Do traditional banks need a Chief AI Officer?

An explorative research project that aims to evaluate the appointment of a Chief AI Officer to overcome challenges that arise when traditional banks adopt AI technologies.

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Abstract: Artificial intelligence is a technology trend that potentially far exceeds the possibilities of all current state technologies, in a sense that these technologies have self-learning abilities. Organizations that manage to adopt and diffuse these technologies may effectively reach a competitive edge over their competitors faster. However, for large organizations such as traditional banks the question arises how to facilitate this transformation to effectively adopt AI technologies. Despite the fact that AI technologies are still in a relatively premature stage of development, traditional banks in the Netherlands are currently exploring its potential. In this exploratory study we interviewed 19 experts in the field of AI and Banking to identify all relevant challenges that arise when traditional banks adopt AI technologies. Additionally, we explored the importance of top management tech-executive roles as a possible solution to address certain challenges. As a result we have found that traditional banks have no common view or approach on how to adopt AI technologies enterprise-wide effectively. Therefore, the appointment of a new Chief AI Officer role may prove to be a valuable solution to address some of these challenges. However, there is still a mixed view on what this roles' position, responsibilities and other managerial characteristics should be.

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1. Introduction

In this qualitative exploratory research project we try to evaluate in what conditions the appointment of the Chief AI Officer (CAIO) can be valuable to address challenges that arise when traditional banks adopt AI technologies.

1.1 Gap

Technological innovation is considered to be one of the most influential developments affecting the financial sector in the near future (IBM, 2012). Innovation carries both opportunities and risks for established and new financial institutions and for the financial sector as a whole (De Nederlandsche Bank, 2016). According to Brandwatch (2017), a big data company that scanned over 80 million websites in december 2016, the year 2017 is all about artificial intelligence and machine learning. The word “intelligence” in combination with “artificial” and “machine learning” was mentioned almost two times more than any other word in the sentence: “2017 will be the year of…..”. Dr. Ronjon Nag (2016) stated that: **“**the companies that become AI-first now, will have strong advantages over their competitors”. To take advantage, companies need to understand what AI can do and how it relates to their strategies. But how should you organize your leadership team to best prepare for this coming disruption? (Ng, 2016). In a world where machines have a strong influence on human interaction, we have to be aware of how AI affects the current landscape of organisations. This not only raises questions for developing competitive advantage but also how technology affects us as a society. When organizations understand what AI can and can’t do, the next step for executives is to incorporate it into their strategies. That means understanding where value is created and what’s hard to copy (Ng, 2016). Once organizations grasp the fact that AI will play a pivotal role in the digital transformation of their company they will realise it needs its own focus (Nag, 2016). According to Buskell (2016) it needs a “Chief AI Officer”, that has a new set of skills and most of all it needs its own budget. However, how do we define its roles and responsibilities? In the following part we will describe what AI is and what its role is within our society and current organizations.

1.2 Problem definition

The Artificial Intelligence (AI) domain gains its intelligence from smart algorithms that can learn immensely fast. However, this new technology may come along with a broad range of new challenges for organizations, and therefore we zoom in on three different types of challenges. First, we want to analyze what organizational challenges arise when organizations start using AI technologies. It may be important to find out how AI based results will be managed and integrated in day-to-day decision-making processes of future organizations. Some leading AI experts say AI needs its own management, apart from the IT department, with its own set of goals, budget and maybe most important: its own leadership (Buskell, 2016). Secondly, we investigate what ethical challenges may arise. According to Janssen (2016) algorithms can systematically introduce inadvertent bias, reinforce historical discrimination, favor a political orientation or reinforce undesired practices. As a result, these algorithms may become increasingly autonomous and invisible, and therefore become harder for the public to detect and scrutinize their impartiality status. Thirdly, we want to analyze what technical challenges arise when organizations start adopting AI technologies. A hundred years ago electricity transformed countless industries; 20 years ago the internet did, too. According to Ng (2016) Artificial intelligence is about to do the same in the near future. In the next part we will describe the practical and theoretical relevance, as well as the scope of this research proposal.

1.3 Practical relevance

With large advances in information technologies like big data, cloud computing and open-source software more and more financial firms are able to implement and use AI technologies to improve their business. 88% of banking executives familiar with cognitive computing are likely to invest in cognitive capabilities in the future (IBM, 2015). According to a global data and analytics survey conducted by PwC in 2016, financial sectors like insurance, banking, capital markets, asset and wealth management firms already rely heavily on machine algorithms ranging from 26% to 54% that inform their next big decisions (PwC, 2016).The trend of technologies becoming increasingly intelligent and autonomous is acknowledged by IBM and many other leading technology firms around the world who are highly involved in developing AI technologies. Recently, with the evolution of IT and the internet, we saw the rise of CIOs to help companies organize their information. As IT matures, it is increasingly becoming the CEO's role to develop the company's digital strategy. According to Ng (2016), many S&P 500 companies wish they had developed their internet strategy earlier. Those that did, now have an advantage. Five years from now, we may be saying the same about AI strategy.

The immense growth of unstructured data, computational power and pressures from new competition brings new challenges for financial institutions. Furthermore, increased regulation and consumer expectations create a highly interesting scenario in where AI will play a key role for financial services. In this research project we focus on the banking industry because of several reasons. First of all, IBM is active as a world class supplier of hardware and cloud services for financial institutions all over the world. It brings deep expertise in all facets of the banking industry and an understanding of the operating models and businesses processes that must be redesigned and fused with new technologies to help banks improve profitability (IBM, 2017). Secondly, in a report of PwC about financial services & technology in 2020, financial firms must build the technology capabilities to get more intelligent about your customers' needs. Digital becomes mainstream and AI technologies are no longer an extension of current business processes but operate enterprise wide with lightning speed.

1.4 Theoretical relevance

Up till now, no academic research has been done towards defining the requirements and necessity of a Chief AI Officer and its corresponding role and responsibilities. However, the development of intelligent and autonomous systems is undeniable and highly interesting for organizations that operate in a digital ecosystem with large amounts of data and transactions. As we will discuss in chapter two, the past two decades there has been a repetitive pattern of emerging tech-executive roles from electrical engineering to manufacturing and information technology. As the trend towards AI based technologies progresses the need for high-tech companies to stay ahead of their competitive environment is large. In order to transform and adapt to an AI driven organization there must be some form of leadership that includes the right capabilities and authority to address not only the organizational and technological impact of AI, but also the ethical perspective. This thesis aims to provide an exploratory framework to identify if it is necessary for high-tech firms to appoint a Chief Artificial Intelligence Officer (CAIO) as a new tech-executive role that is responsible for all AI related activities within an organization. According to a global report from Deloitte, cognitive [AI] technology deployments are different from traditional IT deployments; their impact on organizations requires greater thought (Schatsky et al., 2015). Therefore, the focus of this research is to find out what stakes are at play when traditional banks adopt AI technologies into their business process and how this transformation process can be managed best. Subsequently we can determine whether a new tech-executive role like the CAIO is truly necessary and validate if it can play a supportive role in an organizational transformation process.

1.5 Research objective

For an enterprise, competitiveness refers to the capacity to create and sustain cost and/or product advantages to gain or maintain strong positions in the markets for its products and a high level of profitability (Bennet and Vaidya, 2001). However, since large high-tech corporations chase competitive advantage they must also ask themselves what core moral concepts underlie their technological innovations, such as AI? And can they morally justify these innovations? Therefore, the objective of this research project is to clarify what organizational, technical and ethical issues arise when organizations plan to involve in AI.

The challenging areas that will be affected by AI technologies can range from the development of additional departments, such as the AI department, to changes in duties due to a replacement-based AI, to changes in the power of certain individuals, to changes in regulatory compliance or global machine ethics governance. Many IT- and data-driven firms tend to make the transformation towards the use of AI technologies. As a result, new challenges will emerge from different perspectives like organizational, technical and ethical. Several researchers like Katz and Kahn (1966), and Hersey and Blanchard (1977) have noted that both leadership and power are partially derived from developing expert knowledge, which is the main goal of AI technologies. Accordingly, it is reasonable to expect that AI systems can impact both leadership and power. Additionally, O'Leary and Turban, (1987) said that the potential organizational impact of AI systems can be substantial, and acknowledged that values-aligned design methodology should become an essential focus for the modern AI organization. According to the IEEE (2016), which is a global initiative for ethical considerations in AI and autonomous systems (AS), states that in order to create machines that enhance human well being, empowerment and freedom, system design methodologies should be extended to put greater emphasis on human rights, as defined in the Universal Declaration of Human Rights, as a primary form of human values.

To facilitate this transformation, appropriate management may prove to be an effective solution. Therefore, we aim to analyze what managerial challenges are at stake so that we can evaluate the appointment of a new tech-executive role like a Chief AI Officer and propose a set of roles and responsibilities that address some of these critical challenges.

By determining the value of a Chief AI Officer we can contribute to the improvement of internalisation and adoption of AI technologies at traditional banks. These requirements will be analyzed from a vast array of strategic, managerial, ethical and technological perspectives that are necessary to facilitate the link between all relevant stakeholders within an AI-driven organization. The key question of this research project is therefore:

"Under what conditions would the appointment of a Chief AI Officer, as a new tech-executive role, be valuable to overcome challenges that arise when traditional banks adopt AI technologies?"

1.6 Research questions

In cooperation with multinational technology company IBM we first try to find out what managerial challenges are at stake within financial firms that are currently adopting AI technologies. Secondly, with these challenges defined we can form a solid organizational problem statement that provides input for the second research question: What is a CAIO and why do financial firms need this tech-executive role?

1. **What organizational challenges arise when banks adopt AI technologies?**
   - From an ethical perspective?
   - From an organizational perspective?
   - From a technology perspective?

2. **Under what conditions would a Chief AI Officer be relevant for traditional banks?**
   - What roles and responsibilities would this CAIO need to have?
   - What is the difference between established C-suite tech-executive roles and a CAIO?

2. Literature review

2.1 Literature review protocol

Based on our proposed research objective and questions we can now perform our literature review to see what has already been written about the concepts that lie core to our research subject. First we will visualize all relevant concepts hierarchically, prior to our literature search. In figure two we can see our proposed hierarchical visualization of all related concepts. These concepts will be explained in the next parts of our review protocol. This is not the conceptual model.

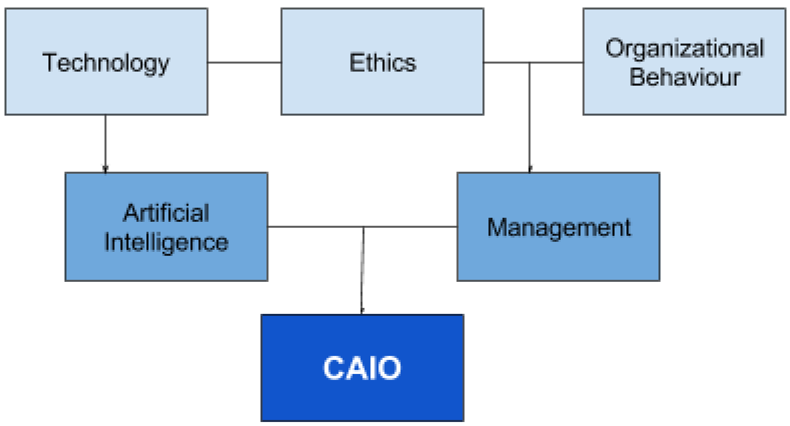

Figure 1: hierarchical overview of concepts

2.1.1. Tech-executive roles

First, we start our literature review journey by looking for any related (academic) literature written about a CAIO role. For now, we describe a CAIO as a tech-executive management role that addresses all AI related activities within an organization. To ensure full literature coverage we assume that a ‘chief cognitive officer’ or ‘CCO’ is similar to a CAIO. The keywords we used for this specific search are: CAIO, Chief Artificial Intelligence Officer, Chief AI Officer, AI manager, CCO, Chief Cognitive Officer, Cognitive manager. In this part we aim to cover all relevant literature regarding an AI/Cognitive technology management role.

Secondly, we will continue with a search towards closely related tech-executive roles that may, or may not, have similarities with a CAIO tech-executive role. We do this in accordance with Gregor & Hevner (2013) saying that the prior literature surveyed should include any prior design theory/knowledge relating to the class of problems to be addressed, including artifacts that have already been developed to solve similar problems. However, since we do not know exactly what we are looking for (hence our explorative research questions) we must assume that these tech-executive roles may cover some management activities related to AI technologies. The tech-executive roles we chose to search for are the following: chief information officer (CIO), chief science officer (CSO), chief data officer (CDO) and the chief technology officer (CTO) in combination with the keywords: roles and responsibilities. Later in this research project we will use this overview of all closely related tech-executive roles, and their features, to validate the necessity of a CAIO as a new tech-executive role. In the next part of this chapter (section 2.2) we will provide a visualization of all relevant literature we found regarding the closely related tech-executive roles.

2.1.2. AI management

The second layer of our hierarchical overview (figure 1) is visualizing the specific domain of our research project. In this domain of AI management we try to find out what literature falls within our specific research subject's class. The keywords used in this part of the review are: AI management, AI organizational decision-making, socio-technical impact of AI on organizations and its stakeholders. As described earlier we will use the terms: expert systems, autonomous systems, cognitive computing and intelligent systems similarly to AI in order to include all closely related literature.

2.1.3. Organizational & Management roles

Since we aim to answer *what* roles and responsibilities a CAIO may include we have to find out what theoretical requirements our research artifact has to meet. Therefore, we will dive deeper into the core concepts underlying our research subject to find out all relevant theories, methods, experiences and insights. Based on our research objective we logically deduct the following core concepts as foundation for our research project: management roles, organizational roles and behaviour (see figure 1).

First, we begin by identifying relevant literature with regards to technology and management. The goal here is to find theories about technology management roles and their corresponding responsibilities to provide a theoretical foundation for the CAIO validation. The keywords used here are: technology management, technology manager, technology manager role, technology manager responsibilities.

Secondly, we focus on organizational behaviour and ethics. These concepts resemble the socio-technical impact of (technological) innovation on organizations. Organizational innovation is in most cases managed by an organization's (c-level) management. Therefore we aim to find out what the role of a c-level executive manager is in dealing with the socio-technical impact of new technologies on organizational stakeholders. We aim to include theory about responsible innovation and organizational ethics. We have not used specific keywords but our search protocol focussed on finding literature about the socio-technical impact of new or emerging technologies in organizations, value for design management, responsible innovation, ethical impact of new or emerging technologies in organizations.

2.1.4 Ethics

From a wide range of sources we find evidence about how to best steer AI technologies in a way that it combines both the aim for innovation and enrichment of our lives as humanity. According to a one hundred year study on AI conducted by Stanford University (2016) policies should be evaluated as to whether they democratically foster the development and equitable sharing of AI's benefits, or concentrate power and benefits in the hands of a fortunate few. It is hard to foresee the effects of AI technologies in perfect clarity but they will need to be re-evaluated in the context of observed societal challenges. Therefore we aim to include literature about the moral complications that arise when organizations implement weak AI technologies into their business processes.

The journals we consulted include machine intelligence research institute (MIRI), frontiers, the Association for the Advancement of Artificial Intelligence (AAAI), IEEE institute (Advancing Technology for Humanity) and Springer. The results based on the keywords AI technology and theory related to responsible innovation, value-aligned design and ethics.

2.2 Review

2.2.1. Review of Tech-executive roles

In our quest to find academic literature about a tech-executive role called CAIO or CCO we have not found anything resembling the description of a technology management role that addresses AI activities within an organization. However, there are some compelling (blog) articles available online on Harvard Business Review (HBR) and CIO.com. These leading AI experts such as Andrew Ng, who leads the global AI strategy for Baidu (Chinese variant of Google) wrote in an november 2016 article for HBR about hiring your first chief artificial intelligence officer. Secondly, Neil Jacobstein, who is a chairman for the artificial intelligence and robotics committee of the Singularity University, argues that organizations should not centralize AI leadership by assigning a c-level CAIO to integrate AI activities. To summarize, there is some interesting literature available online but this will only be used as an introduction for the explorative nature of this research project. We have found no academic research about the concept of a CAIO as we described it. In the next part we aim to provide a summative overview (table 1) of all authors that have shed light on existing tech-executive roles who are active in an IT organizational environment. In accordance with the literature review protocol described by Webster & Watson (2002) we will briefly describe the aim of their work in table 1. In this table we have focussed on the three most dominant tech-executive c-level management roles currently active in the financial industry.

Role(s)	Article	Knowledge contribution
CIO, CTO, CDO	***CIO Roles and Responsibilities: Twenty-Five Years of Evolution and Change*** (Chun & Mooney 2006); ***Executive or functional manager? The nature of a CIO's job*** (Stephens et al. 1992); ***CIO 2.0: The changing role of the chief information officer.*** (Deloitte, 2004); ***CIO/CTO Job Roles: An Emerging***	*...describes the **roles and responsibilities** of tech-executive.*

	Organizational Model (Beatty, Arnett and Liu, 2005); ***The role of the Chief Data Officer in financial services*** (Capgemini, 2013); ***Achieving success as a CTO*** (Hart, 2008); ***The Chief Technology Officer: Strategic Responsibilities and Relationships*** (Smith 2016); ***The evolving role of the chief data officer in financial services*** (Deloitte, 2016)	
CIO, CTO	***Executive involvement and participation in management of information technology*** (Jarvenpaa, 1991)	*...describes the **behaviour** of tech-executive.*
CIO, CTO, CDO	***The leadership style of a CTO in an organizational environment*** (Medcof & Yousofpourfard 2006); ***Executive or functional manager? The nature of a CIO's job*** (Stephens et al. 1992); ***The evolving role of the chief data officer in financial services*** (Deloitte, 2016)	*...describes the **leadership style** of a tech-executive.*
CIO, CTO, CDO	***CIO Roles and Responsibilities: Twenty-Five Years of Evolution and Change*** (Chun & Mooney 2006); ***The chief technology officer*** (Adler & Ferdows 1990); ***The evolving role of the chief data officer in financial services*** (Deloitte, 2016)	*...describes the **tasks** of a tech-executive.*
CIO, CTO, CDO	***Dynamic Technology Leadership*** (Hoven et al. 2012); ***Great expectations: The evolution of the chief data officer*** (PwC, 2015)	*...describes the **complex environment** in where a tech-executive has to perform.*

Table 1: Overview of literature regarding current tech-executive roles and responsibilities.

The review shows that there has been done extensive research into the roles, activities, responsibilities, tasks, environment and style of leadership of tech-executive roles such as the CIO, CTO or CDO. We want to use this overview to compare the features of a these tech-executive roles with the proposed managerial challenges that arise when implementing AI technologies to determine the validity of a future CAIO.

2.2.2 Review of AI Management

O'Leary and Turban (1987) propose a set of potential challenges that arise when implementing expert systems into an organization. Expert systems have large overlap with AI technologies in a sense that they provide expert knowledge to support organizational decision making. The impact is discussed along eight organizational dimensions: decision making, organizational structure, degree of centralization and decentralization, degree of effectiveness and efficiency, organizational roles, leadership and power. They provide a framework for future research into the impact of expert systems and AI technologies on organizations. Some work of Sviokla

(1990) describe the organizational impact of expert systems by analyzing only one system and O'Keefe et al. (1993) used a group of systems. Lawrence (1991) argues in his paper about the impact of AI on organizational decision making that that the imple-
mentation of expert systems will lead to less complex and political decision processes, while the implementation of natural language systems will lead to more complex and political decision processes. In his concluding statements he argues that future research regarding AI and decision making, effort must be made at the social and technological levels to ensure that technology is employed in a productive and beneficial manner (Lawrence, 1991).

Duchessi et al. (1993) discusses the interaction of AI, management and organizations which describe some methodological approaches and theoretical models for studying those interactions. They argue that managers and developers understand very little about how management and organizations affect or are affected by the technology and that the success of an AI system depends on the resolution of a variety of technical, managerial and organizational issues; yet academic research is limited (Duchessi et al., 1993). Some researcher have analyzed the implementation process of expert systems to gain insights and understanding of key performance indicators that guided managers towards successful implementation (Irgon et al., 1990; Meyer and Curley, 1991; Duchessi and O'Keefe, 1993).

Concept(s)	**Article(s)**
Impact of AI technologies on organizations (also included: expert systems, autonomous systems, cognitive computing)	*The organizational impact of expert systems* (O'Leary & Turban, 1987); *Impacts of Artificial Intelligence on Organizational decision-making* (Lawrence, 1991). *Impacts of Artificial Intelligence. An overview.* (Trappl, 1986); *The impact of expert systems in accounting: System characteristics, Productivity and Work unit effets* (O'Keefe et al., 1993); *An examination of the impact of expert systems on the firm* (Sviokla, 1990)
AI management challenges (also included: expert systems, autonomous systems, cognitive computing)	*A research perspective: Artificial Intelligence, Management and Organizations* (Duchessi et al. 1993); *Managing the bots that are managing the business* (O'Reilly, 2016); *Managing with Immature AI* (Ransbotham, 2017); *The three new skills managers need* (Tarafdar, 2016); *Organizing for new technologies* (Kapoor & Klueter, 2016); *What to expect from Artificial Intelligence* (Agrawal, Gans & Goldfarb, 2017); *Understanding expert system's success and failure* (Duchessi and O'Keefe, 1993); *Putting expert systems technology to work* (Meyer and Curley, 1991); *Expert systems development: a retrospective review of five systems* (Irgon et al., 1990)

Table 2: Overview of literature regarding AI management.

As shown in table 2 we can conclude that there is very little work done in the area of AI and management. As a note to the second row of table 2: the literature shown here is mostly of non-academic level but does provide us with early stage insights about management of AI technologies in several corporate domains.

2.2.3. Review of Organizational & Management roles

In the following part we address the underlying organizational and management theories that lay ground to the nature of our research project. We aim to collect all relevant theories regarding the emerging rise of new management roles and the development of roles and responsibilities of a (tech) executive in an organizational environment. Role theory explains how executive leaders in a business determine their roles and how people act in their organizational role among others.

The founding father of this area of organizational expertise was believed to be the french Henri Fayol, who introduced five basic managerial functions: planning, organizing, coordinating, commanding, and controlling in 1916. After the second world war the attentions focussed on different managerial styles. You had for example the humanists that criticized autocratic task-oriented style and vouched for a participative and people-centered management style. The french management theorist Mintzberg felt that too much attention was placed on two basic styles (autocratic and participative) and managers lacked the understanding of interpersonal behaviour among managers and employees. Autocratic theorists include McGregor (1960), Likert (1961). Participative theorists included: Campbell et al. (1970) and Fiedler (1966).

Mintzberg describes in his book: The nature of managerial work (1973) ten managerial roles that are divided into three different groups: interpersonal roles, informational roles and decisional roles. These concepts are in alignment with Fayol's early definitions. These ten roles can be grouped as being primarily concerned with interpersonal relationships, the transfer of information, and decision making (Robbins, 1996). The management executive Chester L. Barnard writes in his book The functions of the executive (1977) about management theory concepts that he called executive function, executive process and the nature of executive responsibility which are early concepts to roles and responsibilities of a managerial executive. One of his three theory highlights is that 'purpose' is used as an underlying driver of cooperation among agents. His work is more focussed on leadership rather than management.

The management theories of Fayol (1916), Mintzberg (1973), Barnard (1977) all fall within the organizational domain, however, they show no clear link between management features and (AI) technology. According to Harvard Business Review, Drucker developed astonishing management theories and has been described as "the founder of modern management." In his book the coming of 'the new organization' he describes a new area of information-based organizations which include 'knowledge specialists' (Drucker, 1988). These knowledge specialists managing roles shift from command-and-control with departments and divisions into the information-based organization that holds fewer middle management, less operational work and more focus on knowledge creation and diffusion.

2.2.4 Review of Ethics of Technology

Mitcham & Frodeman (2000) argue that science should move beyond a strict relationship with society and engage to achieve a common goal. They conclude that "good in science, just as in medicine, is integral to and finds its proper place in that overarching common good about which both scientists and citizens deliberate" (Mitcham & Frodeman, 2000). This form of engagement is a form of responsible innovation (RI). According to Von Schomburg (2011) RI is a transparent, interactive process by which societal actors and innovators become mutually responsive to each other with a view on the ethical acceptability, sustainability and societal desirability of the innovation process and its marketable products. He makes the case that RI should be understood as a strategy of stakeholders to become mutually responsive to each other and anticipate research and innovation outcomes underpinning the “grand challenges” of our time for which they share responsibility (Von Schomburg, 2011).

Stilgoe et al. (2013) have developed a framework to address RI challenges on a project level basis. In their work they have determined that represent aspects of societal concerns, interests in research and innovation and responsible innovation can be seen as a way of embedding deliberation on these within the innovation process. The four dimensions of responsible innovation we propose (anticipation, reflexivity, inclusion and responsiveness) provide a framework for raising, discussing and responding to such questions. The dimensions are important characteristics of a more responsible vision of innovation, which can, in our experience, be heuristically helpful for governance.

Some focus more on specific practical effects by applying anticipatory governance (Barben et al., 2008) and others discuss a more practical elaboration of designing technology through societal inclusion called: Value sensitive design. This term came into existence through Friedman (1996) and is followed up by Fisher et al., (2006) and later by van den Hoven et al. (2012). Value Sensitive Design is a theoretically grounded approach that incorporates the design of technology that accounts for human values in a principled and comprehensive manner throughout the design process (Friedman, 1996). By design, both technical and socio-technical design is meant. A different form of assessing new technologies (Rip et al., 1995; Rip and Schot 1996; Grin and Grunwald, 2000) is explained by the constructive technology assessment (CTA) method, which shifts the focus away from assessing impacts of new technologies to broadening design, development, and implementation processes. Explicit CTA has concentrated on dialogue among and early interaction with new actors (Rip and Schot, 1996).

2.2.5 Review of Ethics of AI technologies

According to the IEEE, which is one of the largest technical professional organizations for the advancement of technology with over 40.000 worldwide members, there are a number of ethical complications that play a role when organizations implement AI technologies into their business processes that arise in the area of framing the principle of human rights, responsibility, transparency and education of awareness. These areas cover a vast array of issues like: lack of universal embedded AI values, conflicting and context specific norms and values, built-in data biases that discriminate members of certain groups, problems with the translation of norms into the computational architecture, achieving correct level of trust between humans and AI and the evaluation of AI value alignment by third parties (IEEE, 2016). The IEEE (2016) also proposes a list of numerous similar issues in the area of economics and law that provide valuable insights into practical issues, for example: AI policy may slow down innovation, lack of understanding regarding personal information, lack of accountability and verifiability of AI technologies, respect of international, national and local rights of humans by AI technologies and the protective capabilities of AI technologies to sustain the integrity of personal data.

2.3 Summary

Academic research regarding a (new) tech-executive role that addresses all relevant AI activities within an organization is not found in the current available academic literature. Therefore, we constructed an overview of the current tech-executive roles that are active in the financial sector. This overview contains literature regarding the roles, responsibilities, tasks, environment and leadership style of current tech-executive roles CIO, CTO and CDO. Additionally, this overview also confirms our failure to find a managerial role that fits with our initial description of a CAIO. If we dig deeper we see that there has been some work with regards to the impact of AI technologies on organizational behaviour but no specific research *what* management features are necessary to manage AI technologies. The next step is to identify theory about management roles and responsibilities and link these features with the domain of AI technologies used in the financial sector.

In section 2.2.2 we included an interesting article, among others, from Duchessi et al. (1993) stating that despite the proliferation of the technology [AI], managers and developers understand little about the practical issues associated with the interaction of AI, management and organizations. O’Leary & Turban (1987) do write about the impact of expert systems [AI] on organizational behaviour, including management. However, academic research is limited on this topic. According to Duchessi et al. (1993) the success of an AI system depends on the resolution of a variety of technical, managerial and organizational issues. Based on our literature review we can draw a framework to discuss the interaction between artificial intelligence, management and organization from Duchessi et al. (1993).

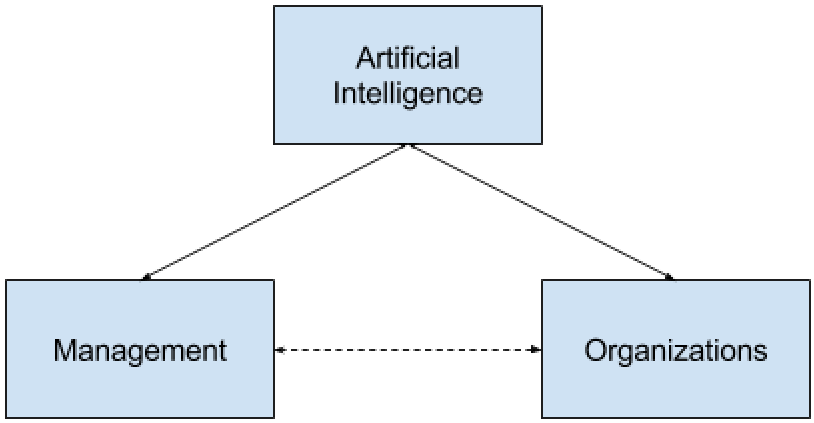

Figure 2: Conceptual model

An organization's management function encompasses defining the organization's goals, establishing an overall strategy for achieving these goals, and developing a comprehensive hierarchy of plans to integrate and coordinate these activities (Robbins, 1997). The management's characteristics we aim for are: roles, responsibilities, tasks, organizational position, and leadership style. The concept of organizations is characterized by the institutional features, size, performance and field of expertise. AI is not the same product in all situations, it shapes and is shaped by the framework's other two components (Duchessi et al., 1993). Organizational effects that occur as a result of AI technologies are for example: power shifts, reassignment of decision-making responsibility and personnel shifts. Despite the fact that management and organizations clearly affect each other we focus on the interaction between AI, management and organizations.

Agrawal et al. (2017) claims that in order to understand how advances in artificial intelligence are likely to change the workplace — and the work of managers — you need to know where AI delivers the most value. Therefore we will first focus on finding out where AI delivers the most value for financial firms and clarify what corresponding challenges arise. Next to organizational and technical challenges that may arise, we also include the perspective of morality and ethics. Responsible innovation and Value Sensitive Design are methods that both aim to incorporate ethical aspects into the process of development and usage of emerging technologies such as AI. In the next chapter we will continue with the research approach and research design in chapter four.

3. Research approach

In this part we have constructed a research framework (see figure 3) that provides a schematic representation of the research objective and includes the appropriate steps in order to achieve it (Verschuren & Doorewaard, 2010).

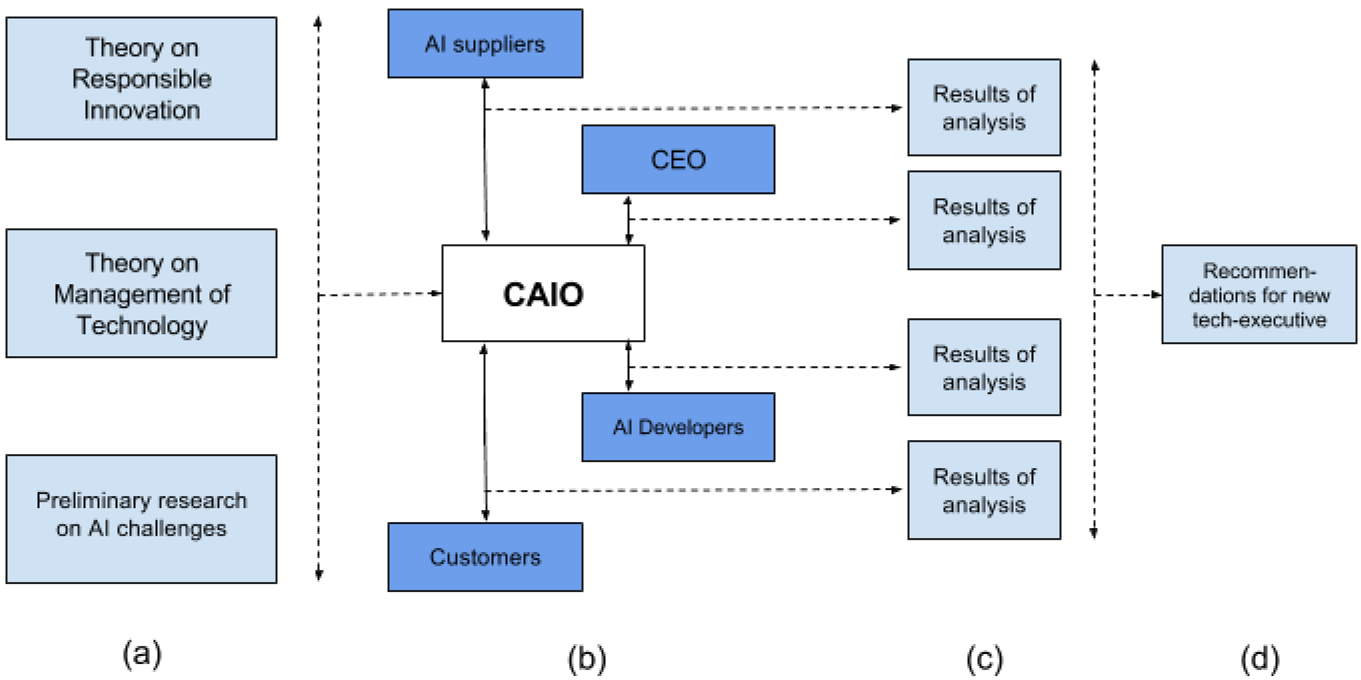

Figure 3: Research framework (Verschuren & Doorewaard, 2010)

The following section examines the steps that should be taken to finally provide answer to the research objective of this project. The steps are marked with letters in figure 3. The research object (CAIO) is the phenomenon under study about which we will be making statements based on the research to be carried out (Verschuren & Doorewaard, 2010). In steps (a), (c) and (d) the boxes contain relevant theory and findings that are linked with a dashed line. In step (b) the dark blue boxes represent actors in the organizational network of a C-level executive. The solid lines show the the link between the actors and the object under study (CAIO).

a. This first step includes the literature review of all relevant theories and preliminary research that has to be done in order to provide a 'first version' of a tech-executive called: CAIO. The literature review will consist of what has already been written about technology management, ethics of technology and current established tech-executive roles. With this information we perform preliminary research among AI experts to determine managerial and ethical challenges that arise when banks adopt AI technologies. More elaborate description of this preliminary research is discussed in section 4.3.2.

b. According to Bennet and Vaidya (2001) the acquisition of a new technological capability is not a one-off process but a cumulative one in which learning is derived from the development and use of technology. There is a view that national competitiveness is obtained by strengthening the science base and developing Research and Development (R&D) capacity. However, activities formally identified as science and R&D are only one part of the overall process which includes learning by doing (increasing the efficiency of production operations), learning by using (increasing efficiency by the use of advanced equipment and complex systems) and learning by interacting with suppliers and customers (Bennet and Vaidya, 2001). Therefore we aim to define a CAIO's 'first version' so that we can then use this as a first point of reference. In step b. we will do more extensive research into the features of a CAIO and its validity. More of this part will be discussed in chapter four.

c. In this third step we collect all the findings from the real world. These findings will be used as the input for our qualitative analysis. We will conduct at least 15 interviews with experts in the domain of AI & Banking. These interviews will be semi-structured, as we will explain in more detail later.

d. In this final step all results regarding the performed research of this project are analysed and used to form a well grounded answer to the research questions and research objective. Conclusions will be drawn by confronting the distinct results of the analysis (Verschuren & Doorewaard, 2010). The confrontation is based on the comparison between the literature review and the performed empirical research. Elaborate information about the evaluation of our research will be discussed in section 4.3.

3.1 Research perspective

Our research perspective will describe the specific angle of approach that will be used throughout this entire research project. It serves as a 'spotlight' that can be used to study the research object more closely (Verschuren & Doorewaard, 2010). Since our research approach is more practice-oriented with a highly explorative research objective we aim to use a design oriented research perspective in order to develop an initial design of a CAIO, based on the findings from the literature review and the empirical research we aim to find an initial "proof-of-concept" in the banking industry domain.

We perform this research in order to provide a deep understanding of how organizations can transform into an AI driven firm by implementing domain specific management concepts in order to create a strategic and ethical link between all relevant organizational stakeholders that will be affected by the new AI technologies. Our research perspective does not stem mainly from a theoretical analysis, but from an empirical study (expert interviews and survey) in which we determine the design specifications (Verschuren & Doorewaard, 2010). In the next paragraph we will elaborate more on the design science research method.

4. Research design

The goal of this research project is to provide in-depth answers about the organizational, technical and ethical challenges that come with the adoption of AI technologies in the Dutch banking industry. Therefore, our aim is to identify these challenges so that we can provide a sound basis for future research to develop theory regarding organizational leadership, technology management, strategy and ethics. Since the nature of this research project is very novel, we will adopt an exploratory research approach to evaluate whether a Chief AI Officer may be a valuable solution to address certain critical challenges that arise when traditional banks adopt AI technologies.

According to Boodhoo & Purmessur (2009) there has been an increasing use of qualitative research in organisations. Due to the subjective nature of this method of research, it can be argued that quantitative research could provide better findings. However, qualitative research can be used to explore several areas such as human behaviour which cannot be quantified but yet important to an organisation (Boodhoo & Purmessur, 2009). Qualitative research is often seen as the approach that uses words, language and experiences rather than measurements, statistics and numerical figures. In order to make an informed analysis we must first explore the full landscape of challenges. This research approach refers to an inductive and holistic view so that we can describe and understand what AI related challenges play a role in the Dutch banking sector. To be more precise, we will use a small scale version of the ethnographic research method that is coming from an anthropological and sociological background in which the researcher studies the shared patterns of behaviors, language, and actions of an intact cultural group (Creswell, 2002). According to Creswell (2002) the data collection involves observations and interviews. The main reason that justifies the use of ethnography (qualitative research) in organisations is that it helps to review and improve the existing systems and processes over time (Hughes et al., 1993).

Our first research question states: “*What challenges arise when traditional banks adopt AI technologies?*” This question follows an exploratory and inductive approach, and will form the basis of this research project. In order to answer it, we will interview a diverse set of experts in the field of AI and Banking so that we can establish a clear view of all relevant challenges that arise when traditional banks adopt AI technologies. It is important to keep an open mind in order to absorb all the impressions received while studying research data and relevant literature. An open mind (also called 'theoretical sensitivity') refers to the attribute of having insight, the ability to give meaning to data, the capacity to understand, and the ability to separate the pertinent from that which is not (Strauss & Corbin, 1990; Verschuren & Doorewaard, 2010).

Subsequently, we will use this broad set of findings to analyse in what conditions the appointment of a Chief AI Officer may be of value to traditional banks. We will achieve this by comparing our primary data (expert interviews) with secondary data from relevant literature and documents to establish a broad range of perspectives. The goal is not to reach one concluding answer but to pre-evaluate the different needs and implications of appointing a new C-level role in the executive management layer of a traditional bank. In this latter phase of the project we aim to provide arguments that answer our second research question: *Under what conditions would the appointment of a Chief AI Officer be necessary for traditional banks to overcome challenges that arise when they adopt AI technologies?*

4.1 Data collection

Our research project will be conducted in cooperation with IBM, a multinational technology company. IBM delivers hardware, software and consultancy services to the financial services industry for decades. As part of their product offerings, they develop and sell AI solutions called: Watson. Their long-term relationship with the largest traditional banks in the Netherlands is therefore extremely valuable and interesting for this research project. IBM has established connections with virtually every management layer, from board till operational level. Secondly, we chose the scope of banking because these large organizations have collected enormous amounts of data in the past decades, which provides them with a solid foundation for applying AI applications in their business processes.

4.1.1 Document analysis

In chapter 2 of this research project we have described all relevant concepts that we found in historical academic and non-academic literature sources. By identifying what already has been written about AI challenges and established tech-related executive roles in the current literature we can determine what features are covered, and which do not. As a result we can make a prediction about the necessity of a new tech-executive role to address AI technologies and what corresponding features may be important for a future CAIO role. The literature review described in section two will serve as the foundation for our empirical research.

The document analysis is an additional form of gaining insights from industry reports, consultancy reports and other domain specific research results. This analysis differs from the literature review in the sense that it focuses on collecting all relevant information about the subject at hand. We will use this information to gain insights about the industry, technology, type of organization, ethics, and other related factors that may support our research.

4.1.2 Expert interviews

The next step is to collect empirical data through conducting in-depth interviews with AI experts that will provide us with insights about what challenges arise when implementing AI technologies in a traditional bank. This empirical research part will address the first and second research questions. It is important that the choice of experts, communication and fine-tuning between them, must be balanced against the importance of the design problem and the opportunities of the designer (Verschuren & Hartog, 2005). Ethnographic research typically uses an informal strategy to start its research. According to Fettermann (2010) the most common used technique is judgement sampling: that is, researchers rely on their judgement to select the most appropriate members of the subculture or unit, based on the research question. In our case we will conduct 15 preliminary and informal talks with employees from IBM that are directly related to the world of AI and Banking. In these informal talks we ask them what members in the domain of AI and Banking we should conduct an in-depth interview with to determine exactly whom we should interview for our research. This provides us with a certain degree of validity to ensure us that we interview the right experts. The reasoning behind this approach is that we want to rule out that we, as the researcher, may narrow the focus prematurely, thus eliminating perhaps the very people or subjects relevant to the study (Fettermann, 2010).

We aim to conduct at least 20 in-depth interviews that will have a semi-structured form to classify general AI challenges but also provide room for creative and well argumented input of the respondents. To establish a good view of what challenges play an important role in the Dutch banking sector, we will aim to connect with project managers and top executives of the three largest Dutch banks (ABN Amro, Rabobank and ING), Dutch financial regulators (AFM and DNB) and providers of AI technologies for these banks (IBM). We aim to cover the following perspectives: Data science, AI consultancy, innovation management, business strategy, legal, compliance and regulations, and ethics. By interviewing key actors in the Dutch banking ecosystem we will provide a multi-perspective analysis of the current situation. The ecosystem scope is centered around these three traditional Dutch banks. We carefully selected experts with direct or indirect ties to the world of AI and/or Banking. These key actors will be active members of at least one of these organizations: IBM (Technology), Rabobank (Traditional Dutch bank), ABN Amro (Traditional Dutch bank), ING (Traditional Dutch bank), AFM (Authority Financial Markets, Dutch regulator) and DNB (Dutch Central Bank, regulator). Rabobank, ABN Amro and ING are the three largest traditional banks in the Netherlands. An overview of all the respondents is attached in the APPENDIX A.

The content of the interviews will be including questions about the respondents background, study, current organizational position, experience with AI projects and experience with AI suppliers. Secondly, we will ask the respondent about what he/she perceives as challenges that arise when traditional banks adopt AI technologies. The important thing here is to get an inclusive overview of the respondents' vision and arguments. Thirdly, we will conduct a series of eight questions that are similar to statements from a survey study on CIOs in the financial service industry, conducted by Institute for Business Value (IBV) of IBM. The aim here is to compare our outcomes with the results of the IBV survey, so that we can benchmark the views of our respondents with the views of CIO's globally. Finally, the last part of the interview will contain questions about the possible appointment of a Chief AI Officer and its corresponding features. We have attached the interviews in the APPENDIX B.

The first three parts (background, challenges and survey questions) are mostly descriptive of nature and the last part (Chief AI Officer role) is more focussed on normative answers. In the next paragraph we will get into more details about how we dealt with certain researcher biases and limitations.

According to Verschuren & Doorewaard (2010) the first stage involved in theory building following a grounded theory approach concerns exploration of the field of study. It is important that we will make use of the available resources in order to develop an inclusive analysis of the current landscape. Therefore, 'sensitizing concepts' is important and means that concepts are vaguely defined, but inspiring or intriguing concepts (Verschuren & Doorewaard, 2010). The aim is to leave the meaning of these concepts open at first, so that the precise meaning of the concept can be gradually attached, based on the findings. Corresponding with this approach we will therefore use 'open coding' to analyze our expert interviews. During this process, data is compared, labelled and classified so that we can acquire more insight into the challenges that underlay the adoption of AI technologies at traditional banks.

4.2 Conceptualization of the Chief AI Officer role

Finally, based on the results of our document analysis and empirical research, we aim to provide a pre-evaluation of a new C-level tech-executive role: the Chief AI Officer. In this final part we will first describe the current tech-executive roles that exist in the banking industry. Based on this analysis we will be better able to validate the need for a new tech-executive role that may address certain AI challenges. As a result we will discuss its possible roles and responsibilities, level of seniority, organizational position, and ability to be embedded in the current organizational landscape of a traditional bank. Additionally, we will describe the potential benefits and drawbacks of hiring a Chief AI Officer, and describe the AI challenges that it may address.

The research parts described in this chapter will logically act as a foundation to answer the research questions of this thesis project in the conclusion of this report.

5. Data collection

According to Offermann et al. (2009) the research question may arise from a current business problem or opportunities offered by new technology. In this chapter we provide a detailed description of the organizational, technical and ethical challenges traditional banks face today. We aim to investigate the challenges that arise when these organizations use AI technologies. As a result we will be able to answer the first research question based on results of our expert interviews. Additionally, we will compare these results with a complementary document analysis in the domain of AI and Banking. The findings from our document analysis and expert interviews are most prevalent to use (Offermann et al., 2009) and will be pre-evaluated in the concluding paragraph of this chapter. We have conducted 19 interviews with experts in the domain of AI and banking in the Netherlands. To safeguard the anonymity of the interviewees we have used simple reference codes to refer to certain respondents views.

First we will describe the capabilities and limitations of historical, current and future AI technologies. Secondly, we will discuss the general challenges that traditional banks face today, to get a well documented overview of the domain's landscape. Thirdly, we will describe the full set of challenges that we identified as a result of findings in relevant literature, documents and results from our expert interviews. Since this is an exploratory research project we aim to be as including as possible, factually describing the broad set of organizational, technical and ethical challenges that arise when traditional banks adopt AI technologies.

5.1 Capabilities and limitations of AI technologies

What is artificial intelligence? Russell & Norvig (2009) define AI as "the designing and building of intelligent agents that receive percepts from the environment and take actions that affect that environment". The most critical difference between AI and general purpose software is in the phrase "take action". AI enables machines to respond on their own to signals from the world at large, signals that programmers do not directly control and therefore can't anticipate (PwC, 2017). This evidently brings certain shifts in responsibility which we will discuss later in this chapter.

According to Schatsky et al. (2014) the impact of cognitive technologies on business should grow significantly over the next five years. They explain this is due to two factors. First, the performance of these technologies has improved substantially in recent years which stimulates continuing R&D efforts to extend this progress. Second, billions of dollars have been invested to commercialize these technologies (Schatsky et al., 2014). Predicted improvement in the areas of artificial intelligence and complex adaptive systems mean that software could, within 5 years, handle problems regarded today as "impossible" (Naylor, 2016). Software as we know it has always been used to solve large problems into simple series of 'yes' and 'no' rules. This is the first wave of AI as the US backed innovation center DARPA calls it. 'First wave' AI systems are capable of implementing simple logical rules for well-defined problems, but are incapable of learning, and have a hard time dealing with uncertainty (DARPA, 2016; Tzezana, 2017).

The second wave is based on statistical learning called: machine learning. These systems are forecasting systems that use fixed relationships between variables based on historical data. This means that the range of problems that can be solved are limited by (i) those areas where the data meets the stability requirements, (ii) those areas which the programmer thoroughly understands prior to starting and (iii) those areas which can be solved by iteration within a reasonable time (Naylor, 2016).

Additionally, the second wave also includes the more advanced statistical learning methods using artificial neural nets (DARPA, 2017). In 2005, Dr Li, the head of Stanford's AI Lab stopped programming computers how to recognize patterns but started labeling loads of raw images and used these to train them. She showed that a machine was able to shape its own rules for deciding whether a particular set of digital pixels was in fact a cat (Naylor, 2016). The image recognition software 'ImageNet' of Dr. Li's team was released in 2015 and successfully recognized 85% of images using artificial intelligence techniques.

Predictions of complex adaptive systems are thus dynamic and can solve problems in areas where the relationship cannot be carefully pre-defined (Naylor, 2016). This is particularly interesting for financial institutions like banks and insurance companies who cope with large amounts of structured and unstructured data every day. However, it's not clear that there actually is a methodology – some kind of a reliance on ground rules – behind artificial neural networks (Tzezana, 2017).

Second wave AI systems are not able to explain their choices well. This is similar to a young child playing with a baseball. It is not able to write down Newton's law of physics just by looking at the ball (Tzezana, 2017). We are currently still in the early stage of the second wave, where we explore the possibilities of statistical learning techniques. A lot of progress has been made in the field of natural-language processing and deep learning data analysis but far less developments have been made on other branches of AI such as decision making and deductive reasoning (Naylor, 2016). The third wave, defined by DARPA (2017), is about contextual adaptation. The AI systems themselves will construct models that will explain how the world works. In other words, these systems discover by themselves the logical rules which shape their decision-making process (DARPA, 2017; Tzezana, 2017).

Progress of AI technologies are not even across all fields. Widespread adoption of cognitive systems and artificial intelligence across a broad range of industries will drive worldwide revenues from nearly $8.0 billion in 2016 to more than $47 billion in 2020. However, banking is named as one of the top two industries to lead the charge (IDC, 2016). According to IBM (2016a), only 28% of 2,009 banking executives are familiar with AI. However, just 17% say their organizations are ready to use it. Therefore we start by asking ourselves, what challenges arise when banks use artificial intelligence technologies?

5.2 General challenges that traditional banks face today

In the following part we will discuss a broad range of challenges that large banks face today. According to PwC (2016b), Deloitte (2015y) and KPMG (2017) the following set of global challenges play a major role in banking: Low interest rates, cyber risk, change management and human talent. According to IBM (2015) a triple set of challenges have emerged that require traditional banks to rethink how they do business. They state that “many banks are struggling with sluggish profits; new classes of customers are easily dissatisfied and disillusioned; possessing ever-growing expectations of engagement and experience; and a new breed of competitor is emerging for banking customers” (IBM, 2015).

The economic factors of the financial service industry keeps changing with rapid pace. The large financial sector in the US saw the United Kingdom as a perfect gateway to Europe but Brexit caused a severe shock in this view. Until now these firms mostly competed against their own. However, they now also face competition from non-traditional market players with skills, funding and attitude (PwC, 2017). Next to large macro economic factors banks have persistent low yields because of low interest rates. These low rates are hurting performance and many now look at cost containment as one of the keys to survival (PwC, 2017).

In the world of banking we see emerging technology trends that pave the way towards a more digital business. Besides developments in AI and robotics we see rising technologies such as blockchain, which is a distributed ledger technology that allows transactions without a central clearinghouse.

Some say that the biggest technological challenge for banks is cybersecurity. To hold off threats that are coming from multiple directions with state-of-the-art techniques banks need to build a robust cyber wall. According to PwC (2016b) and Deloitte (2016), this challenge is even increasing the coming years due to: the use of third-party vendors, rapidly evolving and sophisticated technologies, cross-border data exchanges, increase use of mobile technologies and heightened cross-border information security threats. However, internet banking fraud in the Netherlands has actually fallen from a total of €35.1 million in 2011 to €3.7 million in 2015, which illustrates the effectiveness of the financial institutions’ cooperative efforts in the cyber security domain (TNO, 2017).

KPMG (2017) argues that new fintech disruptors will be the biggest threat to financial institutions. For example tech giants like Google and Apple that already have a prominent brand presence amongst this group are likely to jump in the world of banking anytime soon. KPMG (2017) claims that 84% percent of generation X & Y would consider banking with a tech giant if they are offered a better product or deal. This is in line with the features of this generation, focussing on getting the best value out of their investment and the immense integration of tech giants into their day-to-day activities will be able to offer a full end-to-end experience.

According to IBM (2015): “62 percent of retail banking executives indicate their organizations are able to deliver an excellent customer experience, only 35 percent of retail customers share their view, a 27-percentage-point difference.”

Clearly the management of technology has an increasingly large impact on the banking industry. In the following chapter we will take a deep dive into the specific challenges that arise when banks use AI technologies to enhance their business processes.

5.3 Results of Expert Interviews

In this section we briefly introduce and discuss the results of the expert interviews (APPENDIX E). More extensive results and findings will be discussed in the next paragraphs. First of all we have conducted 19 interviews with experts from traditional banks, regulators and technology companies (APPENDIX A). In total we interviewed seven experts from an AI supplying technology company perspective (mostly IBM). Three experts from Rabobank, three from ING and three from ABN Amro. Additionally, two experts from AFM and one from DNB. We have conducted interviews with experts that had a background in data science, AI consultancy, innovation management, business strategist, legal/compliance and policy development.

As a result of the interviews with the broad range of experts we can conclude that the challenges regarding the development and use of AI technologies are very broad, in a sense that there are many different challenges from different perspectives. In addition, experts state that the technology is still very premature, which results in lack of a clear approach to address these challenges. The most common organizational challenges that were mentioned by the experts are: Talent scarcity, traditional banks’ culture, mindset and organizational structure. In the next paragraphs we will describe and explain these issues in more depth. The ethical challenges that were mentioned by the experts are: privacy issues, biased data and discrimination issues, AI accountability and explainability issues, low awareness of ethical consequences and future job replacement issues. Finally, the technical challenges that arise according to the experts are: data quality, data access and low maturity of current AI technologies.

Next to the topic of AI challenges we asked the experts in our interview about the Chief AI Officer (APPENDIX E). We explained how Andrew Ng proposed his definition of a Chief AI Officer and asked them whether they would find such a new C-level tech-executive role would be valuable in the organization of a traditional bank. A big majority of the experts did acknowledge the need for a new tech-executive role, but there was no consensus regarding the level of authority. Some explained that the role should be introduced, but should not report to a CEO but to a CIO, CTO or COO. Arguments for this claim were generally based on the prematurity or lack of priority of AI technologies within a traditional bank. They explained that AI technology should be a board-level priority topic but should not be represented by one person, but should be part of a tech-executive’s portfolio of technology topics.

The few experts that said ‘no’ to a new tech-executive role like a Chief AI Officer explained that they did not see any value in appointing a new tech-executive role to address AI challenges because: It has no clear business goals, AI should be part of the overall innovation portfolio instead of being addressed as just one specific topic, and such a role would have no priority at a traditional bank. More extensive findings and analysis of the results regarding the Chief AI Officer will be discussed in the next chapter.

5.4 Analysis of the results

In this paragraph we will discuss a broad range of organizational challenges that arise when traditional banks use AI technologies. According to Dooley (2017), Naylor (2016) and Ng (2016) AI systems are particularly interesting for financial services because their core activities are based on understanding risk and balancing a wide range of numeric factors as well as predicting trends. Therefore, traditional banks will be particularly vulnerable for disruptive technologies such as AI (Naylor, 2016). Results from our expert interviews (APPENDIX C) show us that traditional banks have low to moderate understanding of how to use AI technologies to improve their business outcomes (see figure 4). The results from our expert interviews are marked in red, and the results from the Institute for Business Value are marked in the blue (IBM, 2017). Moreover, our results also show that traditional banks have not yet defined a strategy and vision for the use of AI solutions (see figure 5). Based on these initial results we can see that the potential of AI is large, but traditional banks are still scoring low to moderate on dealing with it properly. In the next paragraphs we will describe the broad scala of challenges that arise when traditional banks use, or want to use AI technologies. These findings are the result of our expert interviews and document analysis.

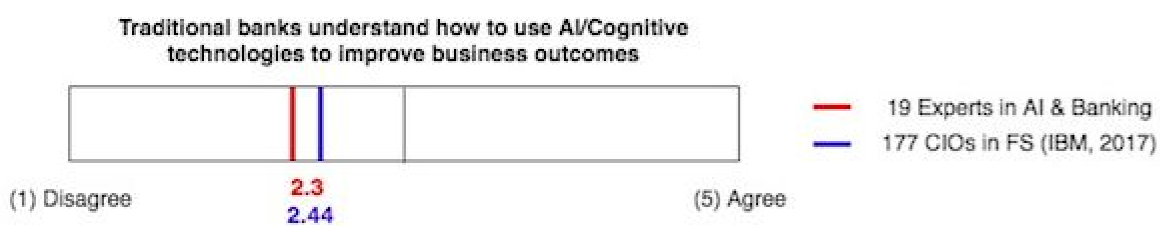

Figure 4

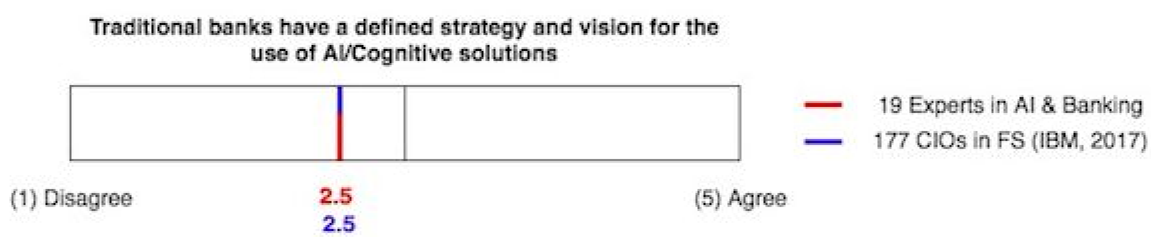

Figure 5

5.3.1 Talent Scarcity

According to five interviewees a major challenge for banks to properly deal with AI in their business is to attract and retain human talent. This is also confirmed by Ng (2016) and Deloitte (2015) who claim that one of the two scarce resources in the world of AI development is: attracting and retaining talent. Results from our expert interviews (APPENDIX C) show that traditional banks score low to moderate on having the necessary data science, machine learning and other AI/Cognitive skills (figure 6). Additionally, our results show that banks score low to moderate on having a plan to re-skill or train their current workforce to be ready to adopt AI technologies (figure 7).

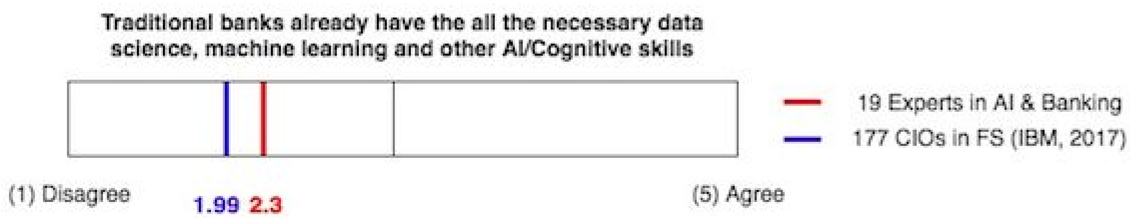

Figure 6

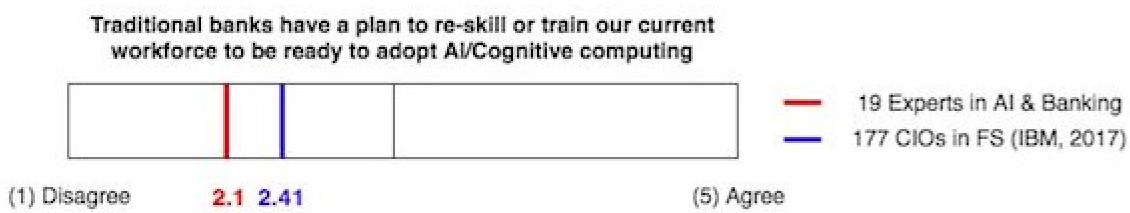

Figure 7

As we discussed at the beginning of this chapter, AI needs to be well trained to fit data with business context. However, the field of AI is highly specialized and the biggest current barrier of AI is that universities are only now starting to create post-graduate courses in data science and machine learning (Ng, 2016). Additionally, the relative unattractiveness of financial institutions to these graduates, in comparison with attractive technology companies, could be a major barrier to attract and retain the right talent (Naylor, 2016)**.** According to a report from McKinsey (2016) banks must build skills for vital roles such as data scientists and data translators, who convert analytical outputs to commercial and customer use cases.

5.3.2 Culture

Interviewees 2, 5 and 12 claim that a tricky but important challenge is creating the right culture and mindset among members of the top management layers in order to drive innovation and change. Culture is the self-sustaining pattern of behavior that determines how things are done (Katzenbach et al., 2016). According to Naylor (2016) and interviewees 2 and 12, banks have a risk averse culture because these organizations have had very little competition in the past.

Secondly, interviewee 1 states that banking is funded on developing trust among its clients and achieves this by mitigating risk to drive performance. Therefore, interviewees 1 and 12 think that transforming banks from a rather conservative culture into a more risk-taking innovative culture will be a tough challenge.

According to PwC (2015) transforming banks into an AI-driven organization will require a diverse set of skills from board members that are able to use the conservative culture to their advantage. The EU has introduced new rules limiting bonuses paid to senior employees that are in risk taking roles (PwC, 2015). One of the challenges of working with culture is that, as we have noted, it changes gradually, often too slow for leaders that face fast-moving competitors (Katzenbach et al., 2016). It takes a courageous board to approve management investing heavily in terms of personal and money in ambiguous projects in the areas where the outcome is uncertain, cash-flow is unstable, and the pathway to success subject to unexpected shifts (Naylor, 2016). Therefore, the conservative culture of a traditional bank hinders the pace of adopting AI technologies to some degree.

5.3.3 Mindset

According to interviewee 6 and 12, whom are employee at a traditional bank, there is still no consensus in the top management layers of their organization about how to make effective use of AI. They claim that this is due to a wrong and fixed mindset. According to Moore (2016) the danger of a fixed mindset is that these people believe that their basic qualities like: character, intelligence and creative ability are fixed traits. However, Moore (2016) explains that character traits like intelligence and talent are just the starting points, supplemented by continual learning. Those who embrace this mindset see challenges as opportunities to grow and learn, and they are resilient, even when faced with failure (Moore, 2016). The board of a large and conservative organization often has ‘groupthink’ and thus may fail to see problems which would be obvious to a person with a different background (Naylor, 2016). According to Gartner (2016) a fixed mindset can lead to a risk-averse culture. However, AI technologies are in such a premature phase of development, without taking risk to experiment, adoption of AI will not be stimulated.

5.3.4 Organizational structure

Interviewees 4 and 13 explain that traditional banks have a very hierarchical organizational structure that is strongly divided into silos which hinders cross-sectional engagement among employees to innovate and respond agile to the changing environment. According to interviewee 14, an additional hurdle to effectively adopt AI technologies for traditional banks is to include data science specialists in the process of adoption. Data Scientists have a certain responsibility over the use of data in their organization. This may eventually slow down the entire AI decision making process because more stakeholders are in involved.

Some of the large Dutch banks are currently transforming to an enterprise wide ‘agile’ workforce. Banks are shifting their traditional organization to an “agile” model inspired by companies such as Google, Netflix, and Spotify (McKinsey, 2017). The Chief Information Officer of ING Netherlands explains in the report of McKinsey (2017) that: “We needed to stop thinking traditionally about product marketing and start understanding customer journeys in this new omnichannel environment”.

5.3.5 Ethics

The European Economic and Social Committee (EESC, 2017) has identified 11 areas where AI raises societal concerns, ranging from: ethics, safety, transparency, privacy and standards to labour, education, access, laws and regulations, governance, democracy, but also warfare and superintelligence. In this paragraph we will focus on the ethical challenges that arise when traditional banks use AI. Based on the results of our expert interviews and document analysis we see that the following salient topics that play an important role are: privacy, biased discrimination, AI transparency and accountability, job losses and low awareness of ethical consequences.

5.3.6 Privacy issues

According to PwC (2017) the challenges that arise when organizations use AI technologies underline the need for a new model of strategic evaluation, governance and delivery. Without it, the uncertainties surrounding AI mean that it will either remain stuck in the lab within many organisations or they will find themselves facing unacceptable and potentially damaging risks (PwC, 2017). Potential damaging risks, as described by PwC (2017), IEEE (2016) and mentioned by ten interviewees are: privacy and biased data issues.

The Dutch Central Bank states in their report regarding the impact of technology on the financial markets (DNB, 2016), that innovation makes more detailed analysis of client data possible, which includes privacy issues. According to ten interviewees privacy and the degree to which they can, or want to use client data, is a real issue in the banking industry. AI systems inherently need some form of data to function properly. Therefore, privacy issues arise when banks want to use personalized data to develop AI solutions that improve customized services or products for their customers. Interviewee 1 explains that customers must feel that their personal data is used to benefit them, otherwise they will lose trust. The question arises: how can you determine what customers experience as a benefit or not? This is a sensitive topic; in fact, if handled poorly, privacy violations could invite a heavy-handed regulatory response (PwC, 2016).

Why is using personalized data an ethical issue? Van den Hoven (2008) explains that there are four moral reasons to protect personal data: To prevent harm, information inequality, informational injustice, discrimination and encroachment on moral autonomy. According to IEEE (2016) personal information fundamentally informs the systems driving modern society, but our data is more of an asset to others than it is to us. The impact of technology on us as humans has never been so transparent, personalized and autonomous. Legislation like the General Data Protection Regulation (GDPR) is designed to strengthen citizens’ fundamental rights in the digital age and facilitate business simplifying rules for companies by unifying regulation within the EU (European Commission, 2016). Enabling individuals to curate their identity and managing the ethical implications of data use will become a market differentiator for organizations (IEEE, 2016). According to the European Commission (2016) the new General Data Protection Regulation will ensure that people receive clear and understandable information when their personal data is processed. Whenever their consent is required, it will have to be given by means of a clear affirmative action before a company can process their personal data. A second rule of this new legislation is that individuals will have the right to be forgotten, which means that if they no longer want their personal data to be processed, and there is no legitimate reason for a company to keep it, the data should be deleted (European Commission, 2016).

A good example that shows the societal impact of banks using personalized data is that of the Dutch bank ING in 2014: Various Dutch media have reported on a pilot that ING NL planned to launch this year with a small number of customers. In this pilot ING was exploring if customers would be interested in receiving tailored discounts from third parties in line with their spending behaviour. The pilot project led to many queries and comments from customers and other stakeholders, and caused debate about the use of customer data. The reactions have made clear that there are many questions and concerns about the protection of customer data. ING Netherlands CEO Nick Jue apologized for the lack of clarity and the unrest caused (ING, 2014). According to PwC (2016) companies will need strong operational controls in place so data is not being misused in – or across – business units. The US Consumer Financial Protection Bureau (CFPB), recently announced its first enforcement action (against a FinTech payment company) related to privacy and cyber-security, and regulators are likely to step up these efforts in the future (PwC, 2016). According to interviewee 19 traditional banks are now mostly focussed on finding out what operational benefits and challenges AI technologies may bring, leaving out privacy- and other ethically related issues in the project. Interviewee 19 explains that: "...banks ask these [ethical] questions too late in process of experimentation, causing disapproval from the compliance department when they want to take the project into production".

The example of ING shows that privacy is a very important ethical factor when dealing with data. According to the European Commission (2016) privacy is a fundamental right for everyone in the EU and must be safeguarded. Interviewee 11 explains that it is, therefore, very important for banks to think about how to communicate certain data related proposals to their customers and stakeholders, in order to avoid resistance and distrust. Interviewee 18 states that it would be helpful if the customer would be able to present its personal preferences regarding personalized data usage. Interviewees 12 and 19 add that this would require a hybrid database solution where the customer can personalize its data preferences for any organization and manage its degree of personal exposure. However, interviewee 22 explains this solution would just address the symptoms, not the real problem, because organizations will just require you to provide them a level of access to your personalized data in order to proceed. According to the European Commission (2016) 71 percent of Europeans feel that there is no alternative other than to disclose personal information if they want to obtain products or services. Therefore it seems that, GDPR or not, the request of personalised data is so widely embedded in people's' beliefs and habits.

5.3.7 Biased data and discrimination issues

A similar ethical challenge that arises with respect to data is the possibility of discriminating biases embedded in data that AI technologies use. According to interviewee 20, there is no clear view on how to address or filter the quality of data that is being used for the training of AI systems. AI is using data that is based on our collective thoughts to train the next generation of AI technologies and it is picking up our biases and making them more visible than ever (Clarck, 2017). According to Janssen & Kuk (2016) algorithms can systematically introduce inadvertent bias, reinforce historical discrimination, favor a political orientation or reinforce undesired practices. However, they claim it is difficult to hold algorithms accountable as they continuously evolve with technologies, systems, data and people, the ebb and flow of policy priorities, and the clashes between new and old institutional logics (Janssen & Kuk 2016). According to interviewee 1 sometimes the best way to deal with a bias in data, is to identify and mention it. According to a data scientist Ralph Winters ((2016) there are techniques for weighting existing data to compensate for the bias, but that will always affect the total data set. Therefore, it is a hard trade off. He explains that if there is a major bias in the data set, data scientists should always mention it and not try to improve it, unless there is clear consensus from all concerned parties (Winters, 2016).

According to interviewee 1 data science, machine learning and other AI technologies are based on discrimination science. Therefore, interviewee 1 states that “we have to make sure that our discrimination is positive, and not negative”. Interviewee 1 explains that positive discrimination is finding a pattern that benefits the customer. Negative discrimination is when the customer is benefitting from the finding. However, according to IEEE (2016) it is understood that there will be clashes of values and norms when identifying, implementing, and evaluating these systems (a state often referred to as “moral overload”). In their report they explain that a stakeholder-inclusive approach is necessary. Systems should be designed to provide transparent signals, such as explanations and diagnostics, to get a clear image of the various actors they serve in the network (IEEE, 2016).

According to IEEE (2016), achieving positive discrimination and values into AI systems is a realistic goal because norms can be considered instructions to act in defined ways and contexts. A community’s network of norms as a whole is likely to reflect the community’s values, and AI equipped with such a network would therefore also reflect the community’s values, even if there are no directly identifiable computational structures that correspond to values (IEEE, 2016). The IEEE (2016) Committee explains three major goals that aim to embed our values into AI systems: 1) Identifying the norms and eliciting the values of a specific community affected by AI; 2) Implementing the norms and values of that community within AI; 3) Evaluating the alignment and compatibility of those norms and values between the humans and AI within that community.

Interviewee 1 explains that while this proposal cannot always eliminate all possible data biases, it does present a proactive inclusion of users and their interaction with AI systems that will increase trust and overall reliability of these systems (IEEE, 2016).

5.3.8 AI accountability gap

Interviewees 12 and 22, who both have experience as a Senior Data Scientist for a large traditional bank, claim that the hardest challenge to address is to ensure the accountability and transparency of AI systems. As we have discussed in the previous chapter, more advanced AI technologies that make use of statistical machine learning (e.g. deep learning) are unable to explain how it reaches a certain result. This issue has a relation to the current gap between the development of increasingly autonomous technologies, such as AI, and the degree in which our society depends on the use of such technologies (Matthias, 2004). This phenomena is defined as the 'responsibility gap'. According to IEEE (2016), lack of transparency both increases the risk and magnitude of harm (users not understanding the systems they are using) and also increases the difficulty of ensuring accountability. Interviewee 22 claims that AI algorithms are so dynamic that the variables it selects on may change every iteration, making it extremely complex to log every historical choice. The complexity of AI technology itself will make it very difficult for users of those systems to understand the capabilities and limitations of the AI systems that they use, or with which they interact, and this opacity, combined with the often-decentralized manner in which it is developed, will complicate efforts to determine and allocate responsibility when something goes wrong with an AI system (IEEE, 2016). AI has huge potential because of its ability to learn and adapt. But this introduces new kinds of risk, depending on how much autonomy the systems are given when they make decisions (PwC, 2017).

According to interviewee 12, the use of highly personalized data to provide customized offerings can also backfire when clients claim they have been misled or experienced poor judgement by AI systems. Interviewee 12 explains that when organizations increasingly try to know more about their clients, and use AI in the process, they should consider that the level of responsibility regarding their welfare also increases. According to IEEE (2016) manufacturers of AI systems must be able to provide programmatic-level accountability proving why a system operates in certain ways to address legal issues of culpability, and to avoid confusion or fear within the general public.

5.3.9 Low awareness of ethical consequences

Findings from our interviews with interviewees 1, 4 and 5 show that there is still a moderate lack of awareness regarding some of the ethical implications described in this chapter. Some say that AI systems are designed to discriminate. Rational discrimination is allowed, but negative discrimination is not allowed. Interviewee 1 explains that AI Developers and Data Scientists normally consult with the legal department of a bank in order to check if a new product or service is (ethically) allowed. However, interviewee 11 explains that in some cases project members of an AI project try to avoid contact with the legal department of a bank, in order to keep the project going, without running into early limitations. According to the IEEE (2016) the low awareness of ethical implications may be because ethics is not part of an engineering degree at many universities. AI engineers and design teams too often fail to discern the ethical decisions that are implicit in technical work and design choices, or alternatively, treat ethical decision-making as just another form of technical problem solving (IEEE, 2016). None of the interviewees mentioned this as an (ethical) challenge but the IEEE (2016) report explains that engineers do not have the ability to cope with ethics because it is imprecise and not readily articulated to process it in the mathematical design of an AI system. This originates in the fact that engineering programs do not often require coursework, training, or practical experience in applied ethics (IEEE, 2016). The incorporation of ethics in engineering can be named ‘responsible innovation’. Stilgoe et al. (2013) defines responsible innovation as: “taking care of the future through collective stewardship of science and innovation in the present.”

Hajer (2003) explains that emerging technologies typically fall into an ‘institutional void’. This means that there are few agreed structures or rules that govern them (Stilgoe et al., 2013). While actors in a particular ecosystem may not individually be irresponsible people, it is the often complex and coupled systems of science and innovation that create what Ulrich Beck (2000) calls ‘organised irresponsibility’ (Stilgoe et al., 2013). One of the the big risks is that AI is allowed to operate beyond the boundaries of reasonable control (PwC, 2017). Therefore, in the case of AI, distributing passive responsibilities (after something has happened) among key management actors will not be enough. Active responsibility will need to be distributed among the key actors in an organization to avoid undesirable behavior of new AI solutions.

According to van de Poel & Royakkers (2011) some philosophers have introduced the notion of ‘collective responsibility’ to deal with the intuition that there is more to responsibility in complex cases than just the sum of the responsibilities of the individuals considered in isolation. However, the collective responsibility model is not very attractive to large organizations such as traditional banks, because it is not possible to allocate responsibility in differing degrees to individual members of the collective (van de Poel & Royakkers, 2011).

In the individual responsibility model, each individual in the organization is held responsible insofar as he or she meets the conditions for individual responsibility (van de Poel & Royakkers, 2011). A benefit of this approach is that it is morally fair. The model also might seem effective because it encourages individuals to behave responsibly (van de Poel & Royakkers, 2011). However, the ‘problems of many hands’ that we described earlier in this paragraph is a big disadvantage of this model. Additionally, the question arises: In case of an individual responsibility model, which actors would be responsible for the adoption of AI within a traditional bank?

5.3.10 Job replacement issues

Historically speaking, whenever a breakthrough in technology, such as AI, is about to disrupt an industry (such as the effect ATM had on the banking industry when it was introduced), skeptics have expressed concern about one thing consistently: job losses (Deloitte, 2016). Addressing this subject is also an organizational culture problem for leaders that want to work towards an AI driven strategy, say interviewees 8 and 22. According to Deloitte (2015) the skeptics have been proved wrong. According to U.S Census Bureau, on average since 1980, occupation with above computer use has grown substantially faster (0.9% per year, 1.61% from 1980 to 2013) than jobs below median computer use (grown by 0.74% during the same period). Interviewee 11 explains that we have seen similar cases of technologies that replace humans' jobs, but the pace of new developments is unprecedented. This is also supported by McAfee and Brynjolfsson (2015) who add that compared with the Industrial Revolution, digital technologies are more likely to create winner-take-all markets because digital technologies allow you to make copies at almost zero cost. Each copy is a perfect replica, and each copy can be transmitted almost anywhere on the planet nearly instantaneously (McAfee & Brynjolfsson, 2015). According to interviewee 11 this time it will cause more problems (in comparison to what happened in the industrial revolution) because the humans have increasingly less time to adjust to these new technologies, causing fast-paced changes to mid-level jobs.

5.3.11 Image barriers that hinders Innovation

Additionally to the case of ING described in the previous paragraph (Naylor, 2016) claims that banks lack the right image to experiment with new concepts among their customers and stakeholders. Technology companies such as Google, Facebook and Amazon are currently relying their entire business on clientele data. Results from our interviews with interviewees 1 and 2, reveal that banks struggle with a conservative image that hinders their ability to freely experiment and innovate.

5.3.12 Trust

IBM (2015) states that the perception of customers' trust is highly overestimated by banking executives. Results from a global IBM survey (2015) show that around 96 of bankers believe their customers trust them more than other non-bank competitors. However, only 70 percent agrees and even fewer (67 percent) still trust their primary bank compared to other bank competitors (IBM, 2015). According to a report from Stanford University (2016) two major challenges are: gaining public trust (low-resource communities, public safety and security) and overcoming fears of marginalizing humans (employment and workplace). PwC (2017) says that the adoption of AI may be met with scepticism from a variety of stakeholders, both within the organisation and clients, regulators and others outside (confirmed by interviewees 2, 5 and 21). It's therefore important to consider how we can build trust among all the affected stakeholders (PwC, 2017).

According to Dr. G. Banavar (2016), who was Chief Science Officer at IBM Research, states that perhaps the biggest obstacle in quelling the general anxiety over artificial intelligence is semantic. He explains that the term "artificial intelligence" historically refers to systems that attempt to mimic or replicate human thought. However, this is not an accurate description of the actual science of artificial intelligence, and it implies a false choice between artificial and natural intelligences (Banavar, 2016). Before trusting a new algorithm, however, the enterprise must review it thoroughly. With the numerous regulations governing financial data, it is possible for such a process to unintentionally breach ethical rules -- for example, profiling individuals according to race or gender (Dooley, 2017). An overall framework on how to govern these developments is what is missing according to interviewee 20.

One of the problems with financial decision making by algorithm, particularly through "black box" deep learning, is the gap between transparency and trust. Users of the machine learning solution need to be able to trust its output because they have no insight into the evaluation itself (Dooley, 2017). According to PwC (2016b) when used properly, AI and data analytics together can help financial institutions understand their customers more than ever before. And they claim that this matters, because FinTech start-ups will be going down the same path; the first one to get it right will earn the customer's loyalty.

5.3.13 Lack of AI awareness

According to nine interviewees say that banks lack awareness and knowledge about the features of AI technologies. Business leaders lack the technical knowledge to see the potential benefits (and problems) of AI (Naylor, 2016). As a result this means that the top-down enterprise diffusion of potential AI benefits (or challenges) are in many cases poorly managed and lack confidence to fully exploit its potential (interviewees 4, 5, 8 and 20). According to interviewee 8 managing expectations is an important part of creating the right type of awareness. Understanding how to obtain the maximum benefit from cognitive technologies requires a careful analysis of an organization's processes, its data, its talent model, and its market (Deloitte, 2015). As we described earlier, AI may be used to enhance or replace the work of humans which changes the way workers allocate their time and requiring them to interact with new systems (Interviewee 9).

5.3.14 Data access and quality

According to seven interviewees a major challenge is getting access to high quality data. The inability to connect data across organizational and department silos has been a business intelligence challenge for years (IBM, 2012). According to interviewee 19, traditional banks have loads of data but this does not mean that it can be used instantly to train an algorithm with. Interviewee 5 explains that almost 80% of the worlds produced data is called 'dark data' which is isolated data stored in secured databases of enterprises. In principle this opens up various opportunities, however, there are numerous barriers to effectively attain this data.

According to three interviewees large Dutch banks struggle with integration and effective use of old legacy systems. Traditional banks are often burdened with inflexible and costly legacy systems that cause lots of challenges with redefining new operating and business models (IBM, 2015). Additionally, interviewee 22 explains that these legacy systems often run on outdated programs and database languages that are not part of the current university data science degrees anymore.

Naylor (2016) explains that another problem to bad data quality is 'false' incoming data. This is the case when a data source is poorly chosen, incorrectly integrated, or able to be manipulated by a third party. Interviewee 22 adds that there are multiple data management problems that cause problems. An important part of data management is who 'owns' the data and who is responsible for the quality of the data. Interviewee 22 explains that the cause of this problem often lies in a misunderstanding between business and IT departments about the responsibility and ownership of data. In contrast, interviewee 1, who is a Senior Data Scientist, says that there actually should not be any data access and/or quality issues, since almost all banking data is already digital and structured. The challenge is to exploit this data in a comprehensive way.

5.4 Conclusion

This chapter aimed to give answer to the first research question: "What organizational challenges arise when banks adopt AI technologies?". Artificial intelligence is becoming increasingly advanced and will not only aim to replace human tasks that are simple and repetitive, but also in more advanced scenarios that requires high-level thinking in areas such as decision making and human interaction. The extremely high potential of AI is advancing investment opportunities and empowering optimism. This could be highly driven by big consultancy and high-tech firms, who may have a commercial motive to drive AI's potential. However, as we have pointed out in this chapter there are a broad range of challenges that may affect traditional banks when they want to use AI technologies. The overall tendency is that AI as a technology is still very premature, which hinders proof of added-value. In certain areas such as conversational and predictive analytics it is more mature than in for example, deductive reasoning. Moreover, our results show that there is still low awareness of what AI is, and what benefits or challenges it may bring. Therefore, a broad range of implications are still unaddressed. In the next chapter we will discuss a potential solution that may address some of the challenges we described in this chapter.

6. Conceptualization of the Chief AI Officer role

The diverse set of organizational challenges described in the previous chapter shows us that the development and use of AI technologies in the banking industry is still in a very early stage. The implications of using AI are still vague and uncertain. The aim of this research project is to explore the need for a new C-level management role that may address some of the challenges discussed in the previous chapter. Andrew Ng, who is a renowned AI Specialist, wrote in an article for the Harvard Business Review that organizations who want to be AI first should hire a Chief AI Officer (or a VP for AI). Ng (2016) explains that in industries which have generated large amounts of data, AI can be used to transform data into value. However, AI is still an immature technology and evolving rapidly, so it is unreasonable to expect everyone in the C-suite to understand it completely (Ng, 2016). Therefore, Ng (2016) recommends hiring a Chief AI Officer to address the challenges of adopting AI technologies. Therefore our second research question is as follows: “Under what conditions would a Chief AI Officer be valuable for traditional banks?”

In the next paragraphs we will first discuss the importance of leadership to address challenges that relate to the adoption of new technologies in an organization. Following up is a short description of what a C-level management role is and why these roles exist, so that we can introduce Ng’s proposal and analyze its theoretical features. As we have pointed out in the literature review, we will compare the Chief AI Officer role with the current C-level technology roles (CIO/CTO/CDO) to explore the possible benefits and challenges of appointment. We also used Andrew Ng’s concept of a Chief AI Officer as a hypothetical concept to discuss its validity and features with our experts in an interview. Based on the findings from the previous chapter and our expert interviews, we can then explore the different aspects. The goal here is to merely explore the validity of its features at various levels of depth, so that can form the basis of more extensive research in the future.

6.1 The importance of organizational leadership

In extensive research reports of renowned universities and consultancy companies, the urge for organizations to get ready for AI is a highly discussed topic. According to Stanford’s 100 years study on AI (2016), organizations should design strategies that enhance the ability of humans to understand AI systems and decisions. This participation may help to build trust and prevent drastic failures (Stanford, 2016). According to KPMG (2016) successful transformation initiatives that create long-lasting value require leadership, strong executive support and a clear vision. In the rapidly accelerating world of AI and the highly regulated environment of financial services, firms need someone, or preferably a dedicated team, to identify potential new solutions, track developments and run internal tests before widespread adoption (NarrativeScience, 2017). According to PwC (2017) a dedicated AI governance is needed to guide the overall implementation of AI technologies enterprise-wide, which could include a nominated member of the C-suite and a central hub of technical expertise.

Capgemini Consulting and MIT show in a study (2012) examining more than 400 companies worldwide that digital leaders are a key factor in any company's success because they understand which technological innovation to adopt at the right time which will yield the maximum returns for the entire organization (Shrivastava, 2017). Additionally, in a management agenda survey of the leadership institute Roffey Park (Lucy et al., 2015) they found that 40 percent of the respondents feel that technology will be a disruptive challenge that will impact their business. It seems that "right" leadership is a key factor in determining what technology fits an organization best. Shrivastava (2017) concludes that a majority of leaders predicted that in the future their organization would need to either develop or recruit leaders with fresh leadership skills who are more digitally inclined.

Results of our expert interviews show that our expert interviewees moderately agree that in order for traditional banks to effectively adopt AI technologies, new organizational roles should be introduced (see figure 8). However, these results are not similar to the results from the Institute for Business Value (APPENDIX D), which shows us that 177 CIOs in the field of Financial Services (FS) moderately disagree on adding new roles to support AI/Cognitive technologies (see figure 8). A side note here is that the financial services industry includes a very broad selection of organizations besides traditional banks, namely: insurance companies, credit card companies and investment companies, Fintech startups, etc. Therefore, the results cannot be perfectly equally compared. However, these results suggest that the traditional banking industry needs to add more new roles to support AI/Cognitive technologies compared to other financial institutions.

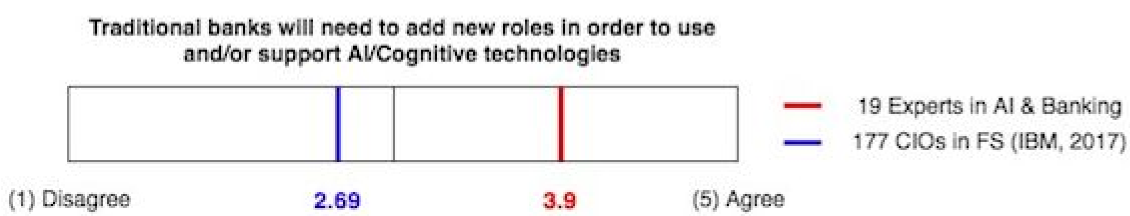

Figure 8

Moreover, our results show that more than 78 percent of the expert interviewees claim that traditional banks should appoint a Chief AI Officer. However, 86 percent of these expert interviewees explain that this role (CAIO) does not necessarily has to be a C-level/board position, but it should report to a C-level/board executive (e.g. a CIO, CTO or CDO).

In the next paragraph we will provide a detailed analysis of the proposed Chief AI Officer role. The aim is to conceptualize a first version of a Chief AI Officer, based on Ng's proposal and our findings, as a potential solution to address particular challenges that arise when traditional banks adopt AI technologies.

6.2 The C-suite management layer

Before we can discuss whether a Chief AI Officer is a potential solution we must first determine its characteristics. Up to this stage we have not gained enough empirical evidence to determine whether a Chief AI Officer is truly necessary in the banking industry or not. However, we do have evidence that such a new role may be valuable to address certain organizational challenges that arise when banks adopt AI technologies. In the next paragraphs we will describe what a C-level management role exactly is, and why an organization would need such a role. Following up is a close analysis of the current tech-executive roles (CIO/CTO/CDO). Based on our conducted expert interviews and the document analysis we will finally conclude this chapter with a detailed exploration on the different roles and responsibilities of a Chief AI Officer.

6.3 What is a C-level management role and why need it?

As described in the literature review, role theory explains how executive leaders in a business determine their roles and how people act in their organizational role among others. The set of most important 'Chief' executives in an organization is often called the "C-suite" in business terms, and operate in the board or directly report to the board of an organization (IBM, 2015). To thrive as a C-level executive, an individual needs to be a good communicator, a collaborator, and a strategic thinker (Groysberg et al., 2011). According to Groysberg et al. (2011) the C-level executives are active members of a firm's senior leadership who advise the Chief Executive Officer on key decisions. In a survey conducted by McKinsey (2015) among C-level executives, organization-wide alignment of business units was found as most critical aspect of effective management. Executives who made the most successful transitions say it was just as important to align their organizations on what not to do, as it was to explain what they would do in their initial agenda (McKinsey, 2015). Additionally, results from our expert interviews (APPENDIX E) show that social skills, intrapreneurship and charismatic leadership are core competences of a C-level position that wants to address the adoption of AI technologies effectively. Another potential driver of an expanding C-suite is the current war for top industry talent. Some believe that adding new positions at the high end of the management structure will allow companies to retain key personnel (Lindzon, 2015). As we have described in the previous chapter, attracting and retaining talent is one of the biggest challenges when traditional banks want to adopt AI technologies. Moreover, results from our expert interviews show that top management of a traditional bank is often mentioned as a key factor for determining strategy, vision, culture and leadership. Later in this chapter we will discuss how the broad range of AI challenges affect the role of a C-level executive in more detail.

6.4 Challenges of appointing a new C-suite role

The challenge of successfully appointing a new C-level executive role is to embed this actor in the current organizational network. Even if the candidate appears to be fit, certain internal obstacles or misperceptions may slow an organization's efforts to define, establish, and empower a new C-level executive's role (Deloitte, 2016). According to Deloitte (2016) some board members or C-level executives may not understand what business value a certain role has. According to interviewee 5 certain peer executives may view a new C-suite position as a threat to their departmental processes and resources. Overlapping responsibilities and ambitions may cause a struggle for power in an organization. According to Atwood & Bacon (2011) developing C-suite executives can be highly challenging for two reasons: the distorting mirror of personal success and the complacency bred by good organizational performance. Deloitte (2016) explains that in the operating model of a traditional bank, a senior executive often has many direct reports. Therefore, it may be difficult to justify a new C-level senior position when the function does not necessarily require a large staff like other C-level posts. Moreover, business cycles that bring shifting priorities and executive emphasis on short-term, cost-savings, and revenue-generation can divert executive attention and financial support from the long-term competitive advantages that an effective C-level executive can deliver (Deloitte, 2016). Later in this chapter we will discuss the challenges that may arise when traditional banks implement a new C-level executive role. In the next paragraph we look at the current landscape of C-level tech-executive roles that are currently active in the banking industry.

6.5 What tech-executive roles are currently in the C-suite of a traditional bank?

Results from a global survey conducted by IBM research (APPENDIX D) among 936 organizations that are active in the Banking and Financial Markets industry show us that the CIO role is adopted in 36 percent of all the organizations. The Chief Executive Officer, Chief Finance Officer, Chief Human Resources Officer, Chief Marketing Officer and Chief Operations Officer are only adopted in 8 to 17 percent of all the organizations. These results show that banks have currently adopted a tech-executive role even more than any other C-level executive roles. The CTO and CDO roles are relatively new and are not included in the research of IBM mentioned above. However, reports from Deloitte (2016) and IBM (2016) show that these alternative tech-executive roles are increasingly appointed in the banking industry. In the next paragraphs we aim to provide a detailed overview of the current tech-executive roles that are most common in the banking industry. The focus is to provide an overview of the roles and responsibilities that are defined by researchers and business professionals in the field of management and organization. As we have pointed out chapter two, we will zoom in on the three most commonly used tech-executive roles: the CIO, CTO and CDO in the next paragraphs.

6.6 CIO’s roles and responsibilities

According to the Institute for Business Value of IBM (2015), the most used C-level tech-executive role that is appointed in the banking industry is a CIO. However, the abbreviation of a CIO is ambiguous. It can either be a Chief Information Officer, Chief Innovation Officer or a Chief Intelligence Officer. The CIO is a tech-executive role that is first introduced in the 1970s. Rockart (1982) found that one of the primary roles of the information systems (IS) manager was to help the organization adapt to a changing technical environment, where the manager needs to assure that the “evolving technical opportunities are understood, planned for, and implemented” in the organization. Rockart (1982) claims that there are four primary critical success factors for the information systems executives which include (Chun & Mooney, 2006):

1) Service, the effectiveness and efficient performance and user perception of necessary technology operations.
2) Communication, understanding the world of key users and top line executives and have them understand the information systems environment.
3) Information systems human resources, assisting executives in finding information systems talent to develop and use information data bases.
4) Repositioning the information systems function, managing the technical, organizational, psychological and managerial aspects related to the firm's information systems.

The senior information systems executive generally reflects one who served the organization by acquiring and setting up the technical infrastructure to process and store information within the firm. According to Chun & Mooney (2006), CIOs in the early 1990s fought to gain credibility within the organization, because they took on the task of running a function that took a lot of resources, but offered little measurable evidence of its value. As the 1990s developed, corporates started to acknowledge the increasing value of CIOs. As a result the role of a CIO transformed from a technical manager to a technical and organizational manager who was able to use IT to add business value to the company.

Around 1999 Chun & Mooney (2006) found that CIOs were active in a broad range of companies that encountered security threats within and outside the organization. This forced these organizations to re-think how to use the technology. As a result, education and implementation of IT governance policies became part of the CIOs responsibilities. These activities ensured proper and appropriate use of the technology. Feeny and Willcocks (1998) defined nine core capabilities of a CIO:

1. **Relationship building**: Getting the business constructively engaged in information systems issues.
2. **Business Systems Thinking**: Encompasses envisioning the business process that technology makes possible.
3. **Architecture planning**: Blueprint for a technical platform that responds to current and future business plans.
4. **Leadership**: Integrating information systems efforts with business purpose and activities.
5. **Making Technology work.**
6. **Informed Buying**: Information systems sourcing strategy.
7. **Contract facilitation**: Success of existing contacts.
8. **Vendor development**: Identifying potential value adding information systems service suppliers.
9. **Contract monitoring**: Protection of the business's contractual position.

Additionally Chun & Mooney (2006) claimed to have found two extra core capabilities:

10. **IT Value proposition:** Utilization of IT to facilitate business agility and deliver new business value in short term through innovative IT investments.
11. **Governance**: Decision rights and accountability framework for encouraging desirable behavior in the use of IT.

Chun & Mooney (2006) claim that in organizations where IT technology is not a core product of the firm, the CIO's tend to be associated with the Chief Innovation Officer role. This role focuses on cross-functional integration, inter-organization integration, visioning & enabling strategy, process & information innovations and reports to the CEO. Deloitte (2004) claims that today's CIO is a business leader—not just an IT manager—steering a mission-critical function as large and complex as any operation in the company, working side by side with business units to help improve performance and efficiency (Deloitte, 2004).

At firms where technology is the primary product or resource of competitive advantage (i.e. digital content provider, business intelligence) the CIOs tend to have been given responsibilities more in line with the Director of IT role (Chun & Mooney, 2006). This role manages IT supply, contains IT costs and reports to the CFO or COO. The key question for the banking industry in order to determine the role of a new tech-executive role is: what does technology mean to traditional banks? And what strategic priority do these organizations want to give it?

6.7 CTO's role & responsibilities

The CTO's role is not that of a Research Director but more of a business person deeply involved in shaping and implementing overall corporate strategy (Lewis & Lawrence, 1990). Uttal et al. (1992) have identified three levels of technology leadership which the CTO might take; functional leadership, strategic leadership, and supra-functional leadership. As their titles suggest, and as will be discussed in more detail below, these involve increasing levels of strategic responsibility (Medcof, 2015). We can compare functional leadership with the early role of a CIO as a technical lead. Functional leadership is similar to the expectations of generating and delivering of new products and services. Strategic leadership is all about aligning technology and innovation strategy with corporate strategy. This can also be compared to the second version of a CIO: the technical and organizational manager that uses technology to add business value. The last form of leadership explained by Medcof (2015) is supra-functional leadership, which is includes the management of technology to ensure that innovation is being effectively adopted enterprise wide. In supra-functional leadership the CTO serves as an technology consultant to the CEO.

Medcof (2015) also claims that the more critical technology is to the success of the firm, the more important these technology considerations are, and therefore, a firm with an underpowered CTO will not be successful. Thurlings & Debackere (1996) show that CTOs themselves feel that one of their most important responsibilities is to monitor, evaluate, and select technologies that can be applied to future products and services. Additionally, Smith (2002) explains that CTOs have the responsibility to oversee the selection of research projects and insure that they have the potential to add value to the company. Smith (2002) adds that they have to provide reliable technical assessments of potential mergers and acquisitions and explain company products and future plans to the media. Moreover, they have to participate in government, academic, and industry groups to promote the company's reputation and to capture valuable data (Smith, 2002).

6.8 CDO's role & responsibilities

According to Deloitte (2016) financial institutions have increasingly come to recognize that their data assets represent highly strategic sources of insight and leverage for a wide array of business functions, including risk management, regulatory compliance, sales and marketing, product development, and operational performance among others. As a result, they have appointed a Chief Data Officer (CDO) to provide strategic guidance and execution support, and also to assure access to and the quality of critical data (Deloitte, 2016). The CDO is increasingly the C-suite's solution to navigating today's disruptive dynamic, data-intensive world (IBM, 2016).

The CDO role came in the aftermath of the 2008 global financial crisis because too little attention has been paid by financial institutions to their data (Deloitte, 2016). They explain that a senior, C-level executive was needed to marshal and govern critical data assets which needed a balanced understanding of the institution's core businesses, products, customers, and supporting data infrastructure's capabilities and needs (Deloitte, 2016). According to IBM (2016) there are three key CDO roles that address primary data needs: The first role is a Data integrator, which drives the implementation of a modern and integrated internal data infrastructure. Secondly, the Business optimizer role focusses primarily on exploiting an established data foundation to make internal and customer-centric business processes as effective and efficient as possible. Thirdly, the Market innovator role focusses on expanding cognitive (AI) capabilities to become digital disruptors. This last role may have great overlap with that of a future CAIO. This is also confirmed by five interviewees how say that the management of AI technologies is heavily dependent on an organization's capability to effectively manage data.

In the Deloitte (2016) report they describe that in 2014/2015 the CDO 2.0 emerged as a transformational leader and innovator and regulators forced traditional banks to hire this new role. The CDO became the lead data governance officer and focussed on instantiating data controls-governance, stewardship, data quality and metadata. In some organizations this role was first introduced under the authority of a CFO or COO. This 2.0 version of a CDO role is similar to the 'data integrator' role of IBM (2016), described earlier, which focusses mostly on addressing internal data issues.

In 2016 the CDO 2.0 evolved into a CDO 3.0 which takes on additional responsibilities of advanced analytics and managing a data foundation to control and deliver business value from their data assets (Deloitte, 2016). This new version emerged as a business enabler supporting growth, cost reduction and risk reductions strategies (IBM, 2016). According to Deloitte (2016) the future evolution of the CDO 4.0 role includes being a business strategy enabler that creates an enterprise wide culture where data truly becomes an asset to the organization and is treated as such at the board level. IBM (2016) describes this future role as the market innovator. Later in this we report we will go provide an extensive analysis of the potential similarities and differences between a CDO 4.0 and a future CAIO role.

6.9 Analysis

We see that the CIO's role evolved throughout the lifecycle of information technology starting in the 1970s and 1980s as a functional lead. Later it transformed towards an organizational IT manager role in the early 1990s where it aligned IT with business goals, and finally the role became a business visionair that drives strategy and uses IT to gain competitive advantage. Somewhat similar to the evolution of the CIO's role, are the CTO and CDO's roles. When the need for specific technological capabilities is rising in an organization, a technical role is introduced that is responsible for addressing functional challenges. The CIO's first role: IT systems to support business processes, CTO's first role: Managing technology to support R&D, and the CDO's first role: Managing the integration of data to support process quality.

The second phase these tech-executive roles evolve to is that of an organizational technology manager. This role aligns technology with the corporate strategy and manages its use enterprise-wide. The CIO's second role includes the management of IT systems to add business value, the CTO's second role includes the alignment of technology and research to add business value, and the CDO's second role focusses on optimizing processes that are tasked with sourcing and managing external data to optimize business value.

The third phase shows that, as the technology matures, the tech-executive roles evolve into a strategic role where technology is not only used to optimize business processes and add business value, but also to drive strategy and innovation. Currently this mature role of a tech-executive manages the innovation in an organization, Technology consultant to CEO, CDO: Market Innovator).

The similarities and differences between C-level tech-executive roles provide us with more insights about how a new tech-executive role may evolve as a result of emerging technologies such as AI. In the next chapter we will discuss the possibility of appointing a new C-level tech-executive role that could address certain challenges that arise when traditional banks adopt AI technologies. Andrew Ng (2016) explains in his article that organizations which are active in an industry that generates large amounts of data, should hire a Chief AI Officer. We will make use of the findings from our expert interviews and document analysis to explore this new C-level tech-executive role, and analyze its possible benefits and challenges.

7. Exploring a new leadership role: Chief AI Officer

7.1 What is a Chief AI Officer?

In this paragraph and the next, we will start by describing the characteristics of a future Chief AI Officer, as proposed by Andrew Ng (2016) in his article for the Harvard Business Review. According to Kolbjørnsrud et al. (2016), for organizations like traditional banks, to prepare themselves for AI, leaders must take the following steps: First, start early with exploring and experimenting. To navigate in an uncertain future, managers must experiment with AI and apply their insights to the next cycle of experiments (Kolbjørnsrud et al., 2016). This is also confirmed by interviewees 8, 9, 12 and 13. According to almost all interviewees, traditional banks are currently in the explorative stage when it comes to the development and adoption of AI technologies. Therefore, it is important to create the right organizational awareness of the potential benefits and challenges of AI by communicating this enterprise wide (confirmed by five interviewees). Interviewee 5 explains that if the top management of a traditional bank acknowledges the potential of AI than this topic should be addressed on board level. Additionally, interviewee 18 explains that it will be absolutely necessary for traditional banks to acknowledge the potential of AI in order to survive in the future.

In our expert interviews we asked all respondents if they think a Chief AI Officer would be a necessary role for a traditional bank. Our results show (APPENDIX E) that around 78 percent of our interviewees say that traditional banks should appoint a Chief AI Officer. However, 86 percent of these interviewees explain that this role does not necessarily have to be a C-level/Board position, but a CAIOI should report to a C-level/Board position. For example, a CIO. The next question naturally arises, what exactly is a Chief AI Officer?

Andrew Ng (2016) explains that a Chief AI Officer ideally should have the following four traits in order to effectively manage AI activities in an organization: First, a CAIO should have a good technical understanding of AI and Data Science. It should have built and shipped nontrivial machine learning systems. This trait is supported by our findings: 61 percent of the experts say that ‘AI development skills’ should be part of a CAIO’s core competences. Secondly, a CAIO should have the ability to operate cross-functionally. AI is a foundational technology that can help existing lines of business and create new products or lines of businesses. Therefore, it is critical for a CAIO to work across silos and with diverse functional teams (Ng, 2016). This trait is supported by our findings: 77 percent of the experts say that ‘social skills’ should be part of a CAIO’s core competences. Thirdly, AI creates opportunities to build new products that might sound like science fiction. Therefore, an intrapreneurial leader is needed manage innovations successfully (Ng, 2016). This trait is supported by our findings: 30 percent of the experts say that ‘intrapreneurial skills’ should be part of a CAIO’s core competences. Additionally, our results show that a CAIO must also have ‘innovation skills’ and ‘charismatic leadership skills’. Fourthly, AI talent is highly sought after. A good Chief AI Officer needs to know how to retain talent, for instance by emphasizing interesting projects and offering team members the chance to continue to build their skill set (Ng, 2016). Leaders should also work on developing a diverse team of managers that balances experience with creative and social intelligence to complement team members and creating sound collective judgement (Kolbjørnsrud et al., 2016).

Results from our expert interviews (APPENDIX E) show that 77 percent of the interviewees think that the Chief AI Officer primarily should have a ‘Business Visionair’ role. Additionally, 50 percent of the interviewees that agree with this statement also say that a Chief AI Officer should have a combination of the roles: ‘Business Visionair’ and ‘Technical Lead’. KPMG (2016) adds to these findings that successful transformation initiatives which create long-lasting value require dedicated leadership, strong executive support and a clear vision. Organizations today need senior leaders to not only manage and govern the data, but also to leverage the data using emerging technologies that can generate actionable analytical insights and tangible business benefits (Deloitte, 2016). Our findings show that the Chief AI Officer role, as described above, is very similar to that of current mature tech-executive roles. Later in this report we will go into more details about the similarities and differences between a CAIO and current tech-executive roles.

7.2 What are the Chief AI Officer’s responsibilities?

In this paragraph we will discuss a selection of possible responsibilities that may belong to the role of a future Chief AI Officer. We will do this by analyzing the responsibilities of current tech-executives and including results from our own expert interviews. We will focus on the responsibilities that these roles had when the corresponding technology was still in an early stage, similar to the current phase of AI now. Additionally we will use the organizational challenges we described in chapter five to explore what characteristics a new Chief AI Officer should need in order to address these challenges.

Artificial Intelligence is still in a very premature phase of development and organizations such as traditional banks are mostly in the exploration phase. This is confirmed by four interviewees interviewees. Therefore, organizations should put more emphasis on understanding and communicating the technology first, and assisting executives in finding the right talent (Rockart, 1982; Chun & Mooney, 2006). A key responsibility of an early CIO’s role in the 1970s and early 1980s was to guide the adoption of the changing technical environment and make sure that they were understood, planned for and implemented (Rockart, 1982). Andrew Ng (2016) explains similarly that in order to make effective use of AI, companies need to understand what AI can do and how it relates to their strategies. This is also confirmed by five interviewees. Interviewees 8, 13 and 18 add that one of the responsibilities of a CAIO should be to assess all current business processes within an organization and determine which can be enhanced or supported by AI technologies in the short, medium and long-term. This responsibility is also described as a core capability of a more matured CIO role by Feeney & Willcocks (1998).

A second responsibility for a CAIO role could be to produce sufficient positive and incremental results to maintain the needed stakeholder’s support and funding (Deloitte, 2016). Therefore a CAIO needs the necessary experience in AI development and data infrastructure to assess whether to develop AI solutions in-house or attain external AI suppliers to realize these projects.

According to six interviewees, a CAIO should need intrapreneurial competencies to drive optimism and innovation.

Thirdly, according to six interviewees, a CAIO should have a proven track record that includes experience and skills to effectively manage data. This is necessary to comply with increasingly demanding regulations about the use of data, data availability and data quality. Most modern organizations are characterized by a division of tasks and roles, and this has implications for who can be held responsible for what in organizations (van de Poel & Royakkers, 2011). However, results from our expert interviews show that there is no clear view on where AI and its ethical responsibilities lay within the organization of a traditional bank. This may be due to the low organizational awareness of the ethical implications at traditional banks, as we described in chapter five. Moreover, some interviewees have even denied the existence of ethical implications when using AI technologies.

In the previous chapter we showed that C-suite executives have the co-responsibility over the wellbeing of their stakeholders. However, a known ethical responsibility issue is ‘the problem of many hands’ which typically describes the problem where a lot of people are involved as a collective, like a complex engineering project, therefore making it difficult to identify where the responsibility for a particular actor in this group lies (Thompson, 1980). As we have pointed out in chapter five this is also an important challenge mentioned by the IEEE (2016) commission on Artificial Intelligence and Ethics. Ethically issues will be reputationally unacceptable, and will also cause boards to question, delay and even shelve innovations (PwC, 2017). However, in many cases ethical reflection is not yet explicitly incorporated into the current curriculum of academic studies that educate AI developers today (IEEE, 2016). Stewardship regarding the moral implications of AI technologies may be a significant part of a Chief AI Officer’s set of responsibilities, because he/she has deep knowledge of AI technologies and its functionalities, as well as the possible business/societal implications that it may bring. Therefore, a future CAIO role may include responsible innovation dimensions to address certain ethical responsibilities. As we have described in chapter five, Stilgoe et al. (2013) mentions that the responsible innovation framework includes four dimensions: anticipation, reflexivity, inclusion and responsiveness. Anticipation may prompt a CAIO to ask ‘what if. . .?’ questions (Ravetz, 1997) because new technologies often have unforeseen effects, where should be dealt with as early as possible. Reflexivity, means holding a mirror up to one’s own activities, commitments and assumptions, being aware of the limits of knowledge and being mindful that a particular framing of an issue may not be universally held (Stilgoe et al., 2013). Following this theory, a CAIO should widen its leadership boundaries from sole operational responsibilities to also include moral responsibilities. Thirdly, inclusion is about moving beyond engagement with stakeholders to include members of the wider public (Stilgoe et al., 2013). This is also confirmed by interviewees 14 and 19. Interviewee 14 adds that a Chief AI Officer’s main responsibility is building and maintaining partnerships in the ecosystem of AI and Banking. This adds to the theory of responsible innovation which explains that managers of organizations (e.g. a CAIO) should also facilitate in engaging with the larger public. Finally, responsible innovation requires a capacity to change shape or direction in response to stakeholder and public values and changing circumstances (Stilgoe et al., 2013). Therefore, a CAIO should not only be able to analyse his changing organizational and societal environment but also be able to respond to these moral changes. However, the ability of a CAIO to effectively respond depends heavily on the level of authority it is given within its organization.

As discussed earlier, PwC (2017) has developed a responsible AI framework that provides a practical mechanism for bringing priorities of AI related activities together, and ensuring effective monitoring and stewardship of AI outcomes. This framework includes the complete process from strategy to design, to implementation, and operations/monitoring of AI development. Managing and leading such a responsible governance framework effectively could be one of the key responsibilities of a CAIO. However, this framework does not show where ethical issues are ought to be dealt with.

Van de Poel & Royakkers (2011) propose the 'hierarchical responsibility model' which says that only the organization's top level personnel is responsible for the actions of the organization. This model is relatively simple and clear, which makes it attractive for organizations to use. However, based on this responsibility model, a CAIO would bear a huge responsibility for the implications of AI development and usage in an organization. Therefore this model may not always be effective according to Van de Poel & Royakkers (2011) because some managers find it very difficult to get hold of the right information to effectively steer the behavior of lower organizational units. Therefore, we might assume that it will be extremely hard to hold a CAIO morally responsible for all AI related activities in its organization.

According to van den Hoven (1998) meta-task (a task that deals with other tasks) responsibilities ensure that responsible decisions can be made in the future by building the right capacity to respond correctly to ethical implications that AI brings. Therefore we may incorporate three key ethical responsibilities in the set of responsibilities of a future CAIO, based on the dimensions of responsible innovation. First, according to Banavar (2016) the alignment of AI and human values is necessary. This is also confirmed by the IEEE report on AI & Ethics (2016). Banavar (2016) explains that AI systems should function according to values that are aligned to those of humans, so that they are accepted by our societies and by the environment in which they are intended to function. Traditional banks may want to introduce an enterprise-wide educational curriculum on the ethical development of AI technologies to increase ethical awareness. A Chief AI Officer could be an important leader to support and establish enterprise-wide awareness of AI ethics. Secondly, Banavar (2016) states that organizations should effectively implement and govern the 'individual responsibility model' for AI development and usage. However, as we have discussed in the previous section, this model has to deal with complex engineering teams and the 'problem of many hands'. The Chief AI Officer may prove to be a valuable actor to accomplish this because it holds domain specific knowledge of the technology to make sure that the governance measures are implemented properly. Creating this intrinsic and collective awareness among employees may prove to be a far more effective approach than holding every single employee accountable for its actions, which may result in an environment based on fear and anxiety to share valuable knowledge and insights. Lastly, as discussed in the previous paragraphs, there should be active engagement with the wider public. Banavar (2016) explains that participation in cross-industry, government and scientific initiatives and events around AI and ethics are necessary to include the broad range of norms and values we hold in our society. Therefore, the Chief AI Officer should not only be able to connect with external businesses, but also engage with other stakeholders like policy makers, politicians, academics, customers, prospects, competitors, etc.

Next to being a technology leader, the Chief AI Officer could also be an ethical leader within the organization of a traditional bank, which addresses issues such as: lack of ethical awareness, ‘problem of many hands’ and the ‘responsibility gap’ as we discussed earlier.

7.3 Comparing the CAIO with established tech-executive roles

In the previous paragraphs we have discussed the possible roles and responsibilities of a new C-level tech-executive role that addresses AI technologies within a traditional bank. In this paragraph we will look into the similarities and differences this new role has, in comparison to the current tech-executive roles. This pre-evaluation will provide us with more insights about the potential value of appointing a Chief AI Officer in a traditional bank, and thereby aiming to provide a well funded answer to the second research question.

The established tech-executive roles CIO, CTO and CDO all have overlap with a CAIO, to some extent. When we compare the roles of any tech-executive role that addresses a certain premature technology, we see that they exhibit functional leadership in the first stages of the technology lifecycle. This type of leadership is valuable to explore, experiment and create organizational awareness about the potential benefits and challenges that this new technology may bring. Results from our expert interviews show that this role addresses the need to build momentum and optimism for adopting AI technologies among relevant stakeholders (confirmed by four interviewees). Moreover, a big part of established tech-executive responsibilities is to evaluate and select technologies that can be applied to future products or services. As pointed out by Andrew Ng (2016) this is exactly the same for a future Chief AI Officer. However, the difference is that a CAIO has this responsibility with the specific AI scope. Eight interviewees confirm this and think that a CAIO should have a significantly high seniority of technical knowledge and experience to address these responsibilities.

As described earlier, there is a clear difference between tech-executive roles that are optimizing technology issues internally, and strategically using technologies to aim for disruption of markets externally (IBM, 2016). For example: The CDO’s role of a ‘Data Integrator’ and the CIO’s role of the ‘Director of IT‘ is more internally focussed on optimizing business processes. In contrast, the CDO’s role of a ‘Market Innovator’ or the CTO’s role including ‘supra-functional leadership’ is more externally focussed on strategy, developing partnerships and building an organizational ecosystem. We have pointed out that the difference between internal and external focus is often based on the maturity of the technology and the organizational capabilities of mastering this technology. Since the maturity of AI technologies is still relatively low, the focus of a new CAIO may be more focussed on addressing internal processes than external. However, we have to note that this finding is solely based on the evolution of established tech-executive roles, and depends heavily on the strategy and prioritization of AI technologies within the organization.

Our interview results show that a significant part of the interviewees agree that a CAIO may be a valuable role, but not at the level of C-level/board. Some of these interviewees say, because the technology is relatively premature, the urgency of specifically appointing a new C-level role in the board is low. However, they do see the value of appointing a CAIO one level under the board. They explain that this CAIO should be reporting to a CIO, COO or CTO to represent AI technologies with close relational links to the C-level/board management layer. A second reason why a CAIO at board level would not be valuable, according to our interviewees, is because there will be increased politics, discussion, bureaucracy, conflicting interests at the top management layer of the organization, which negatively impacts the organization's' decision-making speed and effectiveness.

7.4 Possible organizational positions for a CAIO

In this paragraph we will discuss where exactly a Chief AI Officer should be placed in the organizational structure of a traditional bank. As indicated at the beginning of this chapter, around 78 percent of our interviewees say that traditional banks should appoint a Chief AI Officer. However, 86 percent of these interviewees explain that this role does not necessarily have to be a C-level/Board position, but should report to a C-level/Board position. Interviewee 8 explains that the impact of AI is still low, because the technology is relatively premature. Therefore, according to interviewee 12, managing AI within a traditional bank could be sufficiently done by a CIO, CTO or COO. However, when AI truly matures, and the impact on the organization increases, the need for appointing a specific C-level tech-executive, such as a CAIO, will be increasingly valuable (interviewee 8). Based on the results of our interviews and additional document analysis, we have determined two temporary possibilities of placing a CAIO role at a traditional bank. As shown in figure 9, the first possibility incorporates a CAIO that will report to an established Board / C-level tech-executive, for example a CIO. This means that AI will have a partial role in the portfolio of a CIO, and the CAIO acts as a supportive functional leader that consults the CIO with AI related matters. The functional roles of a CDO, as described earlier, also reports to a CIO according to IBM (2016). According to interviewee 2 and 11, this setup avoids managerial conflicts between established tech-executive roles, but offers AI related matters with sufficient authority and links to the top management layer of a traditional bank to address AI challenges effectively.

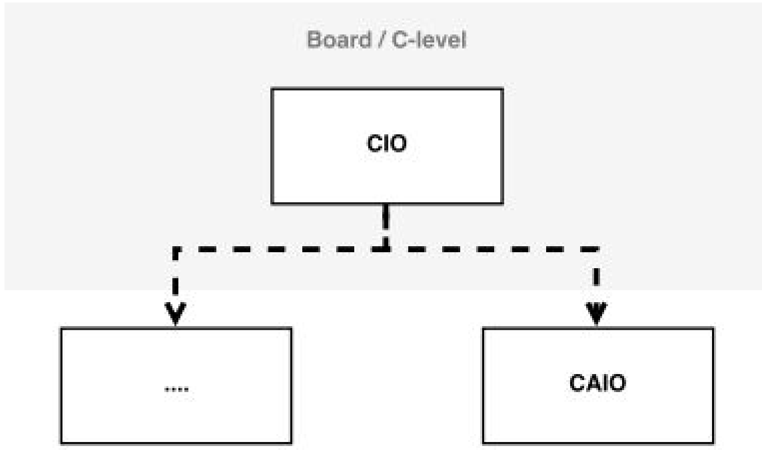

Figure 9

Additionally, five interviewees say that a Chief AI Officer would be a valuable C-level/Board role for a traditional bank, if it is also responsible for the effective use and management of data. If we look at the roles of a Chief Data Officer described by IBM (2016), we see that the ‘Business Optimizer’ and ‘Market Innovator’ role has significant overlap with that of a Chief AI Officer. For example, the CDO roles create algorithmic and machine-managed processes that lay foundation for cognitive computing capabilities (IBM, 2016). Therefore, we have illustrated the combination of the CAIO and CDO roles that represent AI and its corresponding data aspects in the C-level/Board of a traditional bank in figure 10. However, according to interviewee 22 the AI and data department should not be combined, because the bank’s data is not only used for AI activities, but also for simple business processes and operations. Therefore, these two areas should be clearly separated (interviewee 22).

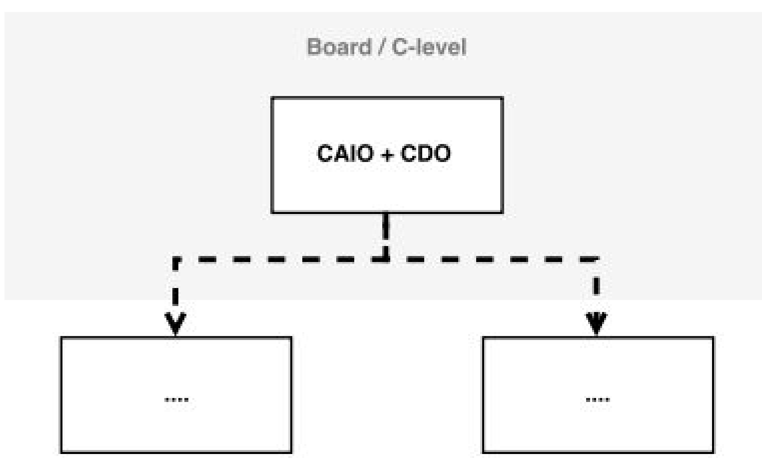

Figure 10

Traditional banks will have to make a deliberate assessment of their current business processes and AI capabilities, in order to find out where current AI roles and responsibilities lie in their organization. Developing this view is important because it may increase the chance of successfully re-aligning organizational roles. Interviewee 5 explains that this alignment is also the role of a CEO and is crucial to avoid conflicts of interest in the panel of leadership. Embedding the Chief AI Officer with current tech-executives is a real challenge, as Andrew Ng (2016) also pointed out: “some Chief Data Officers and forward-thinking CIOs are now effectively taking on this [Chief AI Officer] role in organizations.” Interviewee 14 adds that AI is hard to successfully embed in an organization because it is so interrelated and interdependent with current data roles, rules and architectures. This indicates that aligning AI strategies with the current tech-executive’s agendas will be critical to ensure a shared vision and priority for holistic development of a data related technology roadmap (Deloitte, 2016).

8. Limitations

This study shows that there are several technical, organizational and ethical challenges within traditional banks that use, or want to use AI technologies, to improve their business. Based on these challenges we have pre-evaluated the potential value of appointing a new C-level tech-executive role in a traditional banking organization. In this chapter we look back on the complete research process and discuss its limitations and potential need for future research. As we described in the early parts of this report, the development of AI and the corresponding literature regarding AI technology's effect on organizations is still very premature. Most literature is published by big consultancy firms that may have a commercial motive to present optimistic views of what AI's benefits and challenges are. However, as we have pointed out, there are also governmental and humanitarian agencies that do a lot of research into the implications of AI, which presumably offers a perspective without commercial motives. Research and literature published by academic institutions regarding the effects that AI technologies have on an organization is still marginal. Therefore, we have proposed a highly exploratory research approach to classify what challenges play an important role in this domain.

We have interviewed a limited sample of experts in the domain of AI & Banking, in the Netherlands. Therefore, the set of challenges that arise when traditional banks adopt AI technologies may be larger and more comprehensive in reality. Moreover, we noticed that there is a small bias regarding the current capabilities of AI technologies between interviewees that are working for an AI supplying company, and interviewees that work for a traditional bank or a Dutch regulator. Interviewees that work for a AI supplying company have a slightly more positive view of AI's current capabilities than the interviewees that work for the latter group.

Additionally, organizational, cultural and regulatory contexts may have significant influences on the perceptions of interviewees that are active in similar organizations, but different countries. This clearly is one of the downsides of performing a qualitative research. Although many research is done in the area of the more established tech-executive roles, it is hard to determine a general set of characteristics for an organizational role, because it is subject to an enormous amount of contextual factors. Therefore, more qualitative, and eventually quantitative research is needed to richly illustrate and synthesize contextual factors that provide a potential profile of an "ideal" Chief AI Officer. This research will be needed to further confirm, or disconfirm, the true value of appointing a Chief AI Officer at a traditional bank. Additionally, further research may be valuable to determine the CAIO's tasks, skills, education, experience and other role characteriscs.

9. Conclusion

This study sets out to explore a wide range of organizational challenges associated with the adoption of AI technologies in traditional banks. Hence our first research question: “What organizational challenges arise when banks adopt AI technologies?” We thereby provide tentative insights on how these challenges interrelate with organizational leadership, ethics and management of technology. As a result, we have identified a number of issues that challenge the current organizational and ethical leadership of traditional banks, so that they can prepare themselves for AI by setting up leadership capabilities that stimulate exploration and experimentation in a responsible manner. The most common organizational challenges that were mentioned by our experts are: Talent scarcity, traditional banks’ culture, mindset and organizational structure. Secondly, the most prevalent technical challenges that were mentioned are: Data quality, data access and low maturity of AI technologies. And finally, the ethical challenges that were mentioned are: Privacy issues, biased data and discrimination issues, AI accountability and explainability issues, low awareness of ethical consequences and AI’s future job replacement issues. Overall we can conclude that the challenges regarding the development and use of AI technologies are very broad, in a sense that there are many different challenges from different perspectives. Additionally, AI technologies are still relatively premature. However, the potential is enormous for organizations such as traditional banks, which drives high-tech companies and consultancy firms to invest heavily in research and development. In contrast, we see that there is still no clear and standard approach among traditional banks on how to adopt AI technologies effectively. Leadership continues its learning cycle by aligning AI solutions with their current corporate strategy to set up an enterprise wide governance framework that includes the responsible development of AI technologies. As we pointed out in chapter seven, the responsible AI framework designed by PwC (2017) should also include measures to ensure responsible innovation that clearly defines what the ethical responsibilities are of dealing with AI technologies. Managers could apply these learnings to next cycle experiments and use this momentum to create organizational awareness of AI’s potential and implications.

Additionally, we explored top management leadership as a possible solution to address certain AI challenges that arise when traditional banks adopt AI technologies. Hence our second research question: “Under what conditions would a Chief AI Officer be relevant for traditional banks?” In chapter six we have clearly identified similarities and differences in the evolution of existing tech-executive roles, such as the CIO, CTO and CDO. Emerging tech-executive roles often start with a functional leadership role when the technology is still relatively immature and enterprise-wide knowledge is low. The functional leadership role is focussed on internal activities and scoped narrowly to serve certain departments within the organization. As the technology matures and enterprise-wide knowledge of the new technology increases, the role of a tech-executive gradually shifts towards strategic leadership, where enterprise wide adoption of the technology is aimed for. Finally, when the technology fully matures, the role of a tech-executive transforms from an organizational manager into a business visionair that encompasses supra-functional leadership. This role uses technology to drive innovation, corporate strategy and aims to use technology to disrupt markets.

In chapter seven we introduced a potential contribution to the arena of top management by exploring the characteristics of a new C-level tech-executive role: the Chief AI Officer. As a result from our interviews we can conclude that a Chief AI Officer, as a new tech-executive role may be a valuable actor to address certain organizational, technical and ethical challenges. However, the views on where to position this role in the organization, and with what level of authority, depends heavily on the priority of this technology within the organization. Some experts say the Chief AI Officer should not be a C-level/Board position, but should report to a C-level/Board position, for example a CIO. They argue that AI technology is just a small part of the overall technology and innovation portfolio, which should not be represented by one specific role in the top management of a traditional bank. Others do say that a Chief AI Officer should operate on C-/Board-level, but with the inclusion of a CDO's data management role and responsibilities. They argue that this combination of roles is necessary because AI is a technology that is fundamentally dependent on data science, and should therefore be combined.

Next to these organizational and technical findings we have identified multiple ethical challenges that arise when traditional banks adopt AI technologies. The most prevalent challenges that were mentioned by our experts are about data privacy, biased data and discrimination issues, AI accountability (responsibility gap), AI explainability issue, and lack of awareness of AI ethics. Notably, the explainability issue is rooted in the technical immaturity of AI to develop an effective solution which explains how an AI system (based on statistical learning) has come to its results. As we discussed in chapter seven, the 'problem of many hands' and the 'responsibility gap' are real challenges for business leaders who have to deal with AI today. Currently, traditional banks in the Netherlands do not address all ethical challenges concretely. Some of them did appoint an ethical board of examiners, but these examiners only review new AI projects that have proven business results and validity. Some experts argue that ethical considerations should be involved earlier in the process of development to prevent expensive changes or cancellations of the project later on.

The Chief AI Officer could be a valuable factor in the 'problem of many hands' by taking full leadership responsibility for all AI ethics related issues to increase the organizational awareness of AI ethics. The Chief AI Officer as an ethical front-runner can develop a group sense among all stakeholders involved, that creates awareness of the ethical repercussions of dealing with AI technologies. Creating this intrinsic and collective awareness among employees may prove to be a far more effective approach than holding every single employee accountable for its actions, which in turn may result in fear and anxiety to share valuable knowledge and insights. Secondly, a Chief AI Officer may also address the 'responsibility gap' that develops as a result of technologies, such as AI, becoming increasingly autonomous. By ensuring the implementation of necessary responsible AI governance measures it can control the 'responsibility gap' better and earlier in the development phase. Additionally, it will enable traditional banks to reassure their stakeholders and society that AI will be developed in a responsible and value-sensitive way. Therefore we can conclude that the appointment of a Chief AI Officer could be valuable to accomplish responsible innovation at traditional banks, because there is currently no clear standard on how to adopt AI effectively. Moreover, AI is a technology that requires extensive cross-functional cooperation of multiple business units, which increases the difficulty for large enterprises, such as traditional banks, to effectively manage those activities. The Chief AI Officer can operate from a unique position if it is granted with sufficient authority to govern the the complete process of responsible AI design, development and usage at a traditional bank.

References

Agrawal, A., Gans, J.S. and Goldfarb, A. (2017). What to expect from Artificial Intelligence. MIT Sloan Management Review. Retrieved on 20-03-2017 from: http://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence/

Atwood, N., Bacon, T. (2011). Developing your C-suite. *The Korn/Ferry Institute.* Retrieved on 09-06-2017 from: https://www.kornferry.com/institute/176-developing-your-c-suite

Banavar, G. (2016). Learning to trust artificial intelligence systems Accountability, compliance and ethics in the age of smart machines. *IBM Research.* Retrieved on 09-06-2017 from: https://www.research.ibm.com/software/IBMResearch/multimedia/AIEthics_Whitepaper.pdf

Barben, D., Fisher, E., Selin, C., Guston, D. (2008). *Anticipatory governance of nanotechnology: foresight, engagement, and integration.* The Handbook of Science and Technology Studies (3rd ed.). MIT Press, Cambridge, MA, 979–1000.

Barnard, F.M. (1977). Socialist Pluralism and Pluralist Socialism. *Political Studies Association*, 25, 4, 474-490

Beck, U. (2000). *Risk society revisited: theory, politics and research programmes.* In: Adam, B., Beck, U., Van Loon, J. (Eds.), The Risk Society and Beyond: Critical Issues for Social Theory, 211 - 230.

Bennett, D., Liu, X., Parker, D., Steward, H. F., & Vaidya, K. (2001). Technology transfer to China: a study of strategy in 20 EU industrial companies. *International Journal of Technology Management*, *21*(1-2), 151-182. DOI: 10.1504/IJTM.2001.002899

Bell, C.E. (1989). Maintaining project networks in automated artificial intelligence planning. *Management Science, 35, 10,* 1192-1214.

Beatty, R.C., Arnett, K.P. and Liu, C. (2005). CIO/CTO Job Roles: An Emerging Organizational Model. *Communications of the IIMA*, 5, 2.

Boodhoo, R. and Permusser, R.D. (2009). Justifications for Qualitative Research in Organisations: A Step Forward. *The Journal of Online Education.*

Bostrom, N. (2003). *Ethical Issues in Advanced Artificial Intelligence*. Nick Bostrom.

Boulton, C. (2017). Think twice before you hire a chief AI officer. *CIO.com*. Retrieved on 09-06-2017 from: http://www.cio.com/article/3177427/artificial-intelligence/think-twice-before-you-hire-a-chief-ai-officer.html

Buskell, M. (2016-08-04). Should there be a Chief Artificial Intelligence Officer (CAIO)? *Rainbird.ai.* Retrieved from: http://rainbird.ai/should-there-be-a-chief-artificial-intelligence-officer-caio/

Campbell, J.P. (1970). *Managerial behavior, performance, and effectiveness.* McGraw-Hill, New York, NY.

Capgemini. (2012). Global Study Reveals That the Most Digitally Mature Companies are 26 Percent More Profitable Than their Industry Competitors. *Capgemini.* Retrieved on 09-06-2017 from:

https://www.capgemini.com/news/global-study-reveals-that-the-most-digitally-mature-companies

Capgemini. (2013). The Role of the Chief Data Officer in Financial Services. *Capgemini.* Retrieved on 10-06-2017 from: https://www.capgemini.com/resource-file-access/resource/pdf/the_role_of_the_cdo_in_financial_services.pdf

Chun, M., Mooney, J. (2006). CIO Roles and Responsibilities: Twenty-Five Years of Evolution and Change. *Proceedings of AMCIS 2006*, 376.

Clarck, B. (2017). Artificial intelligence is quickly becoming as biased as we are. *TNW.* Retrieved on 09-06-2017 from: https://thenextweb.com/artificial-intelligence/2017/03/22/artificial-intelligence-is-quickly-becoming-as-biased-as-we-are/#.tnw_fVBILdDA

Cuhls, K. (2005): The Delphi Method. *UNIDO,* 93–112.

Creswell, J. W. (2002). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research.* Upper Saddle River, N.J: Merrill.

DARPA. (2017). DARPA perspective on AI. *DARPA.* Retrieved on 09-06-2017 from: http://www.darpa.mil/about-us/darpa-perspective-on-ai

De Nederlandsche Bank. (2016-01). Technological innovation and the Dutch financial sector. *DNB.* Retrieved from: https://www.dnb.nl/en/binaries/Themaonderzoek%20%20uk_tcm47-336322.PDF

De Nederlandsche Bank. (2015-11-30). Perspective on the structure of the Dutch banking sector. *DNB.* Retrieved from: https://www.dnb.nl/en/binaries/DNB-study%20Perspective%20on%20the%20structure%20of%20the%20Dutch%20banking%20sector_tcm47-323322_tcm47-334492.pdf

Deloitte. (2004). CIO 2.0. The changing role of the Chief Information Officer. *Deloitte.* Retrieved on 10-06-2017 from: http://www.providersedge.com/ehdocs/ehr_articles/CIO_2-The_Changing_Role_of_the_CIO.pdf

Deloitte. (2015y). Banking on the future: Vision for 2020. *Deloitte.* Retrieved on 09-06-2017 from: https://www2.deloitte.com/content/dam/Deloitte/in/Documents/financial-services/in-fs-deloitte-banking-colloquium-thoughtpaper-cii.pdf

Deloitte. (2016). The evolving role of the chief data officer in financial services: From marshal and steward to business strategist. Deloitte. Retrieved on 09-06-2017 from: https://www2.deloitte.com/content/dam/Deloitte/uy/Documents/strategy/gx-fsi-evolving-role-of-chief-data-officer.pdf

Dooley,B.J. (2017). *AI, Deeplearning, and Financial services.* Retrieved on 09-06-2017 from:https://upside.tdwi.org/articles/2017/03/13/ai-deep-learning-and-financial-services.aspx

Drucker, P.F. (1988). The Coming of the New Organization. *Harvard Business Review.* Retrieved on 01-03-2017 from: https://hbr.org/1988/01/the-coming-of-the-new-organization

Drury, N., Lipp, A., Marshall, A., Handa, R. (2015). Innovating banking: Lessons from the world's leading innovators. *IBM Institute for Business Value.* September 2015. http://www-935.ibm.com/ services/us/gbs/thoughtleadership/innovatingbanking/

Duchessi, P. and O'Keefe, R.M. (1993). *Understanding expert system's success and failure*. Decision Sciences and Engineering Systems, Rensselaer Polytechnic Institute, Troy, NY.

EESC. (2017). Artificial Intelligence: Europe needs to take a human-in-command approach. *European Economic and Social Comittee.* Retrieved on 09-06-2017 from: http://www.eesc.europa.eu/m?i=portal.en.press-releases.43541

Eisenhardt, K.M. (1989). Building Theories from Case Study Research. *The Academy of Management Review* 14, 4, 532.

European Commission. (2016). How does the data protection reform strengthen citizens' rights? *European Commission.* Retrieved on 25-06-2017 from: http://ec.europa.eu/justice/data-protection/document/factsheets_2016/factsheet_dp_reform_citizens_rights_2016_en.pdf

Fayol, H. (1916). *Administration industrielle et générale; prévoyance, organisation, commandement, coordination, controle*. Paris, H. Dunod E. Pinat.

Fettermann, D.M. (2010). *Ethnography: Step by step* (3rd ed.). Thousand Oaks, CA: Sage.

Fiedler, F.E. (1966). Leadership Style and the Performance of Co-acting Groups. *University of Illinois. Technical Report*, 44.

Fisher, E., Mahajan, R., Mitcham, C., (2006). Midstream modulation of technology: governance from within. *Bulletin of Science, Technology and Society*. 26, 485–496

Friedman, B., (1996). Value-sensitive design. *ACM Interactions* 3, 6, 17 - 23.

Gangwani, T. (2017-01-13). Hiring a chief artificial intelligence officer (CAIO). *CIO.com.* Retrieved from: http://www.cio.com/article/3157214/artificial-intelligence/hiring-a-chief-artificial-intelligence-officer-caio.html

Gartner. (2016). Leadership Practices to Foster a Growth Mindset. *Gartner.* Retrieved on 09-06-2017 from: http://www.gartner.com/smarterwithgartner/leadership-practices-to-foster-a-growth-mindset-2/

Gregor, S., Hevner, A.R. (2013). Positioning and Presenting Design Science Research for Maximum Impact, *MIS Quarterly*, 37, 2, 337-355.

Grin, J., Grunwald, A. (2000). *Vision Assessment: Shaping Technology in 21st Century Society. Towards a Repertoire for Technology Assessment.* Springer, Berlin.

Groysberg, B.L., Kelly, K., and MacDonald, B. (2011). The New Path To the C-Suite. *Harvard Business Review.* Retrieved on 09-06-2017 from: https://hbr.org/2011/03/the-new-path-to-the-c-suite

Guadalupe, M., Hongyi, L., Julie, W. (2013). Who lives in the C-suite? Organizational structure and the division of labor in top management. *Management Science, 60, 4*, 824-844.

Hammond, K.J. (2017). Please Don't Hire a Chief Artificial Intelligence Officer. Harvard Business Review. Retrieved on 09-06-2017 from: https://hbr.org/2017/03/please-dont-hire-a-chief-artificial-intelligence-officer

Hajer, M., Wagenaar, H. (2003). *Deliberative Policy Analysis: Understanding Governance in the Network Society*. Cambridge, UK: Cambridge University Press.
Hart, S. (2008). *Inside the Minds: Achieving Success as a CTO*. Boston, MA: Aspatore Books.
Hersey, P., Blanchard, K.H. (1988). *Management of organizational behavior (5th Ed.)*, pp. 169-201. Englewood Cliffs, NJ: Prentice Hall.
Hevner, A. (2007). A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems* 19, 2, 87-92.
Hevner, A., March, S., Park, J., Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly* 28, 1, 75-105.
Hoeschl H.C., Barcellos V. (2006) Artificial Intelligence and Knowledge Management. *Artificial Intelligence in Theory and Practice*. 217. Springer, Boston, MA.
Hoven, van der C., Probert, D., Phaal, R. and Goffin, K. (2012). Dynamic Technology Leadership: The Adaptive Role of the CTO. *Research Technology Management*, 55, 5.
Hughes, J.A., Randall, D. and Shapiro, D. (1993). From ethnographic record to system design: some experiences from the field. *Computer Supported Cooperative Work*, 1, 123-141.
IBM. (2012). Analytics: The real-world use of big data How innovative enterprises extract value from uncertain data. *IBM Research*. Retrieved on 09-06-2017 from: https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?htmlfid=GBE03519USE
IBM. (2015). Banking redefined: Disruption, transformation and the next-generation bank*. IBM research.* Retrieved on 09-06-2017 from: https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?subtype=XB&infotype=PM&htmlfid=GBE03704USEN&attachment=GBE03704USEN.PDF
IBM. (2015b). Redefining boundaries: Insights from the global C-suite study. IBM Research. Retrieved on 09-06-2017 from: http://www-01.ibm.com/common/ssi/cgi-bin/ssialias?subtype=XB&infotype=PM&htmlfid=GBE03695USEN&attachment=GBE03695USEN.PDF
IBM. (2016a). The Cognitive Bank. *IBM research.* Retrieved on 09-06-2017 from: https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?htmlfid=GBE03768USEN&
IBM (2017). *IBM research.* Retrieved from https://www-03.ibm.com/press/us/en/presskit/42846.wss
IDC. (2016). *Worldwide Cognitive Systems and Artificial Intelligence Revenues Forecast to Surge Past $47 Billion in 2020, According to New IDC Spending Guide.* Retrieved on 09-06-2017 from: http://www.idc.com/getdoc.jsp?containerId=prUS41878616
IEEE Global Initiative for Ethical Considerations in Artificial Intelligence and Autonomous Systems. Ethically Aligned Design: A Vision For Prioritizing Wellbeing With Artificial Intelligence And Autonomous Systems, Version 1. IEEE, 2016. http://standards.ieee.org/develop/indconn/ec/autonomous_systems.html.
ING. (2017). ING and the use of customer data. *ING.* Retrieved on 09-06-2017 from: https://www.ing.com/About-us/ING-and-the-use-of-customer-data.htm
Irgon, A., Zolnowski, K.J., Murray, M. and Gersho, M. (1990). Expert systems development: a retrospective review of five systems, *IEEE Expert,* 5, 3, 25-39.
Janssen, M., Kuk, G. (2016). The challenges and limits of big data algorithms in technocratic governance*. Government Information Quarterly. 33,* 371–377

Jarvenpaa, S.L., Ives, B. (1991) Executive involvement and participation in the management of information technology. *MIS Quarterly, 15, 2,* 205-227.
Joyce, G. (2017-01-03). New year, new data: Social data predicts what will be a thing in 2017. *Brandwatch*. Retrieved from: https://www.brandwatch.com/blog/react-predictions-for-2017/
Kaplan, A., Skogstad, A. L., Girshick, M. A. (1950) The Prediction of Social and Technological Events. *The Public Opinion Quarterly*, 14, 93-110.
Kapoor, R. and Klueter, T. (2016). Organizing for new technologies. *MIT Sloan Management Review*. Retrieved on 20-03-2017 from: http://sloanreview.mit.edu/article/organizing-for-new-technologies/
Katz, D., Kahn, R. L. (1966). The social psychology of organizations. New York: Wiley.
Katzenbach, J., Oelschlegel, C., Thomas, C. (2016). 10 Principles of Organizational Culture. *Strategy+Business.* Retrieved on 09-06-2017 from: https://www.strategy-business.com/article/10-Principles-of-Organizational-Culture?gko=71d2f
Kelnar, D. (2016-12-02). The fourth industrial revolution: a primer on Artificial Intelligence (AI). *Medium.com*. Retrieved from: https://medium.com/mmc-writes/the-fourth-industrial-revolution-a-primer-on-artificial-intelligence-ai-ff5e7fffcae1#.jevd83hn9
KPMG. (2017). Banking on the future: The roadmap to becoming the banking partner of Gen Y professionals. *KPMG*. Retrieved on 09-06-2017 from: https://home.kpmg.com/content/dam/kpmg/au/pdf/2017/banking-on-the-future-edition-3.pdf
Kolbjørnsrud, V., Amico, R., Thomas, R.J. (2016). How Artificial Intelligence Will Redefine Management. *Harvard Business Review.* Retrieved on 11-06-2017 from https://hbr.org/2016/11/how-artificial-intelligence-will-redefine-management?referral=03758&cm_vc=rr_item_page.top_right
Kuechler, W.L., Vaishnavi, V.K. (2008). Theory Development in Design Science Research: Anatomy of a Research Project. *Proceedings of the Third International Conference on Design Science Research in Information Systems and Technology*, 7, 9, 1–15.
Lewis, W.W., Lawrence, H.L. (1990). A new mission for corporate technology. *Sloan Management Review*, 31, 4.
Likert, R. (1961). *New Patterns of Management*. McGraw-Hill, New York, NY.
Lindzon, J. (2015). 10 C-suite jobs of the Future. *Fastcompany.* Retrieved on 09-06-2017 from: https://www.fastcompany.com/3048398/10-c-suite-jobs-of-the-future
Lucas, C.H., Agarwal, Jr.R., Clemons, E.K., Sawy, O.A., Weber, B. (2013). *Impactful research on transformational information technology: An opportunity to inform new audiences.* MIS Quarterly 37, 2, 371-382.
Management Science. (2017). About Management Science. *pubsonline.informs.org.* Retrieved on 2017-01-16 from: http://pubsonline.informs.org/journal/mnsc
Matthias, A. (2004). The responsibility gap: Ascribing responsibility for the actions of learning automata. *Ethics and Information Technology*, 6, 3, 175 - 183

McAfee, A., Brynjolfsson, E. (2015). The Great Decoupling: An Interview with Erik Brynjolfsson and Andrew McAfee. Harvard Business Review. Retrieved on 09-08-2017 from: https://hbr.org/2015/06/the-great-decoupling

McGregor, D. (1960). *The Human side of Enterprise*. McGraw-Hill, New York, NY.

McKinsey. (2015). Ascending to the C-suite. *McKinsey & Company.* Retrieved on 09-06-2016 from: http://www.mckinsey.com/global-themes/leadership/ascending-to-the-c-suite

McKinsey. (2016). A Brave New World for Global Banking: McKinsey Global Banking Annual Review 2016. *McKinsey & Company.* Retrieved on 09-06-2017 from: https://modopayments.com/wp-content/uploads/2017/01/McKinsey_GBAR2016_A%20Brave%20New%20World%20for%20Global%20Banking_2016.pdf

McKinsey. (2017). ING's agile transformation. *McKinsey & Company.* Retrieved on 09-06-2017 from: http://www.mckinsey.com/industries/financial-services/our-insights/ings-agile-transformation

Medcof, J.W. (2008). The organizational influence of the Chief Technology Officer. *R&D Management*, 38, 4.

Meyer, M.H. and Curley, K.F. (1991). Putting expert systems technology to work, *Sloan Management Review*, 32, 5, 21-31.

Mintzberg, H. (1973). *The Nature of Managerial Work*. Harper & Row, New York, NY.

MIS Quarterly. (2017). About MIS Quarterly. *Misq.org.* Retrieved on 2017-01-16 from: http://misq.org/about/

Moore, S. (2016). Leadership Practices to Foster a Growth Mindset. Gartner. Retrieved on 25-6-2017 from: http://www.gartner.com/smarterwithgartner/leadership-practices-to-foster-a-growth-mindset-2/

Mykytyn, K., Mykytyn, P.P., Slinkman, C.W. (1990). Expert systems: A question of liability? *MIS Quarterly, 14, 1*, 27-42.

Nag, R. (2016-01-12). AI: We need the chief AI officer. *Geek.ly*. Retrieved from: http://geek.ly/AdU

NarrativeScience. (2017). The Rise of AI in Financial Services. NarrativeScience. Retrieved on 09-06-2016 from: https://www.google.nl/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&cad=rja&uact=8&ved=0ahUKEwjV-Pm0lJzUAhVPLFAKHU_xDucQFggtMAE&url=https%3A%2F%2Fnarrativescience.com%2FDesktopModules%2FEasyDNNNews%2FDocumentDownload.ashx%3Fportalid%3D0%26moduleid%3D2058%26articleid%3D623%26documentid%3D115&usg=AFQjCNEw-mcBFFtSZB_lISuh39bGNNHqcA&sig2=2r8Z6obGN0AMMCQJ7cu7yA

Naylor, M. (2016). *A Perfect Storm in Insurance: How to Survive the Looming waves of Disruptive Technology.* Massey, New Zealand. MJPublishers.

Niederman, F., March, S. (2012). Design Science and the Accumulation of Knowledge in the Information Systems Discipline. *ACM Transactions on MIS* 3, 1, 1.

Ng, A. (2016-11-09). What Artificial Intelligence can and can't do right now. *Harvard Business Review.* Retrieved from: https://hbr.org/2016/11/what-artificial-intelligence-can-and-cant-do-right-now

Ng, A. (2016-11-11). Hiring your first chief AI officer. *Harvard Business Review.* Retrieved from: https://hbr.org/2016/11/hiring-your-first-chief-ai-officer

Nunamaker, J., Chen, M., Purdin, T. (1991). Systems Development in Information Systems Research. *Journal of Management Information Systems* 7, 3, 89-106.

O'Keefe, R., O'Leary, D., Rebne, D. and Chung, Q. (1993). The impact of expert systems in accounting: system characteristics, productivity and work unit effects, I*nternational Journal of Intelligent Systems in Accounting, Finance and Management*.

O'Leary, D., Turban, E. (1987). The organizational impact of expert systems. *Human Systems Management*, 7, 11-17.

O'Reilly, T. (2016). Managing the bots that are managing the business. *MIT Sloan Management Review*. Retrieved on 19-03-2017 from: http://sloanreview.mit.edu/article/managing-the-bots-that-are-managing-the-business/

Offermann, D., Gusev, O., Donner, M., Forbes, J.M., Hagan, M., Mlynczak, M.G., Oberheide, J., Preusse, P., Schmidt, H. and Russell, J.M. (2009). Relative intensities of middle atmosphere waves. *Journal of Geophysical Research, 114.*

Orlikowski, W.J., Barley, S.R. (2001). *Technology and Institutions: What Can Research on Information Technology and Research on Organizations Learn from Each Other?* MIS Quarterly, 25, 2, 145-165.

PwC. (2015). EU Bonus cap: The Net Widens. *PwC.* Retrieved on 09-06-2017 from: http://www.pwc.com/us/en/financial-services/regulatory-services/publications/assets/eu-banker-bonus-cap.pdf

PwC. (2016). Top financial services issues of 2017: Thriving in uncertain times. *PwC.* Retrieved on 09-06-2017 from: https://www.pwc.com/us/en/financial-services/research-institute/assets/pwc-top-financial-services-issues-2017.pdf

Ransbotham, S. (2017). Managing with Immature AI. *MIT Sloan Management Review Website*. Retrieved on 20-03-2017 from: http://sloanreview.mit.edu/article/managing-with-immature-ai/

Ravetz, J. (1997). The science of 'what-if?'. *Futures* 29, 533 - 539.

Rip, A., Misa, T., Schot, J. (1995). *Managing Technology in Society: The Approach of Constructive Technology Assessment.* Thomson, London.

Rip, A., Schot, J. (1996). The Past and Future of Constructive Technology Assessment. *Elsevier Science Inc.* Technological Forecasting and Social Change 54, 251-268

Robbins, S.P. (1996). *Organizational Behavior* (7th ed.). New York, NY. McGraw-Hill Education.

Rockart, J.F. (1982). The Changing Role of the Information Systems Executive: A Critical Success Factors Perspective. *Sloan Management Review*. 3, 13.

Lucy, D., Poorkavoos, M., Wellbelove, J. (2015). The Management Agenda 2015. *Roffey Park*. Retrieved on 25-06-2017 from http://www.roffeypark.com/wp-content/uploads2/The-Management-Agenda-2015-Exec-Summary.pdf

Ross, J. W. (2003). Creating a Strategic IT Architecture Competency: Learning in Stages. *MISQ Executive, 2(1)*, 31-43.

Russel, S.J., Norvig, P. (2009). *Artificial Intelligence: A Modern Approach.* New Jersey, US: Prentice Hall.

Schatsky, D., Muraskin, C., Gurumurthy, R. (2014). Demystifying artificial intelligence: What business leaders need to know about cognitive technologies. *Deloitte.* Retrieved from: https://dupress.deloitte.com/dup-us-en/focus/cognitive-technologies/what-is-cognitive-technology.html

Schatsky, D., Muraskin, C., Gurumurthy, R. (2015). Cognitive technologies: the real opportunities for businesses. *Deloitte.* Retrieved from: https://dupress.deloitte.com/dup-us-en/deloitte-review/issue-16/cognitive-technologies-business-applications.html

Shrivasta, A. (2017). Building leaders with a digital mindset. Peoplematters. Retrieved on 09-06-2017 from: https://www.peoplematters.in/article/leadership-development/building-leaders-with-a-digital-mindset-14782?utm_source=peoplematters&utm_medium=interstitial&utm_campaign=learnings-of-the-day&utm_source=peoplematters&utm_medium=interstitial&utm_campaign=learnings-of-the-day&utm_source=peoplematters&utm_medium=interstitial&utm_campaign=learnings-of-the-day

Sikora, R., Shaw, M.J. (1998). *Management Science, 44, 11(2),* S65-S78.

Simon, H. (1996). *The Sciences of Artificial,* 3rd Edition, MIT Press, Cambridge, MA, 1996.

Smith, R.D. (2002). The Role of the Chief Technology Officer in Strategic Innovation, Project Execution, and Mentoring. *Titan Systems Corporation*. Retrieved on 09-06-2017 from: https://www.cs.princeton.edu/courses/archive/spring12/cos448/web/readings/smith.pdf

Sviokia, J. (1990). An examination of the impact of expert systems on the firm, *MIS Quarterly*, 14, 2, 127-40.

Stanford University. (2016). *Artificial Intelligence and Life in 2030*. One Hundred Year Study on Artificial Intelligence: Report of the 2015-2016 Study Panel, Stanford University Retrieved on 09-06-2017 from: http://ai100.stanford.edu/2016-report

Stephens, C.S., Ledbetter, W.N., Mitra, A., Ford, F.N. (1992). Executive or Functional manager? The nature of the CIO's job. *MIS Quarterly, 16, 4,* 449-467.

Stilgoe, J., Owen, R., Macnaghten, P. (2013) Developing a framework for responsible innovation. *Research Policy, ScienceDirect*. 42, 9, 1568–1580.

Strauss, A. & Corbin, J. (1990). *Basics of qualitative research: Grounded theory procedures and techniques*. Newbury Park, CA: Sage Publications

Tarafdar, M. (2016). The three new skills manager needs. *MIT Sloan Management Review*. Retrieved on 20-03-2017 from: http://sloanreview.mit.edu/article/the-three-new-skills-managers-need/

Thompson, D.F. (1980). Moral responsibility and public officials. *American Political Science Review*, 74, 905 - 916.

TNO. (2017). Innovating in Cyber Security. *TNO.* Retrieved on 09-06-2017 from: https://www.tno.nl/media/9419/innovating-in-cyber-security.pdf

Tzezana, R. (2017). Artificial Intelligence will arrive in three waves. *Futurism.* Retrieved from: https://futurism.com/artificial-intelligence-tech-will-arrive-in-three-waves/

Uttal, B., Kantrow, A., Linden, L.H. and Stock, S. (1992). Building R&D leadership and credibility. *Research Technology Management*, 35, 3, 15 - 24.

Van de Poel, I., Royakkers, L. (2011). *Ethics, Technology, and Engineering: An Introduction.* West-Sussex, UK: John Wiley & Sons Ltd.

Van den Hoven, M.J. (2008). Information technology, privacy, and the protection of personal data. *Cambridge University Press*, 301- 322.

Van den Hoven, M.J., Lokhorst, G., van de Poel, I. (2012). Engineering and the problem of moral overload. *Science and Engineering Ethics* 18, 1–13

Verschuren, P., Somers, N. et al. (1997). The need for qualitative methods in agricultural economic research. *Tijdschrift voor Sociaal-Wetenschappelijk Onderzoek van de Landbouw*. 12, 4, 367–376.

Verschuren, P. et al. (1997). The need for qualitative methods in agricultural economic research. *Sociaal-Wetenschappelijk Onderzoek van de Landbouw*. 12, 4, 367–376.

Verschuren, P., Hartog, R. (2005). Evaluation in Design-Oriented Research. *Quality & Quantity: International Journal of Methodology*, 39, 733.

Verschuren, P., Doorewaard, H. (2010). *Designing a research project (2nd ed)*. The Hague, Netherlands. Eleven International Publishing

von Schomberg, R. (2011). *Prospects for technology assessment in a framework of responsible research and innovation*. In: Dusseldorp, M., Beecroft, R.(Eds.), Technikfolgen Abschätzen Lehren: Bildungspotenziale Transdisziplinärer. Vs Verlag, Methoden, Wiesbaden.

Walls, J., Widmeyer, G. El Sawy, O. (1992). Building an Information System Design Theory for Vigilant EIS. *Information Systems Research.* 3, 1, 36-59.

Walls, J., Widmeyer, G. El Sawy, O. (2004). Assessing Information System Design Theory in Perspective: How Useful was our 1992 Initial Rendition. *Journal of Information Technology Theory and Application.* 6, 2, 43-58.

Webster, J., Watson, R.T. (2002). Analyzing the past to prepare for the future: Writing a literature review. MIS Quarterly, 26, 2.

Weill, P., & Ross, J. (2005). Designing IT governance. *MIT Sloan Management Review*, *46, 2*, 26-34.

Winters, R. (2016). How do we deal with biased data in machine learning? *Quora.* Retrieved on 24-06-2017 from: https://www.quora.com/How-do-we-deal-with-biased-data-in-machine-learning

Yin, R.K. (1994). *Case study research: design and methods* (2nd ed.). London: SAGE Publications.