commonplace.

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