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"Development and evaluation of cognitive risk and regulatory compliance management strategies for financial institutions."

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ACRONYMS AND ABBREVIATIONS

AAR	Annual Account Review
ACM	Association for Computing Machinery
AI	Artificial Intelligence
AT	general part (ger. Allgemeiner Teil)
BaFin	Federal Financial Supervisory Authority (ger. Bundesanstalt für Finanzdienstleistungsaufsicht)
BI	Business Intelligence
BPMN	Business Process Model and Notation
BT	paticular part (ger. Besonderer Teil)
BTO	particular part organisational and operational structure
BTR	particular part risk management and risk control processes
CCMA	Crime and Compliance Management Analytics
CPM	Celonis Process Mining
CRD	Capital Requirements Directive
CSV	Comma-separated values
DB	Davies-Bouldin
di	Number of documents that contain a specific term i
DOI	Digital Object Identifier
ECB	European Central Bank
EMEA	Europe, Middle East and Africa
EPC	Event-Driven Process Chain
ERP	Enterprise Resource Planning
EU	European Union
FI	financial institution
FinTech	financial technology
GRC	Governance Risk Compliance
G-SIFI	global systemically important financial institution

IBM	International Business Machines
ID	identifier
IDF	inverse term frequency
IEEE	Institute of Electrical and Electronic Engineers
IQ	interview question
IT	information technology
KPI	key performance indicator
KWG	German Banking Act (ger. Kreditwesengesetz)
LCR	Liquidity Coverage Ratio
LPM	LANA Process Mining
MaRisk	Minimum Requirements for Risk Management (ger. Mindestanforderungen an das Risikomanagement)
MiFID	Markets in Financial Instruments Directive
MIT	Massachusetts Institute of Technology
MPA	myInvenio Process Analyst
MS	MetricStream
n	Number of documents
NSFR	Net Stable Funding Ratio
PC	personal computer
PDF	Portable Document Format
PRC	Process Control
ProM	Process mining framework
QPA	QPR ProcessAnalyzer
RCCM	Regulatory and Corporate Compliance Management
RegTech	regulatory technology
RICM	Regulatory Intelligence and Content Management
RQ	research question
SE	Societas Europaea
SPI	Signavio Process Intelligence

SQ	survey question
SSM	Single Supervisory Mechanism
UML	Unified Modeling Language
WRC	Watson Regulatory Compliance
XBRL	eXtendable Business Reporting Language
XML	eXtendable Markup Language

1 INTRODUCTION

1.1 INITIATION

At the opening ceremony of the Leverhulme Centre for the Future of Intelligence at Cambridge University in October 2016, Stephen Hawking gave a speech about the future of Artificial Intelligence (AI). He said that

"...the rise of powerful AI will be either the best, or the worst thing, ever happen to humanity. We do not yet know which"

(Hern, 2016; Titcomb, 2016). In recent years, Hawking has often warned that the creation of AI could become a major risk for humanity if it was managed and used in the wrong way. He was opposed to making unchecked advances in this technology (Hern, 2016; Titcomb, 2016). Therefore, Hawking was one of more than 100 leading academic experts who signed an open letter called "Research priorities for robust and beneficial artificial intelligence" in 2015. The letter claims that research should focus on maximizing the social benefits and avoid potential risks of AI. Besides, it is recommended that research, aimed to ensure that AI systems are robust and beneficial, is expanded (Future of Life Institute, 2017). However, the deceased British physician also pointed out that

"...the potential benefits of creating intelligence are huge".

Furthermore, Hawking was convinced that

"...every aspect of our daily lives will be transformed. In short, success in creating AI could be the biggest event in the history of our civilisation"

(Hern, 2016; Titcomb, 2016). With this statement, he emphasized that AI is one of the most important fields of action for both organizations and private individuals in the near future. In research and practice, AI technologies are commonly combined with other technology systems like cloud computing, data mining and machine learning. The combination of these allied technology systems is commonly summarized by the term cognitive computing (see chapter 2.5) (Haun, 2014, p. 125).

With regard to the economic system, Hawking said that AI

"...will bring great disruption to our economy"

(Hern, 2016; Titcomb, 2016). For organizations of all economic sectors, the question becomes whether they are going to be a disrupter or disrupted through the increasing importance of cognitive computing systems that feature AI. Therefore, it will be critical for organizations all over the world to engage in this field of action to become a disrupter in their economic sector. According to an estimation of the Institute of International Finance[1] (2016a, p. 14), those institutions that proactively search for innovative, integrated and reliable AI featured cognitive computing applications in order to enhance their products and business processes will be in a significantly better position than their competitors. For this reason, several companies have started partnerships to develop new AI cognitive computing solutions. In September 2016, the industry leading American technology companies Amazon, Google, Facebook, International Business Machines (IBM) and Microsoft announced the foundation of a non-profit organization called "Partnership on AI" to formulate and share best practices on the potentials and challenges of AI and other cognitive computing technologies. The major objective of this organization is to benefit civilization as well as society and to maximize the potential of these technologies. The members conduct and publish research together in different areas such as ethics, privacy, reliability and transparency (Partnership on AI, 2017). Besides, companies have also started to cooperate with leading institutes and universities to encourage a joint cognitive computing research. In September 2017, the American technology company IBM announced a partnership with the Massachusetts Institute of Technology (MIT) to create an AI research lab called the "MIT - IBM Watson AI Lab". One major objective of their partnership is to unlock new advantages and breakthroughs in AI and cognitive computing. Furthermore, they are searching for new ways to apply these technologies to several industries (Rosen, 2017).

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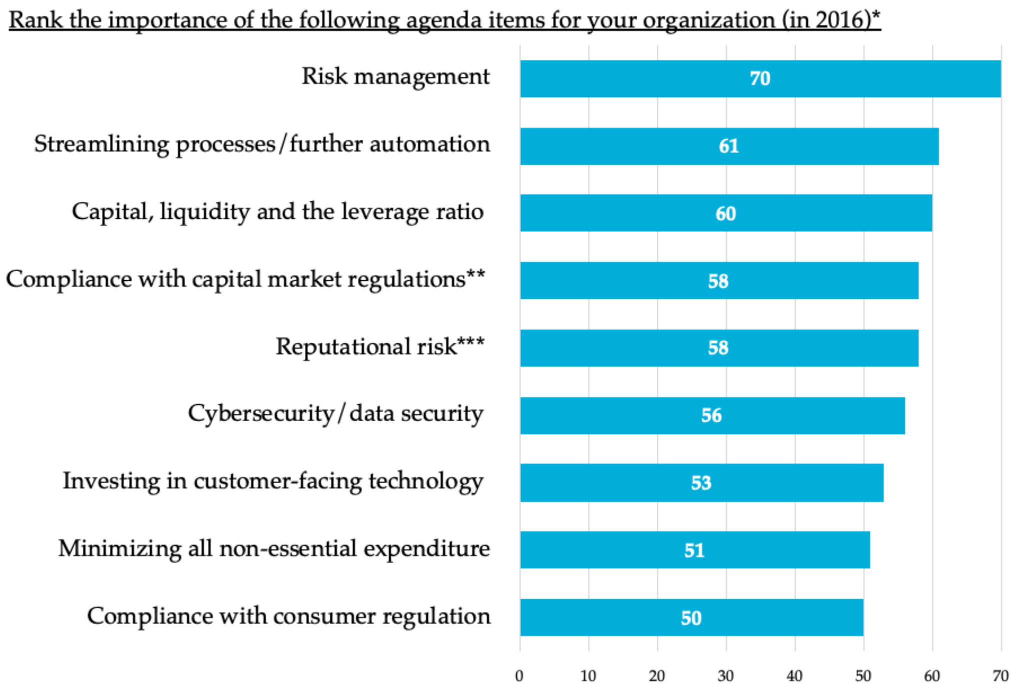
1 The Institute of International Finance is an association of several financial organizations. The institute counts more than 500 members from 70 countries, which include amongst others investment banks and central banks. One objective of this organization is to support the financial sector in the management of risks and regulations to encourage and preserve the stability of the financial system (Institute of International Finance, 2017).

Partnerships like this between one of the leading technology companies and one of the world's most renowned technical universities show that organizations have identified the future potential of AI featured cognitive computing technologies and are investing in its technical development.

Regarding the financial sector, banks and other financial institutions (FIs) have also realized the increasing importance of AI and cognitive computing. In 1990, Hawley, Johnson and Raina (1990) already predicted first potential AI featured solutions for FIs. Accordingly, the first established fields of action for AI in combination with other cognitive computing technologies were financial forecasting (Kaastra and Boyd, 1996; LeBaron, Arthur and Palmer, 1999) and bankruptcy prediction (Varetto, 1998; Zhang et al., 1999; Shin and Lee, 2002). Nowadays, amongst typical banking tasks like portfolio management, customer service and granting of credit, AI can be integrated into almost any issue banks and other FIs have to deal with (Bahrammirzaee, 2010; Aktan and Ince, 2009; van Liebergen, 2017). Furthermore, cognitive computing technologies that include AI systems enable FIs to develop and implement new business models, reduce expense and increase their productivity (Institute of International Finance 2016a, p. 2; Fethi and Pasiouras, 2010).

Since the global financial and economic crisis of 2008, FIs focus considerably more on their risk and regulatory compliance management activities (Chen, Olsen and Wu, 2014; Eggert, 2014, p. 7). It has become a major target for banks and other FIs to enhance their regulatory compliance management systems (Institute of International Finance, 2016a, p. 9). In 2014, the Deutsche Bank, the largest bank in Germany, has spent 1.3 billion Euro on implementing new regulatory requirements (Institute of International Finance, 2015, p. 1). According to the European Banking Barometer of 2016, a survey that was carried out by the consulting company Ernst & Young, risk management was ranked the most important strategic priority for European banks in 2016 (Ernst & Young, 2016, p. 30).



Base excludes respondants answering "Does not apply."
* Ranking of the importance on a scale of 0 (not important) to 10 (very imp.)
Numbers show the percentage of respondents selecting either 8, 9 or 10.
** Compliance with capital market regulations includes MiFID/EMIR.
*** Reputational risk includes tax transparency, remuneration and cultural issues.

Figure 1: Ranking of the importance of banking activities in 2016

[source: own presentation based on (Ernst & Young, 2016, p. 30)]

The survey includes 250 interviews with selected senior bankers across twelve European markets (Ernst & Young, 2016, p. 4).[2] The chart above (figure 1) shows that risk management and banking regulation issues have a high priority for bankers in the European Union (EU). 70 % of the interviewed bankers regard risk management as a highly important task for their organizations. Another high priority on the agenda (61 %) is the automation and optimization of business processes.

2 The interviews were taken with bankers from Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, the Nordics, Poland, Spain, Switzerland and the United Kingdom (Ernst & Young, 2016, p. 30).

A malfunctioning risk management is not only expensive, but also a significant risk for FIs (Cornett et al., 2011). If a FI does not comply with the overall regulations, it will experience a financial penalty through the national or international supervisory agencies or it could lose its banking license in the worst-case scenario (Institute of International Finance, 2016a, p. 10). Therefore, it must be considered that an efficient risk management is a critical factor for the long-term success of FIs. However, the quality and efficiency of risk management activities do not correlate directly with the business success in form of revenue and gross profit. For this reason, financial organizations generally purpose to keep their costs for risk and regulatory compliance management activities low. Therefore, they are constantly searching for innovative ways to make their risk and regulatory compliance management processes more efficient and more accurate in order to save costs and enhance their productivity. Since compliance management activities are commonly repetitive and involve the evaluation of steadily increasing amounts of data, cognitive computing solutions that contain AI technologies are able to support the affected departments with these tasks (Institute of International Finance, 2016a, p. 10).

In summary, it is critical for banks and other FIs to deal with AI featured cognitive computing technologies in order to control costs and increase efficiency in the heavily-regulated risk and regulatory compliance management environment (Institute of International Finance, 2016a, p. 10). However, it must be considered that AI and other cognitive computing technologies are still at a comparatively early stage of implementation. There are several considerations for institutions that have to be addressed. For instance, one question that could arise during the development of cognitive computing solutions is how to determine if an AI featured cognitive computing technology system provides inappropriate advice (Institute of International Finance, 2016a, p. 11). Therefore, the potential impacts and risks of AI cognitive solutions need to be evaluated.

1.2 PROBLEM STATEMENT

FIs are legally required to disclose their financials, risk situation and management information regularly to national and international public supervisory agencies (e.g. BaFin Federal Financial Supervisory Authority, 2011). These demands are an essential part of today's international financial regulation policies (Mishkin and Eakins, 2016, p. 470 f.; Hanson, Kashyap and Stein, 2011). Financial organizations have been confronted with a significant increase of regulations since the international financial and economic crisis of 2007 and 2008. According to an evaluation of the Tech and Finance magazine (2016), more than 20,000 new and extended regulatory requirements for banks and other FIs were created in the year 2015 alone. Moreover, the catalogue of regulations for FIs is expected to exceed 300 million pages by the end of the year 2020 (Tech and Finance Magazine, 2016). This extensive regulation makes it nearly impossible for the affected departments of FIs to be able to implement new requirements at all time (Eggert, 2014, p. 84; Young, 2013).

However, not only the quantity of new regulatory requirements for FIs increases continuously, but also the degree of complexity of the new regulations (Eggert, 2014, p. 7). For instance, Krug, Lengnick and Wohltmann (2015) are convinced that the Basel III regulations of 2010 have significantly increased the complexity of financial regulation in Europe. Governments all over the world purpose to ensure that the financial sector is stable and reliable since it has a significant impact on the overall economy (Matejasak, Teply and Cernohorsky, 2009). In recent years, the development of new products and globally integrated structures made the financial system significantly more challenging to regulate (Allen, Goldstein and Jagtiani, 2018). According to Cao (2012), one of the main reasons for this development is the creation of financial products and services that are getting more complicated (Cao, 2012, p. 78). As a result, it is required to develop detailed regulations in order to minimize the risk that a FI experiences financial difficulties. The liquidation of a single bank or other FI can have a significantly negative impact on both the local and the global economy (Hull, 2015, p. 16; Becker and Buchkremer, 2018b).

It is therefore a high risk for banks and other FIs to be non-compliant with financial regulations (Deutsche Bundesbank, 2017a). Moreover, it is not only difficult to manage, but also cost-intensive for a single FI to stay up to date with the permanent changes of regulations (Herring, 2018). In consequence, FIs are required to deal with the development and implementation of new technological solutions to be capable of managing the increasing amount and complexity of regulations more efficiently in the future (Goltz and Mayo, 2017). Applications that use new technologies can help to ensure that FIs are capable of staying up-to-date regarding the changes of financial regulations (Boella et al., 2013). A further field of action for FIs in this area is subjectivity of decisions. The subjectivity component in people's interpretation of regulatory requirements can lead to mistakes and misinterpretations that can be critical for an institution. Therefore, cognitive computing solutions using AI technologies could be able to help the affected compliance management experts to make knowledge-based decisions rather than choices that are influenced by their subjective interpretation of the stated requirements. When judgment is applied, according to el Ata and Schmandt (2016), the answers are more accurate using AI technologies that consider all decision-relevant data (el Ata and Schmandt, 2016, p. 34). Consequently, the development of AI solutions provides compliance management experts with the chance to focus on other critical tasks and therefore enhance their productivity and intellectual content (Baxter, 2016).

In terms of risk management, according to the global banking risk management survey of 2016 that was executed by Ernst & Young and the Institute of International Finance (2016b), banks and other FIs focus more on non-financial risks like operational risk and topics concerning cybersecurity. For a growing number of FIs, the supervision of non-financial risks is getting more demanding than the supervision of traditional financial risks like credit risk, liquidity risk and market risk. Operational risks and issues concerning cybersecurity are, apart from information technology (IT) risks, primarily driven by errors of human beings, misconduct or lack of information (Lemieux, 2012, p. 47 f.; Ashby et al., 2018). To manage these types of risk in an efficient manner, it is required to process and evaluate a large set of both structured and unstructured data. However, unstructured data are generally challenging to measure and to analyze by using traditional risk management software tools (Arner, Barberis and Buckley, 2017).

Therefore, the global survey highlights that the participating FIs consider new technologies and advanced data analysis methods to be necessary to deal with these types of risk in the near future. In this context, a further field of action is the exponential increase of evaluation data. In 1996, Fayyad (1996) first evaluated a need for technological solutions to analyze and understand the large amount of stored data in the areas of banking and finance (Fayyad, 1996). Since the digitalization of business activities and processes leads to an increase of both structured and unstructured data, FIs are required to deal with the implementation of powerful analysis applications that are capable of dealing with large data sets more efficiently, while offering more comprehensive analysis capabilities (van Liebergen, 2017).

In summary, FIs all over the world struggle with the heavy regulation of the financial sector. Not only the increasing extent of regulations is difficult to manage, but also its increasing degree of complexity. Moreover, banks and other FIs also have to cope with the increasing risks of errors and misinterpretations of regulations by the affected regulatory compliance management experts. With regard to risk management procedures of financial organizations, it must be considered that the supervision of non-financial risks like operational risk and topics concerning cybersecurity have become considerably more challenging in recent years. Therefore, especially FIs have to cope with an increasing extent of unstructured data that is challenging to measure and to analyse. Consequently, it is a strategic priority for several banks and other financial organizations to implement new solutions to deal with these challenges in an efficient manner in the future.

In the following section, the major objectives of this research and the accompanying research questions (RQs) of this dissertation are introduced. Moreover, the structure of the research is outlined.

1.3 RESEARCH QUESTIONS AND STRUCTURE

The main objectives of this research are to develop and analyse strategies to enhance the risk and regulatory compliance management activities and business processes of banks and other FIs by implementing and using new cognitive computing technologies. For this purpose, three RQs are going to be investigated in this dissertation. In a first step, the major fields of action to improve the risk and regulatory compliance management need to be identified and classified. Therefore, the first RQ is:

RQ1 What are the major fields of action to improve the risk and regulatory compliance management of financial institutions?

This first question needs to be regarded from both a theoretical and a practical perspective. In order to answer this question in a theoretical context (RQ 1.1), the available scientific literature is analyzed and evaluated by using text data mining approaches in combination with a cluster analysis and AI technologies. The aim of this method is to discover specific patterns in the analyzed literature and to provide a chronological distribution of the development of this research field. The practical part of this question (RQ 1.2) is addressed by carrying out a survey and expert interviews on the subject matter. The target audience of both the survey and the interviews are executive risk managers and compliance officers of certain FIs in a defined geographic region. To increase the insights of this approach, the survey results are compared to the scientific literature and selected existing acknowledged studies on the subject matter in order to discover correspondences and possible differences.

The second RQ that is addressed in this dissertation focuses on the management of compliance with the increasing number of regulatory requirements. Therefore, the second RQ is:

RQ2 How can the management of regulatory requirements be improved by cognitive computing technologies?

This question is answered from a practical perspective by developing and evaluating an implementation strategy for a cognitive computing application. The aim of this approach is to enhance the management of regulatory requirements by using new technological solutions. In a subsequent step, the developed strategy is compared to traditional regulatory compliance management approaches to discover potential enhancements.

Besides the improvement of the management of regulations, this research deals with the need to develop and evaluate approaches to improve the risk and compliance management business processes through the use of new cognitive technological solutions. For this purpose, the third RQ is:

RQ3 How can risk and compliance management business processes be enhanced by cognitive computing technologies?

This question is also answered by using a practical approach. In particular, a process mining application is used with the aim to improve the execution of risk management business processes at a selected FI. For this purpose, the newly developed strategy is implemented and used to analyse the real-life execution of risk management business process steps to discover potential bottlenecks and non-compliant activities.

In summary, the presented approaches to address these three RQs are illustrated in table 1.

	Fields of action (RQ 1)	**Solutions (RQs 2 & 3)**
Theory-based approaches	Literature research and systemic literature review (RQ 1.1)	-
Practical approaches	Expert interviews and survey (RQ 1.2)	Implementation and usage of cognitive computing technologies (RQs 2 & 3)

Table 1: Approaches to address the research questions

Despite the fact that the Basel Committee on Banking Supervision publishes regulations that affect most banks in the EU, the individual countries also develop banking regulations for banks and other FIs located in a specific country or region. These country-specific regulations can vary significantly (Herring, 2018). For this reason, this research is limited to the financial sector in Germany. Therefore, the following chapters focus on the banking regulations that apply to banks and other FIs in this country. However, to some extent, the overall research results can also be applied to other institutions within and outside the EU. Accordingly, the term "financial institutions" is limited to institutions that provide banking services in Germany. In the context of this research, FIs are defined as all organizations that belong to the banking sector in Germany.[3]

It must be considered that every bank and other FI has different risk and regulatory compliance management strategies and approaches. Consequently, it is not possible to create universal cognitive computing strategies that are adaptable by all institutions in the same way. Therefore, the major goal of this research is not to develop general solutions that can be applied by any institution in Germany. Instead, the aim of this research is to develop a strategy framework that can be regarded as the starting point to concretize specific solutions for an institution.

The first chapter of this research provided an introduction of cognitive computing technologies in the financial sector in general and in the risk and regulatory compliance management environment in particular. Furthermore, the problem statement of this research was discussed in the second section. In this part, the RQs were presented. Chapter two covers an overview of the research background, which comprises foundations of the banking sector in Germany, business process management, risk and compliance management as well as corporate governance, cognitive computing technologies and fields of application for "regulatory technology". In chapter three, a systemic literature review is carried out and the insights of six expert interviews and a survey regarding the future of risk and regulatory compliance management at FIs in Germany are presented and compared to existing acknowledged studies that cover similar thematic fields.

The fourth chapter deals with the development of two cognitive risk and regulatory compliance management strategies. The developed strategies were

[3] The German banking sector is presented in chapter 2.1.

implemented at a selected FI in Germany. Chapter five discusses the research results and provides limitations as well as recommendations for further research on the subject matter. The final chapter of this research (chapter 6) draws a conclusion of this research. The structure of this dissertation is depicted in figure 2.

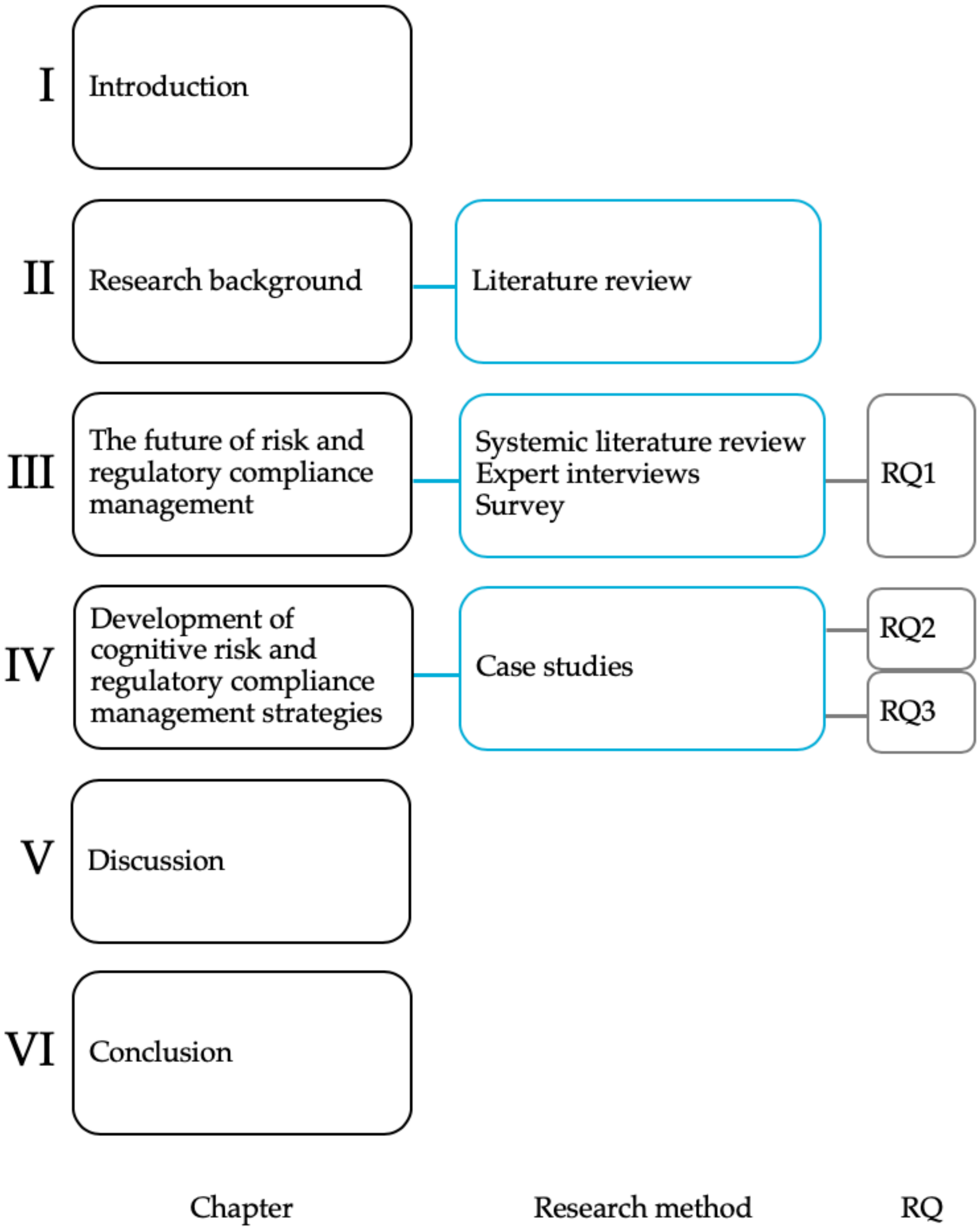


Figure 2: Research structure

2 RESEARCH BACKGROUND

2.1 BANKING SECTOR IN GERMANY

The current structure of the banking sector in Germany developed historically and has its origins in the 19th century. Today's banking system is known as a "Three-Pillar-System" that consists of three different groups of banks and other FIs. The three pillars refer to the legal forms of the institutions. This system is unique compared to the banking sectors of other countries[4] (Deutsche Bundesbank, 2018; Langenohl, 2008).

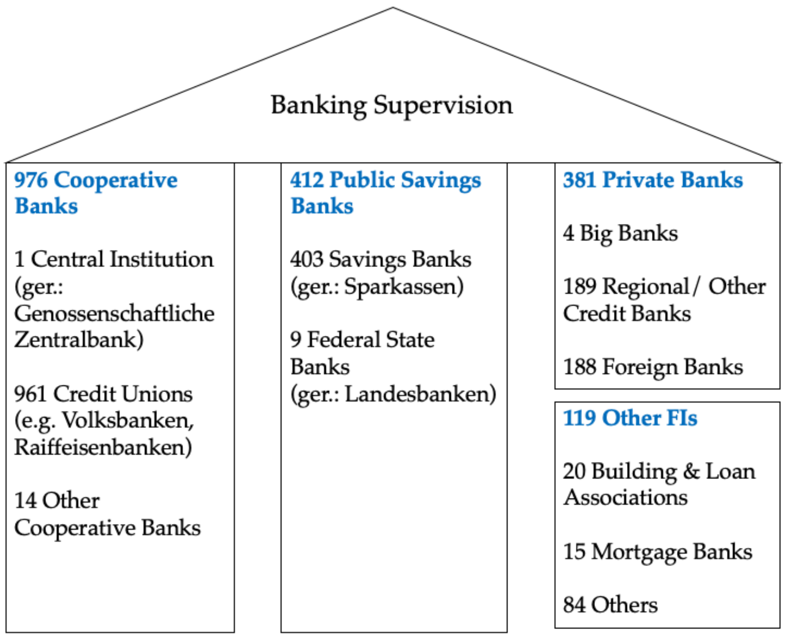


Figure 3: Three-Pillar banking system in Germany

(reporting date: December 31, 2016) [source: own presentation based on (Deutsche Bundesbank, 2017c, p. 3)]

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4 The only country that has a similar banking system is Austria (Deutsche Bundesbank, 2018).

Figure 3 illustrates the individual numbers of institutions in each pillar. The first number of each column is written in blue color and represents the total number of institutions in a pillar (reporting date: December 31, 2016). In total, there were 1,888 banks and other FIs in the German banking sector in 2016. However, it must be considered that the sizes of the individual institutions vary considerably. Regarding the chronological development, it is noteworthy that the total number of institutions decreased significantly in recent years. In the year 1990, there were about 4,700 banks and other FIs in the German banking sector. One major reason for this development have been several mergers and acquisitions in the financial sector (Deutsche Bundesbank, 2018; Achim, 2015).

With regard to the individual numbers of institutions, the cooperative banks are the largest pillar with a total of 976 organizations. The German cooperative banks are legally defined as economic associations that are organized mainly under the Cooperative Law. Most of the 961 credit unions act according to the regional principle (Greve, 2009). The central institution of the cooperative banks is connected to the individual credit unions. The second pillar represents the 412 public savings banks in Germany. They are organized under public and private law. The German public savings banks act according to the principle of subsidiarity and the regional principle. In particular, the regional principle means that the 403 savings banks shall each operate in a specific and different region in Germany. Accordingly, the nine federal states banks (ger. Landesbanken) also cover defined areas. The principle of subsidiarity signifies that savings banks serve the majority of local clients in their geographic regions. However, if a customer exceeds a defined size of business, one of the nine federal state banks takes over the support of the customer. The third pillar consists of 381 private banks and 119 other FIs[5] (Deutsche Bundesbank, 2017c; Deutsche Bundesbank, 2018; Hallerberg and Markgrad, 2018). Private banks are organized under private law. Amongst private banks, there are four so called "big banks". These four institutions perform business operations in many different countries.

[5] The 119 other FIs do not belong to the group of private banks. However, since the group of other FIs is heterogeneous, it is not illustrated as a pillar of its own. For the purpose of this research, the other FIs are allocated to the third pillar.

The largest bank in 2016 was the Deutsche Bank with a balance sheet total of 1,590 billion Euro (reporting date: December 31, 2016). It is one of the leading investment banks in the world (Deutsche Bank, 2017). The three other German big banks of 2016 are the Commerzbank, the Postbank and the UniCredit Bank (reporting date: December 31, 2016). However, in the year 2018, the Postbank was taken over by the Deutsche Bank (Deutsche Bank, 2018). In addition, there are 189 regional or other credit banks and 188 foreign banks in Germany. Foreign banks typically have bank branches in Germany, but their headquarters are in a different country (Deutsche Bundesbank, 2018). Regarding the business operations of the individual organizations, the 1,888 institutions are divided into 1,769 universal banks and 119 special banks. Universal banks carry out a variety of banking and other financial services including credit business, deposit business, investment business, insurance business and others. In contrast to that, special banks focus on one or few specific banking tasks. Among the special banks, there are mortgage banks, building and loan associations and others. As a result, universal banks tend to compensate the risk of a single business division in a better way than special banks (Deutsche Bundesbank, 2018). In the overview in figure 3, special banks are illustrated as other FIs.

Most universal banks are connected to an IT service provider. The Finanz Informatik is the service provider of most public savings banks in Germany. The Fiducia & GAD IT[6] is the provider of most credit unions and credit banks. In recent years, these IT service providers have focused more on delivering process-oriented IT systems for FIs in Germany. Therefore, there are more process-relevant data that are available. This streamlines the implementation of process data evaluation procedures like process mining (Moormann, 2014, p. 12 f.).

With regard to the supervision of the banking sector in Germany, the European Central Bank (ECB) introduced the Single Supervisory Mechanism (SSM) for selected institutions in the EU in November 2014. The SSM regulates that selected meaningful banks are under direct supervision of the ECB (Lackhoff, 2017, p. 1). Therefore, the SSM comprises the national supervisory authorities of the participating countries and the ECB (Pizzolla, 2018). The term significant in this

[6] The Fiducia & GAD IT was founded in 2015 as a merger of the two IT service providers Fiducia and GAD.

context means that an institution is particularly important for the European banking system. In total, 119 institutions are regarded as significant (reporting date: December 5, 2017) (European Central Bank, 2018).

Among those are 19 institutions from Germany.[7] The remaining banks and other FIs in Germany are supervised by the national banking supervisory authority (European Central Bank, 2018).

2.2 BUSINESS PROCESS MANAGEMENT

The organizational structure divides a FI into partial systems, such as divisions, business units and departments, with their individual tasks. The execution of these tasks is carried out through business processes. Furthermore, business processes are required for the coordination of the single tasks (Becker and Kahn, 2003, p. 4). Therefore, according to Becker and Kahn (2003, p. 4), a process can be defined as

"a completely closed, timely and logical sequence of activities which are required to work on a process-oriented business object."

This definition is in accordance to Davenport (1993, p. 5), who defines a process in a broader sense as

"a structured, measured set of activities designed to produce a specific output for a particular customer or market."

An example of a process-oriented business object, as stated in the definition of Becker and Kahn, can be the risk disclosure statement of a FI. On the basis of Porter's model of a value chain, business processes can be divided into core processes and supporting processes. With regard to FIs, a core process is directly related to the products and services offered by the institution, e.g. bank accounts and loans. Consequently, a core process directly contributes to the value creation of a FI. In contrast to that, supporting processes do not create a direct value from the customer's perspective, e.g. back office activities. However, supporting

[7] The current list of significant supervised entities can be viewed on the website of the European Central Bank: https://www.bankingsupervision.europa.eu/banking/list/who/html/index.en.html

processes are also necessary for the business operations of an institution. In general, supporting processes often support the execution of core processes. For this reason, a synonym for supporting processes is the term enabling processes. The boundaries between these two types of processes are not solid. Depending on different contexts, the same process can be categorized as a core process or a supporting process. Moreover, actions that are related to the management of an institution are referred to as management processes (Becker and Kahn, 2003, p. 4 f.; Schmelzer and Sesselmann, 2013, pp. 65-73).

Moreover, the management of business processes

"includes concepts, methods, and techniques to support the design, administration, configuration, enactment, and analysis of business processes"

(Weske, 2012, p. 5). The following sections provide an overview of modeling techniques of business processes in the financial sector. Besides, the lifecycle of business process management is exemplified and the related research fields "process mining" and "Business Intelligence" (BI) are introduced in this context. In the fourth section, the thematic field compliance of business processes is presented.

2.2.1 Modeling of business processes

According to a study in the banking industry that was carried out by Becker et al. (2010), the most relevant techniques to model business processes in financial industries are the Business Process Model and Notation (BPMN), the Event-Driven Process Chains (EPCs) and the activity diagrams from the Unified Modeling Language (UML). These models offer different ways to visualize both business processes and organizational information (Grossmann and Rinderle-Ma, 2015, p. 123 f.). One characteristic that these three process modeling techniques have in common is that they can be applied to several business purposes as they are not domain-specific (Eggert, 2014, p. 12 f.). BPMN is one of the most common business process languages and a widely used standard for process modeling (Dumas et al., 2013, p. 17). For this purpose, the modeling technique BPMN is explained exemplarily in this section.

BPMN provides more than 100 different symbols and various modeling concepts. The basic principles of this language are "event", "activity", "control object" and "sequence flow" (Dumas et al., 2013, p. 64). An event corresponds to something that happens automatically without a defined duration. An event can, for instance, initiate the sequential execution of an activity or a series of activities. These activities take time and therefore have a duration (Dumas et al., 2013, p. 3). Control objects are decision points of a process. Depending on defined conditions, the process takes a different path. Therefore, control objects are also called gateways. Sequence flows or arcs define the order of executions of different parts of a process. In BPMN, events are illustrated through circles with a black frame. Circles with a thin frame line illustrate events that start a process and circles with a thick frame line illustrate the end of a process. Typically, these circles have a white colored filling. Activities are pictured as rounded rectangles and control nodes are illustrated as diamond shapes. Several activities and control objects are connected through the use of arcs. They are pictured as arrows. The direction of a process is illustrated through the position of the arrowheads. Moreover, artefacts can be used to present additional information about a business process. Typically, the model of a business process contains one or more lanes. Each lane shows the activities performed by a particular participant (Dumas et al., 2013, p. 17; Weske, 2012, p. 208 f.). Figure 4 illustrates the visualization of the basic elements of BPMN.

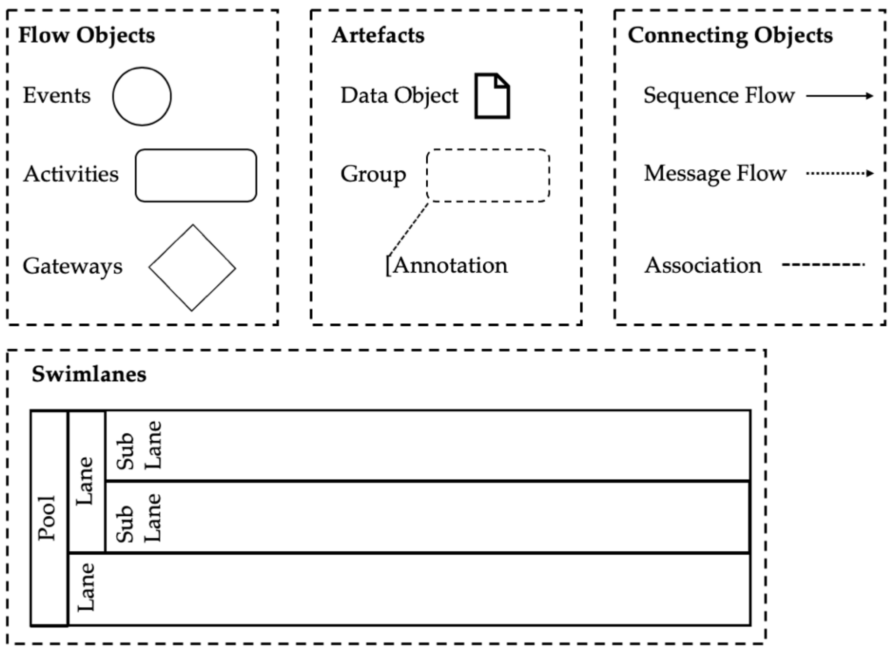

Figure 4: BPMN basic elements

[source: own presentation based on (Weske, 2012, p. 209)]

The basic elements presented in figure 4 allow modeling of simple structures of business processes, while the usage of the complete set of elements allows to model more complex processes. The basic elements of BPMN are simple and therefore easy to understand without extensive training and education. The notation of a business process can be extended with a selection of attributes. The attributes of BPMN can be linked both to a complete process and to particular elements. For instance, if a gateway triggers an individual outgoing edge from a defined set of different outgoing edges, the gateway is labeled with an “X” symbol that indicates its split semantics (Weske, 2012, p. 207). An example of a simple business process modeled with BPMN 2.0 is illustrated in figure 5.

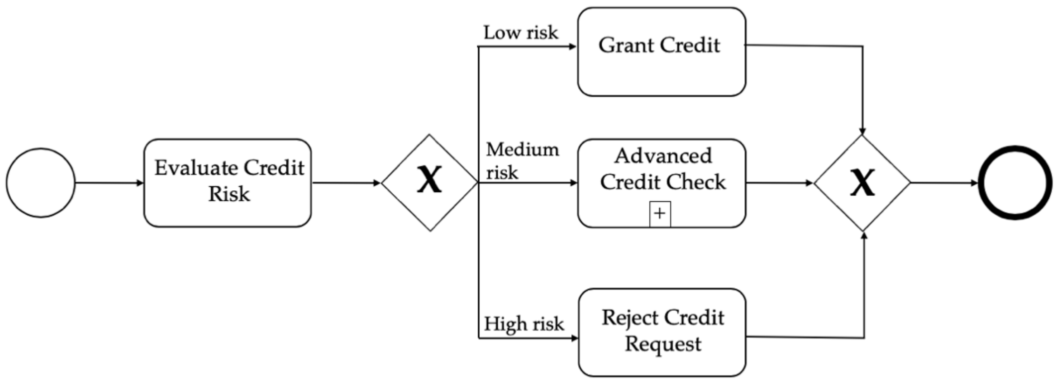

Figure 5: Visualization of a business process using BPMN

[source: own presentation based on (Weske, 2012, p. 227)]

Figure 5 illustrates the process of evaluating a credit request. The participant of this process is a credit analyst of a bank. After the credit risk is assessed by the analyst, a split gateway is reached. The gateway defines which of the three processing activities is executed under defined conditions. These situations are assessed in a defined order. The first condition that is regarded to be true is selected. In this example, it is assumed that the conditions are assessed in descending order from top to bottom. The credit is granted if the credit risk is low. If a medium credit risk is detected, a sub process that performs an advanced credit check is executed. If none of these two conditions is fulfilled, the request is rejected (Weske, 2012, p. 226 f.). The process in figure 5 is modeled at a high level of abstraction. It is intended to give an overview of what happens in this process. The level of detail shown in a business process model generally depends on its purpose (Göpfert and Lindenbach, 2013, p. 21).

The financial market in Germany is characterized by a supply oligopoly. This means that there are only a few market players who have a relative high share in the market (Deutsche Bundesbank, 2018). As a result, there are constant benchmarking activities necessary to discover competitive advantages and disadvantages of the individual institutions. One possible way for FIs to learn from their competitors is an approach called "process benchmarking". By identifying business processes that are adopted by competing FIs, an institution has the chance to gain important information to build a profitable process design (Becker and Kahn, 2013, p. 6). In order to make business processes comparable, it is recommended to visualize them with the same technique.

In this research, the modeling technique BPMN is used to illustrate the business process and its sub-processes that are evaluated through process mining procedures (see chapter 4.2).

2.2.2 Lifecycle of business process management

In general, organizations are intended to constantly review and optimize their business processes for a variety of possible reasons (Sallos, Yoruk and Garcia-Perez, 2017). In terms of risk and regulatory compliance management of FIs, two major reasons for the optimization of business processes tend to be an increase in productivity and therefore a reduction of cost and securing compliance with regulatory and internal requirements (Dumas et al., 2013, pp. 15-21).

According to Dumas et al. (2013, pp. 15-21), the first step of a process review is to identify the business processes that are intended to be improved. This initial phase is called "process identification". Secondly, the identified processes need to be modeled and understood in detail. Dumas et al. call this phase "process discovery". Afterwards, the occurring issues in a specific process are identified and analyzed. Moreover, the issues are assessed and opportunities for process optimization are developed. This phase is hereby called "process analysis". In a further step, the analyzed process is revised with regard to its optimization potential. This phase is named "process redesign". This step is followed by the practical implementation of the optimized business process in order to put it in execution. Accordingly, this phase is called "process implementation". However, this newly-developed process might require small adjustments or even major changes over time if it does not meet the intended expectations. For this reason, the subsequent step is to monitor and control the execution of business processes. Consequently, this phase is named "process monitoring and controlling". Once a business process is identified to be insufficient, the process eventually needs to be redesigned again. For this reason, the different phases are meant to be regarded as being circular. The results of the process monitoring and controlling phase are the starting point for a further discovery, analysis and redesign of a business process (Dumas et al., 2013, p. 15-21; Afflerbach, Hohendorf and Manderscheid, 2017).

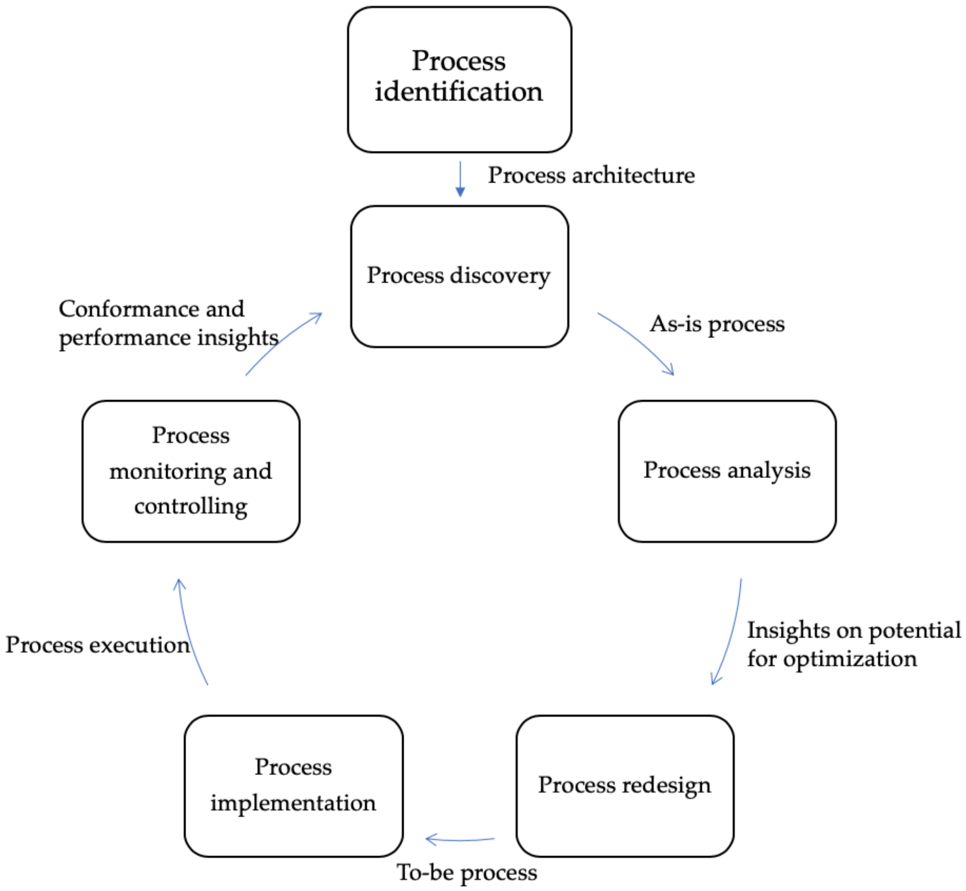

Figure 6: Business Process Management Lifecycle

[source: own presentation based on (Dumas et al., 2013, p. 21)]

Figure 6 shows the different phases of business process management as a continuous cycle. The overarching aim of this method is to discover a current as-is process model and to develop a future to-be process model (Dumas et al., 2013, p. 16). The business process lifecycle can help to understand how technological solutions can be used as a key instrument for the enhancement of business processes (see chapter 4.2.2). In most organizations, technology has become a major tool to manage and execute a large amount of processes (Dumas et al., 2013, p. 23). However, not only the management of existing processes, but also the analysis of needs for improvements can be performed through technological solutions. A modern approach to improve the efficiency of business processes is "process mining". This comparatively young research field is presented in the following chapter (see chapter 2.2.3).

2.2.3 Process Mining and Business Intelligence

Van der Aalst (2016, p. 31) defines process mining as a field of research between the modelling and analysis of processes on the one side and the usage of data mining and machine learning methods on the other side. Therefore, the purpose of process mining is to

"discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's systems"

(van der Aalst, 2016, p. 31). The potential application areas of process mining are wide-ranging. In general, process mining procedures can be implemented in any area where business processes are executed. Regarding the financial sector, a study by Hassel and Leyer (2012) presents the implementation of a process mining tool with the aim to optimize credit business processes at the German Westerwald Bank. Besides, Werner and Gehrke (2015) used process mining procedures for the improvement of financial audits through an analysis of data from financial transactions.

In a broader context, data mining and process mining can be regarded as core parts of the research field of BI (Han, Kamber and Pei, 2012, p. 27). In 1989, Howard Dresner defined BI as an umbrella term for various methods with the aim to enhance business decision making by using computerized systems (Nylund, 1999; Grossmann and Rinderle-Ma, 2015, p. 1).

This general definition of the term BI was specified through various different definitions in the following years. However, the basic intention of BI according to Dresner's definition remained similar (Grossmann and Rinderle-Ma, 2015, p. 1 f.). When the expression “business intelligence” is used, it must be considered that the word “intelligence” does not mean “in an intelligent manner”. In this context, the word “intelligence” can be described as

“gaining insight and understanding of information”

(Hansen and Neumann, 2005, p. 831). The plurality of today's definitions is a sign for an established diverse use of the term BI in research (eds. Rausch, Sheta and Ayesh, 2013, p. 4). The research field of BI became increasingly relevant for businesses in recent years due to a rising digitalization of business processes and an exponential increase in data (Laursen and Thorlund, 2017, p. 18). The basic concepts of both process mining and BI are to process data in a specific manner to reach optimal business-related decisions (Davenport, 2006). In comparison, process mining normally uses more precise approaches to analyze business process data whereas BI applications focus on understanding the real-world behavior of a process (Grossmann and Rinderle-Ma, 2015, p. 8).

BI approaches normally combine different types of algorithms in order to provide a solution for the methodical goal within a defined model. In this context, algorithms are often characterized by the term “mining”. The types of algorithms used in a specific environment can be related to the business perspectives of the analysis goal. In general, the three major business perspectives are “operation” or “production”, “customer” and “organization”. A detailed explanation of the three business perspectives can be found, for instance, in Grossmann and Rinderle-Ma (2015). Figure 7 shows exemplary relations between the different types of mining algorithms and the three basic business perspectives. Note that the figure only intends to give an overview and therefore illustrates common connections between mining algorithms and BI perspectives (Grossmann and Rinderle-Ma, 2015, pp. 13-19).

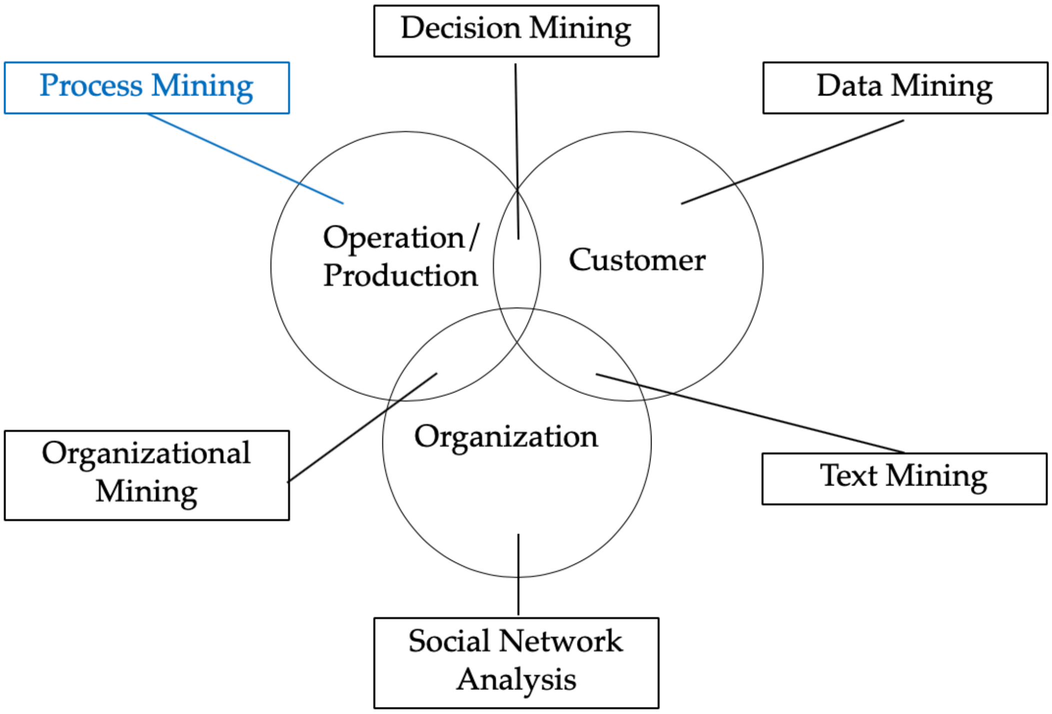

Figure 7: Mining algorithms along the three BI perspectives

[source: own presentation based on (Grossmann and Rinderle-Ma, 2015, p. 19)]

The three circles represent the basic perspectives in a BI analysis. The intersections of the circles show that analytical goals often concern multiple BI perspectives (Grossmann and Rinderle-Ma, 2015, p. 17). Around the circles, the mining algorithms are stated. The line from an algorithm to the circles represents the connection between the BI perspectives and the algorithms. The term "process mining" is highlighted with a different font and frame color than the other algorithms as it is regarded in further detail in this research (see chapter 4.2). Besides the business perspectives, the selection of mining algorithms mainly depends on the view on the data and the methodical goals (Grossmann and Rinderle-Ma, 2015, p. 20). Figure 7 shows that process mining is mainly regarded from an operation or production perspective.

2.2.4 Compliance of business processes

Independent of the modelling technique, FIs have to ensure that the established business processes follow regulations. Therefore, it is critical for FIs to develop compliance-checking approaches in order to ensure that business processes fulfil mandatory regulatory and business requirements at all times (Eggert, 2014, p. 13; Becker et al., 2016).

Since the global financial and economic crisis of 2007-2008, the regulation of business processes is more in the focus of banking supervisory authorities (Dolpp, 2017, p. 13). As a result, FIs regard compliance of business processes as one of the top priorities in the risk and compliance management environment (Becker et al., 2016). According to Ly et al. (2015), compliance management of business processes includes to review and ensure that the implemented processes are compliant with both the internal guidelines and the regulatory framework (Ly et al., 2015).

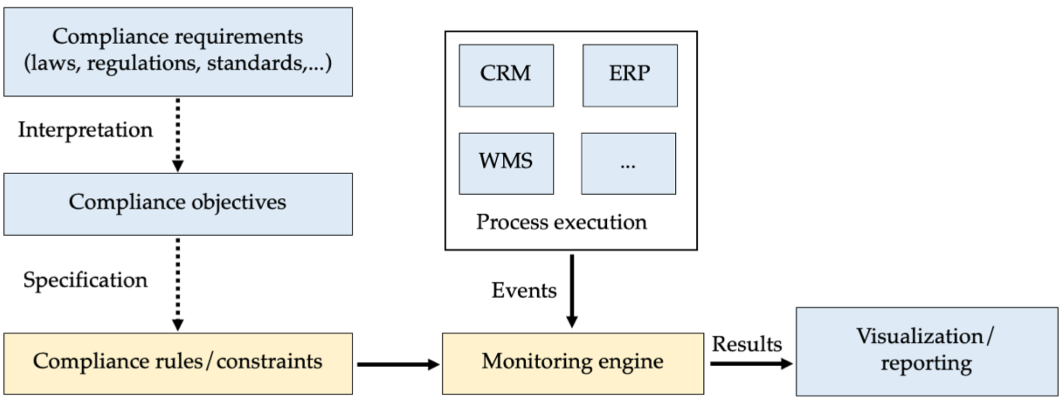

Figure 8: Compliance monitoring for business processes: general approach

[source: own presentation based on (Ly et al., 2015)]

Figure 8 visualizes the different subsequent steps of compliance monitoring activities for business processes. In a first step, it is required to analyze and interpret all relevant compliance requirements and define overall compliance objectives. Furthermore, these objectives are specified to compliance rules and constraints. These rules are then verified over the concerning process execution events in a monitoring engine. In a last step, the results of this verification are visualised and reported (Ly et al., 2015). In the process execution phase, it must be considered that business processes are normally carried out over different information systems like Enterprise Resource Planning (ERP) or Customer Relationship Management applications (Ly et al., 2015).

To ensure business process compliance is an activity that is carried out through all stages of the business process lifecycle (see figure 6). In the discovery and analysis phases, it is required to monitor process compliance and to respond in case violations are detected. At the following (re-)design stage, it is mandatory to review and ensure that all constraints are reflected in the process model. In the implementation and execution phases, it is necessary to check that a running process is compliant with requirements that could not have been reviewed during the process design phase (e.g. output data and real-life run time). Besides, challenges may also arise in the process monitoring and controlling phase. It has to be guaranteed that monitoring and controlling procedures comply with internal and external regulations. However, in many cases, the indication of a violation with internal or external constraints is not sufficient to enable the parties concerned to deal with the violation in an efficient manner. Therefore, strategies with the aim to handle various types of compliance violations need to be developed. Until today, compliance of business processes is often reviewed manually in the risk management environment, for instance by both internal and external auditors (Grossmann and Rinderle-Ma, 2015, pp. 268-271).

However, the manual performance of these activities is often expensive and time-intensive for FIs. Moreover, it is also susceptible for mistakes. Consequently, a cognitive approach to ensure compliance is suggested. In order to deal with compliance violations efficiently, compliance checking tools are required to analyse the reasons for potential violations in further detail. Moreover, tools that are empowered with AI and other cognitive computing technologies can also offer possible solution strategies when a violation is detected or proactively warn the affected users when potential violations are discovered (Grossmann and Rinderle-Ma, 2015, p. 271). A process mining approach that includes compliance checking approaches is developed and presented in this research (see chapter 4.2).

2.3 RISK MANAGEMENT

Risk management is one of the most critical tasks for banks and other FIs. Therefore, banking supervisory agencies especially focus on the risk management activities and processes of these institutions. The financial and economic crisis of 2007-2008 has shown that the world-wide financial system is fragile and can collapse if banks and other FIs fail to manage their risks appropriately. The financial crisis and its negative impacts on the financial sector caused a stricter and more restrictive regulation of FIs, especially with regard to their risk management activities (Adrian, 2017; Lastra and Wood, 2010). In the first part of this section, the European regulatory framework Basel III is presented. Basel III was developed after the financial crisis and has the overreaching goal to prevent such a crisis from occurring again in the future. Besides, the Minimum Requirements for Risk Management for banks and other FIs that belong to the financial sector in Germany are presented. The second part of this section covers the risk reporting activities of FIs.

2.3.1 Basel III and MaRisk

In response to the global financial and economic crisis of 2007-2008 and its negative effects on the overall economy, the Basel Committee on Banking Supervision published a comprehensive regulatory framework, called Basel III, in December 2010.[8] Basel III is a set of reform measures that aims to strengthen the risk management and regulation of financial organizations in the EU (Lall, 2012). However, it must be considered that Basel III is only a framework which was to be transferred into European and national law. Basel III includes and extends the International Convergence of Capital Measurement and Capital Standards document of 2004, known as Basel II (Bank for International Settlements, 2017; Deutsche Bundesbank, 2017d). One major example for the transformation of Basel III regulations into European law is the Capital Requirements Directive (CRD) (Bongaerts and Charlier, 2009).

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8 The original framework, that was published on December 15, 2010, has been reviewed and complemented several times over the years.

With regard to the banking regulations in Germany, a national law that comprises the contents of Basel III is the German Banking Act (ger. Kreditwesengesetz (KWG)).

In terms of risk management, the German Federal Financial Supervisory Authority BaFin (ger. Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin)) regularly publishes revised versions of the Minimum Requirements for Risk Management (ger. Mindestanforderungen an das Risikomanagement (MaRisk)) that are mandatory regulations for all credit institutes and FIs in Germany. The MaRisk aim to specify the requirements stated in section 25a of the German Banking Act KWG regarding the risk management of German FIs. In the MaRisk, the BaFin regulates how the undefined legal concepts of section 25a of the KWG have to be applied in practice. The MaRisk is divided into a general part (ger. Allgemeiner Teil (AT)) and a particular part (ger. Besonderer Teil (BT)) that specifies particular topics. In detail, there are particular parts that cover the internal control systems, the structure of the internal revision and the risk reporting of German FIs (BaFin Federal Financial Supervisory Authority, 2014). The latest version of the MaRisk was published in October 2017.[9] Table 2 shows the structure of the general part of the MaRisk version that was published on October 27, 2017.

[9] The referenced version of the MaRisk can be downloaded using the following URL:
https://www.bafin.de/SharedDocs/Veroeffentlichungen/DE/Rundschreiben/2017/rs_1709_marisk_ba.html

AT 1	**Preliminary Remarks**
AT 2	**Subject matter**
AT 2.1	Scope
AT 2.2	Risks
AT 2.3	Business transactions
AT 3	**Joint responsibility of the management board members**
AT 4	**General risk management requirements**
AT 4.1	Internal capital adequacy
AT 4.2	Strategies
AT 4.3	Internal control system
AT 4.3.1	Organisational and operational structure
AT 4.3.2	Risk management and risk control processes
AT 4.3.3	Stress tests
AT 4.3.4	Data management, data quality and aggregation of risk data
AT 4.4	Special functions
AT 4.4.1	Risk control function
AT 4.4.2	Compliance function
AT 4.4.3	Internal audit function
AT 4.5	Risk management at group level
AT 5	**Organisational guidelines**
AT 6	**Documentation**
AT 7	**Resources**
AT 7.1	Staff
AT 7.2	Technical and organisational resources
AT 7.3	Contingency plan
AT 8	**Adjustment processes**
AT 8.1	New product process
AT 8.2	Modifications of operational processes or structures
AT 8.3	Mergers and acquisitions
AT 9	**Outsourcing**

Table 2: General part of the MaRisk

[source: own presentation based on (BaFin Federal Financial Supervisory Authority, 2017)]

The detailed structure of the general part of the MaRisk shows that the BaFin aims to provide a holistic guideline for FIs how they are supposed to organize their risk management activities and processes. Section AT 4.3.4 is highlighted in a blue font color since this chapter is new in the version of October 2017. In addition to the general part, there is a particular part that covers selected topics in a more detailed manner. Table 3 shows the particular part regarding the organisational and operational structure (BTO).

BT 1	**Special requirements relating to the internal control system**
BTO	**Requirements relating to the organisational and operational structure**
BTO 1	**Credit business**
BTO 1.1	Segregation of duties, and voting
BTO 1.2	Requirements relating to credit business processes
BTO 1.2.1	Granting of loans
BTO 1.2.2	Further processing of loans
BTO 1.2.3	Credit processing control
BTO 1.2.4	Intensified loan management
BTO 1.2.5	Treatment of problem loans
BTO 1.2.6	Risk provisioning
BTO 1.3	Procedure for the early detection of risks
BTO 1.4	Risk classification procedures
BTO 2	**Trading**
BTO 2.1	Segregation of duties
BTO 2.2	Requirements relating to trading processes
BTO 2.2.1	Trading
BTO 2.2.2	Settlement and control
BTO 2.2.3	Capturing in risk control

Table 3: Particular part organisational and operational structure of the MaRisk

[source: own presentation based on (BaFin Federal Financial Supervisory Authority, 2017)]

The regulations of this part of the MaRisk aim to specify certain organisational and operational aspects of section 25a KWG. The regulations in section 25a KWG demand, for instance, valid procedures for the identification, evaluation, governance, monitoring and statement of risks affecting an institution (Bretz, 2015, p. 6). This general requirement is specified in the MaRisk in various sections. In the particular part 1.2 (BTO 1.2), the obligations for the processes regarding the credit businesses are regulated. Furthermore, section BTO 2.2 regulates the risk management processes regarding commercial transactions (BaFin Federal Financial Supervisory Authority, 2017). In a broader context, Claaßen and Matzen (2015, p. 175) state that the MaRisk requirements regarding the process design can be referred to nearly any type of processes concerning the risk management activities of German FIs. Table 4 illustrates the particular part that relates to risk management and risk control processes (BTR).

BTR	**Requirements relating to risk management and risk control processes**
BTR 1	**Counterparty and credit risk**
BTR 2	**Market risk**
BTR 2.1	General requirements
BTR 2.2	Market risk in the trading book
BTR 2.3	Market risk in the banking book (including interest rate risk)
BTR 3	**Liquidity risk**
BTR 3.1	General requirements
BTR 3.2	Additional requirements relating to capital market-oriented institutions
BTR 4	**Operational risk**
BT 2	**Special requirements relating to the internal audit function**
BT 2.1	Tasks of the internal audit function
BT 2.2	General principles relating to the internal audit function
BT 2.3	Planning and conduct of the audit
BT 2.4	Reporting requirement
BT 2.6	Reaction to identified findings
BT 3	**Requirements relating to risk reporting**
BT 3.1	General requirements relating to risk reports
BT 3.2	Reports of the risk control function

Table 4: Particular part risk management and risk control processes of the MaRisk [source: own presentation based on (BaFin Federal Financial Supervisory Authority, 2017)]

The structure of the particular part BTR displays that the BaFin specifies four major risk categories: credit risk (BTR 1), market risk (BTR 2), liquidity risk (BTR 3) and operational risk (BTR 4). These four categories are analysed in more detail in chapter 3.4.3.2.

However, it must be considered that the MaRisk only provide a regulatory framework for the realization of risk management activities and processes. The individual banks and other concerned FIs are responsible for the concrete design and fulfilment of the stated requirements. According to Gerber (2015, p. 120), there are various possible ways to implement these requirements, depending on the type, extent and complexity of their business activities (Gerber, 2015, p. 120). The BaFin defines this as the "proportionality principle" (BaFin Federal Financial Supervisory Authority, 2011).

For global systemically important financial institutions (G-SIFIs), there are even further and more detailed regulatory requirements on the European level. In Germany, for instance, the Commerzbank and the Deutsche Bank belong to the list of G-SIFIs. One significant example for a regulation that especially applies to G-SIFIs is the "Basel Committee on Banking Supervision's Principles for Risk Data Aggregation", which is referred to as regulation number 239 (Basel Committee on Banking Supervision, 2013c). This regulation sets explicit standards for systemically important banks to strengthen their reporting infrastructures and IT systems. G-SIFIs are required to aggregate data mainly automatically and consistently across the institution and its groups (van Liebergen, 2017; Alparslan and Kannemacher, 2015, p. 107 f.). Moreover, it is required that the internal data architecture and IT infrastructure generate precise and reliable risk data (Riediger, 2015, p. 17). In general, it must be considered that the benefits of the risk management activities of an institution primarily depend on the implemented risk management processes and strategies. Therefore, a valuable process management is a key factor for the long-term success of the risk management activities of banks and other FIs. In chapter 4.2, a process mining application is used to analyse and evaluate a risk management business process of a selected German FI.

The subsequent section provides an overview of the risk reporting obligations of FIs in Germany.

2.3.2 Risk reporting

To be capable of monitoring banks and other FIs, national and international supervisory agencies are required to request detailed information about the full range of actions and risk management procedures of the regulated institutions (BaFin Federal Financial Supervisory Authority, 2011; Barakat and Hussainey, 2013). In Germany, FIs are required to submit several regulatory-driven reports to the German Federal Bank (ger. Deutsche Bundesbank). The individual reports that have to be created by German FIs can be downloaded from the web page of the German Federal Bank (Deutsche Bundesbank, 2017b). The web page shows that FIs are required to submit up to more than 100 reports on a regular basis, depending on their individual business environment (Deutsche Bundesbank, 2017b; Eggert, 2014, p. 12). This large extent of mandatory reports makes it challenging for banks and other FIs in Germany to fill out each report manually. Therefore, electronic systems are required that create some of these reports automatically (Eggert, 2014, p. 12 f.).

One system that is used by FIs in this context is the eXtendable Business Reporting Language (XBRL). It is able to produce several financial and business reporting data automatically based on available financial data. Moreover, XBRL supports a transparent electronic exchange of regulatory-driven reports between FIs and supervisory agencies (Hodge, Kennedy and Maines, 2004). XBRL is a platform-independent data exchange technology standard that is based on the common eXtendable Markup Language (XML). XML is a computer language that is used to integrate databases over the internet. A major advantage of XML compared to other computer languages is that it is extensible. The vocabulary of XML can be extended in order to include almost any type of data. In contrast to that, the vocabulary of XBRL is established by standard committees and is not extendable. Therefore, XML is defined as a computer language, whereas XBRL is both a language and a data exchange standard (Bergeron, 2004, pp. 1-10; Institute of International Finance, 2016c, p. 20). XBRL enables FIs to integrate two or more disparate reporting systems that are compatible with the XBRL standards (Bergeron, 2004, p. 12).

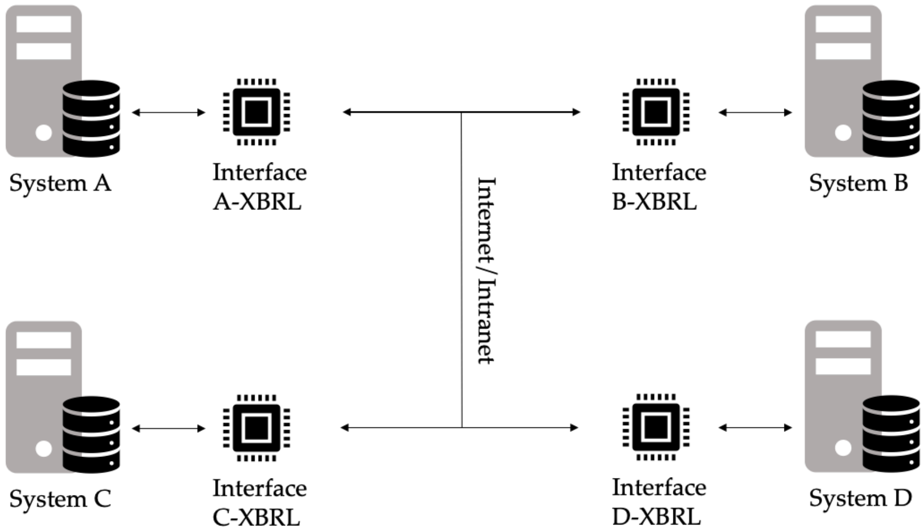

Figure 9: Integration of disparate systems using XBRL

[source: own presentation based on (Bergeron, 2004, p. 13)]

Figure 9 shows that it is sufficient that different systems are compatible with XBRL in order to be compatible with each other through communication over the internet or intranet (Bergeron, 2004, p. 12 f.). This allows a streamlined data transfer between institutions and the supervisory agencies. According to Hodge, Kennedy and Maines (2004), XBRL can enhance the transparency of financial reporting and can therefore reduce information asymmetries between FIs and supervisory agencies. Moreover, they find that XBRL-enhanced search engines can help individual stakeholders that use financial statements of FIs by enhancing the transparency of the financial statement information. For instance, capital investors can improve their investment decisions based on the additional insights available through the use of XBRL (Hodge, Kennedy and Maines, 2004)

There are several risk and regulatory compliance management applications available for FIs that offer an automated data transfer between institutions and supervisory agencies. In chapter 4.1, a selected system-based solution is presented in detail that allows FIs to transfer specific content using XBRL.

2.4 COMPLIANCE MANAGEMENT AND CORPORATE GOVERNANCE

In the year 2012, the Federal Financial Supervisory Authority BaFin implemented compliance regulations into the Minimum Requirements for Risk Management for banks and other FIs in Germany (Beiersdorfer and Buchholz, 2014, p. 510). Therefore, every institution that is affected by the MaRisk is required to establish a compliance function that reports directly to the management of the institution (BaFin Federal Financial Supervisory Authority, 2017: MaRisk AT 4.4.2). Moreover, it is required that the MaRisk compliance function is independent (Beiersdorfer and Buchholz, 2014, p. 510).

In general, there are two major types of compliance requirements for FIs. One of them is the compliance of business processes, which refers to an accurate design and execution of business processes. The other type deals with the aspects of financial reporting and banking supervision requirements. The compliance management activities of FIs are required to address both of these types (Becker et al., 2016). Therefore, Eggert (2014, p. 7) defines the term compliance management

"as the sum of all organizational and technical activities that support the alignment of business processes and information systems with regulatory requirements"

(Eggert, 2014, p. 7). Hauschka (ed. 2007, p. 2) defines compliance in a broader sense as the observance and accordance to defined commandments. Based on this definition, Rath and Sponholz (2014, p. 27) formulate that compliance describes the knowledge and observance of all regulatory specifications and requirements related to an institution. Moreover, compliance includes the initiation and implementation of appropriate processes and to raise the awareness for the conformance of regulations within the institution as well as the control and documentation of the observance of all relevant regulatory requirements towards both internal and external addresses. This comprehensive definition of the term compliance by Rath and Sponholz is used for the purposes of this research.

According to Rath and Sponholz (2014, p. 25), the primary goals of compliance are the prevention of damages, the limitation of losses through an early detection of violations and the observance of organizational duties. The statement of these targets shows that compliance is an ongoing process that has to be embedded into the operational and organizational structure, the business process management and the risk management of an institution. However, several financial organizations are lacking a sufficient compliance management at their institutions (Becker et al., 2016). One major reason for this is that the fulfilment of compliance requirements is not only time-, but also cost-intensive. Especially small and medium-sized institutions are concerned with this issue as they often do not have the necessary capacities to manage compliance matters properly (Mustapha et al., 2018). One further reason for the insufficiency of compliance management is that some institutions do not realize compliance as a benefit for their institutions. Instead, they claim that compliance complicates their businesses and that it does not provide a measurable value for them (Eggert, 2014, p. 8). Therefore, some institutions do not pay enough attention to the subject matter.

A term that is closely connected to compliance management is "corporate governance" (Shleifer and Vishny, 1997). In August 2002, the German Corporate Governance Codex was initially published by the German government commission. Since then, the commission has repeatedly reviewed the codex with regard to new regulations and practical implementations and regularly publishes a new version of the codex.[10] The latest version comprises 15 pages (excluding appendices) and was published on February 7, 2017. In this document, the term compliance is used five times (Regierungskommission Deutscher Corporate Governance Index, 2017). This confirms the close relation of these two fields of action. The combination of regulatory compliance with corporate governance and risk management is referred to as Governance-Risk-Compliance (GRC). This comparatively young research discipline was defined by Racz, Weippel and Seufert (2010) as follows:

"GRC is an integrated, holistic approach to corporate governance, risk and compliance ensuring that an organization acts in accordance with its self-imposed rules, its risk appetite and external regulations through the alignment of strategy, processes, technology and people, thereby leveraging synergies and driving performance".

In a further step, the discipline of GRC can be applied to the business process management of an institution. Based on Rath and Sponholz (2014, p. 55), figure 10 shows the interdependencies of GRC for business processes.

10 The current version of the German Corporate Governance Codex can be viewed using the following URL: http://www.dcgk.de/de/kodex/aktuelle-fassung/praeambel.html

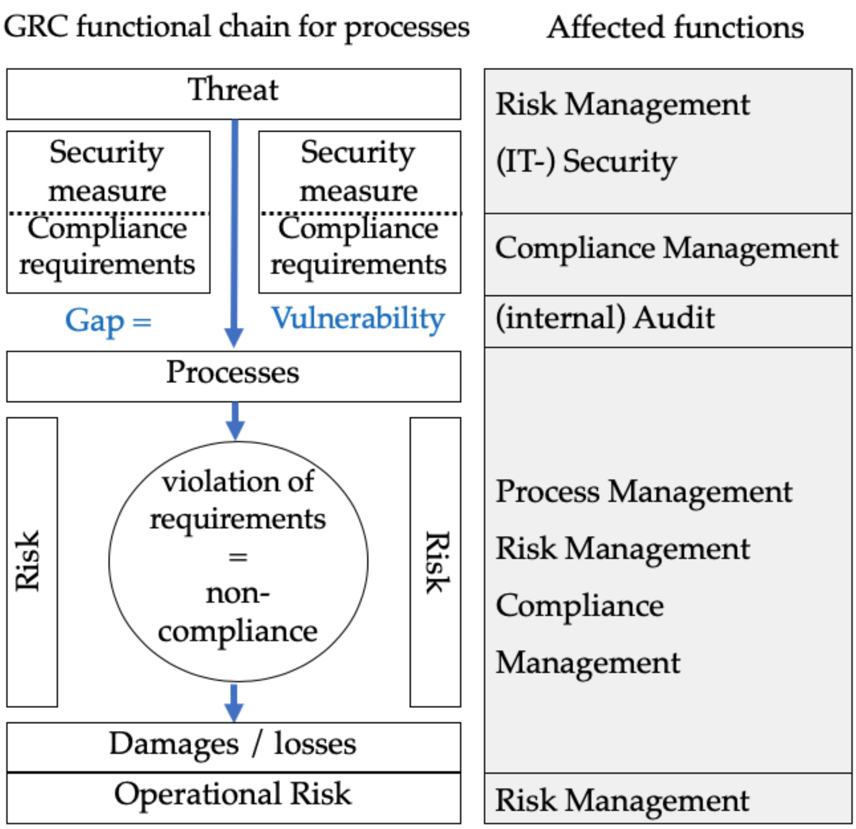

Figure 10: General GRC functional chain for business processes

[source: own presentation based on (Rath and Sponholz, 2014, p. 55)]

The following fictitious case that is based on Rath and Sponholz (2014, pp. 55-57), refers to figure 10 and illustrates the GRC functional chain for business processes on a bank-related example:

Mister A (threat) works as a customer consultant at a bank in Germany. He mainly attends large business clients. One day, a strategically important customer for the bank asks for a credit. Due to the high credit volume, Mister A requires both an approval from the credit review department and from the risk management department (process). Because of an excellent credit rating of the customer, Mister A receives an approval from the credit review department. Unfortunately, the risk management department rejects his credit request for the reason that the required credit volume could cause a major bulk risk for the bank (security measure/

compliance requirement). Fortunately, Mister A finds out that the two risk managers who rejected his request both personally hold shares of the company of his customer. Therefore, Mister A invites the two risk managers for a coffee and explains to them that the rejection of the credit request might have a tremendously negative influence on the stock price of the company of his client. Fearing personal financial losses, the risk managers approve the credit request from Mister A (violation of requirements).

This fictitious example shows how a violation of defined separated business processes can lead to a significant operational risk for a bank. Despite the application of a separation of functions and the four eyes principle, a thread for the institution has occurred. It is the duty of the risk managers to evaluate the situation from a risk management perspective. However, their final decision is influenced by personal aspects that are in contrast to the risk management regulations of the bank (Rath and Sponholz, 2014, pp. 55-57). In this fictitious example, process management applications provided with cognitive computing technologies could have detected and prevented such violations and therefore reduce the operational risk of the institution.

In chapter 4, selected system-based applications that can assist FIs to deal with governance, risk and compliance issues, are presented.

2.5 THE ERA OF COGNITIVE COMPUTING

One term that is commonly used in the context of digitalization is cognitive computing. According to the Gartner Hype Cycle for Emerging Technologies of 2017, cognitive computing as an umbrella term and several cognitive computing technologies in particular, are technology trends that have the potential to deliver a significant competitive advantage for businesses in the near future (Gartner, 2017).

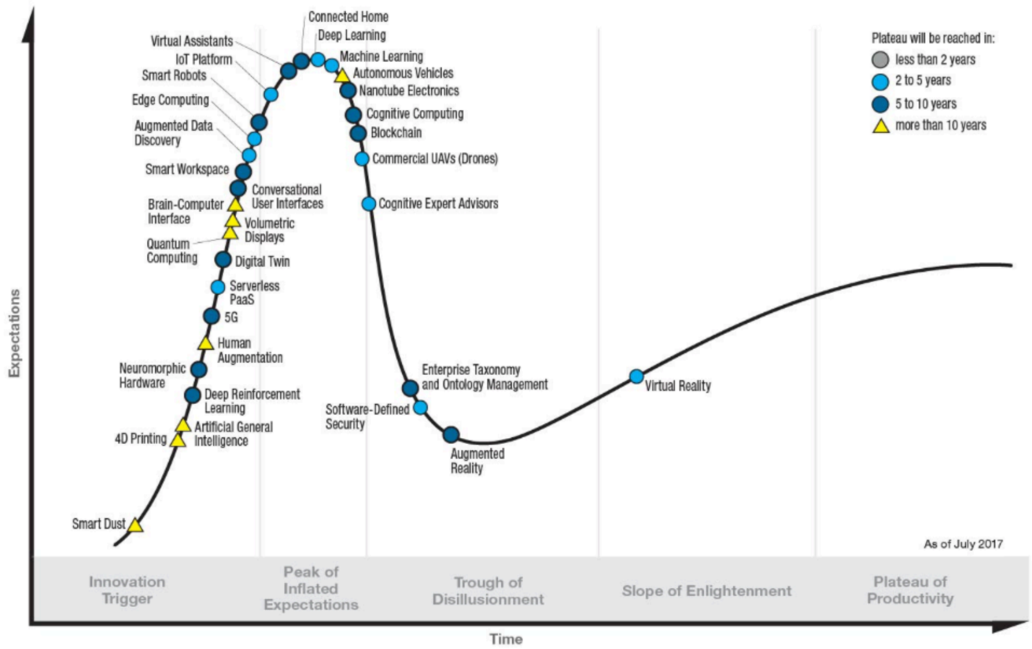

Figure 11: Gartner Hype Cycle for Emerging Technologies 2017

[source: (Gartner, 2017)]

Figure 11 shows that cognitive computing is considered as being a thematic field that is at the peak of inflated expectations. The blue circle next to the term cognitive computing means that its plateau is expected to be reached in the following five to ten years (Gartner, 2017). Moreover, several cognitive computing technologies like AI, machine learning, augmented data discovery, deep learning and cognitive expert advisors are also listed in the Hype Circle for Emerging

Technologies of 2017. This shows the great business potential of cognitive computing technologies.

Haun (2014, p. 4) defines cognitive computing in a general context as an academic discipline that creates cognitive models and uses them as a template to develop and implement problem-solving software and hardware systems. Therefore, cognitive computing describes technology systems that include and combine, for instance, AI technologies, big data, cloud computing, information retrieval, written and spoken language recognition, mining procedures and machine learning.[11] In particular, these technologies combine symbolic and subsymbolic approaches to create problem-solving solutions that could not have been developed through a unique use of these technologies. In this context, symbolic approaches are, for instance, production rules, fuzzy logic[12] and recursive algorithms and subsymbolic approaches are neural networks. In this research, subsymbolic approaches are defined as information processing systems that consist of many simple, combined processing elements that exchange information (Hurwitz, Kaufman and Bowles, 2015, pp. 1-6; eds. Raghavan et al., 2016, p. 6; Haun, 2014, pp. 2-5 and p. 79).

Moreover, cognitive computing is an interdisciplinary field of research that combines several specialist disciplines like philosophy, psychology, biology, computer science, mathematics and physics. Therefore, cognitive computing systems are adaptive, learn, evolve over time, and are able to think and act autonomously. In addition, cognitive systems can deal with complex, uncertain and incomplete information (Hurwitz, Kaufman and Bowles, 2015, pp. 1-6; eds. Raghavan et al., 2016, p. 6; Haun, 2014, pp. 2-5 and p. 79). Figure 12 provides an overview of the interdisciplinary research field of cognitive computing.

[11] It is noteworthy that single cognitive computing techniques are also referred to as soft computing, computational intelligence, organic computing, ubiquitous computing or automatic computing (Haun, 2014, p. 5). These related disciplines will not be further examined in this research.

[12] In this context, fuzzy logic is defined as a method that imitates human behavior to present and manipulate data.

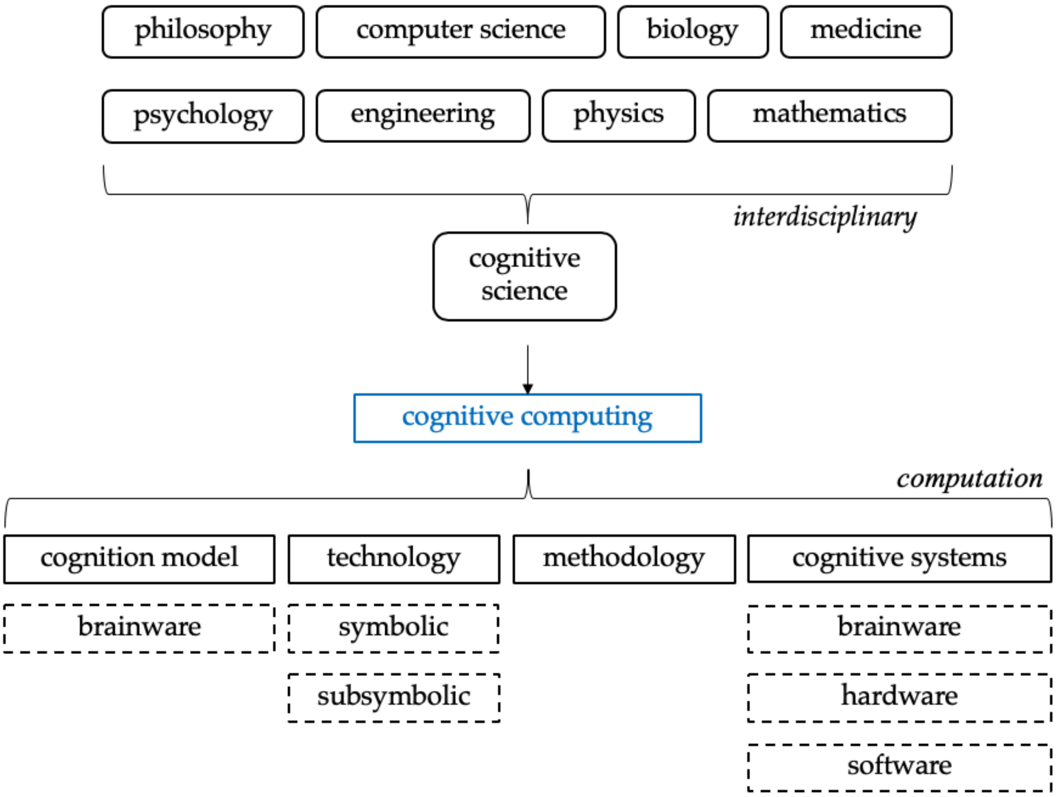

Figure 12: Cognitive computing as an interdisciplinary research field

[source: own presentation based on (Haun, 2014, p. 125)]

Figure 12 shows that cognitive systems combine brainware, hardware and software components. In this context, brainware is defined as a system that manages and carries out all intelligent functions of an artificial system. When brainware is added to hardware and software systems, this allows the development of cognitive solution systems. In comparison to human intelligence, the brain itself would be the hardware component, knowledge and information systems would be the software and intelligence would be the brainware of a human being (Haun, 2014, p. 31 f.). Therefore, cognitive computing combines various aspects of theoretic research and practical application. Cognitive computing systems are required to enhance themselves autonomously in order to solve problems that have not existed yet when these systems have been developed (Haun, 2014, p. 125).

In summary, the overreaching goal of cognitive computing systems is the ability to solve problems that could only be solved by human beings so far. Therefore, human cognition is the natural model for cognitive computing models (Haun, 2014, pp. 1-5). The comparatively young research field of cognitive computing has become significantly more relevant in recent years. One major scientific research project that deals with cognitive computing is called "Human Brain Project" and is promoted by the EU. This project focuses on the development of a platform and a computer simulation of the human brain. In particular, the goal of the human brain research is to increase insights of the human brain as an organ and the cognition as an artefact of this organ through the combination of cognitive sciences and computer sciences. For this purpose, a model of the human brain is developed that includes all the structures of this organ. Based on this model and through the use of super computers, the activities of the human brain are simulated[13] (Human Brain Project, 2018; Haun, 2014, p. 11 f.).

The most advanced cognitive computing system that exists nowadays is named "Watson" and was invented by the American technology company IBM. The company introduced Watson as a cloud-based cognitive system that uses deep natural language understanding, includes contextual information into its autonomous decision making, and is able to reason with incomplete data (eds. Raghavan et al., 2016, p. 7). Watson was introduced to the public in February 2011 when it won the American quiz show "Jeopardy!" against two former human winners of the show. Watson used the knowledge it has stored and combined it with probability calculation methods to answer the questions of the quizmaster (Markoff, 2011). With regard to the thematic field of regulatory compliance management, Watson and other cognitive computing systems could be able to read and memorize all available regulatory requirements in a short period of time. The cognitive capabilities of a selected computing system could then be able to recognize and handle regulatory changes, understand obligations and make suggestions for necessary actions (Agarwal et al., 2017; IBM, 2016).

13 The current status of the "Human Brain Project" can be viewed using the following URL: http://www.humanbrainproject.eu/

Therefore, regulatory compliance management strategies using cognitive computing technologies like Watson can assist FIs to stay up-to-date with the changes of regulations (see chapter 4.1).

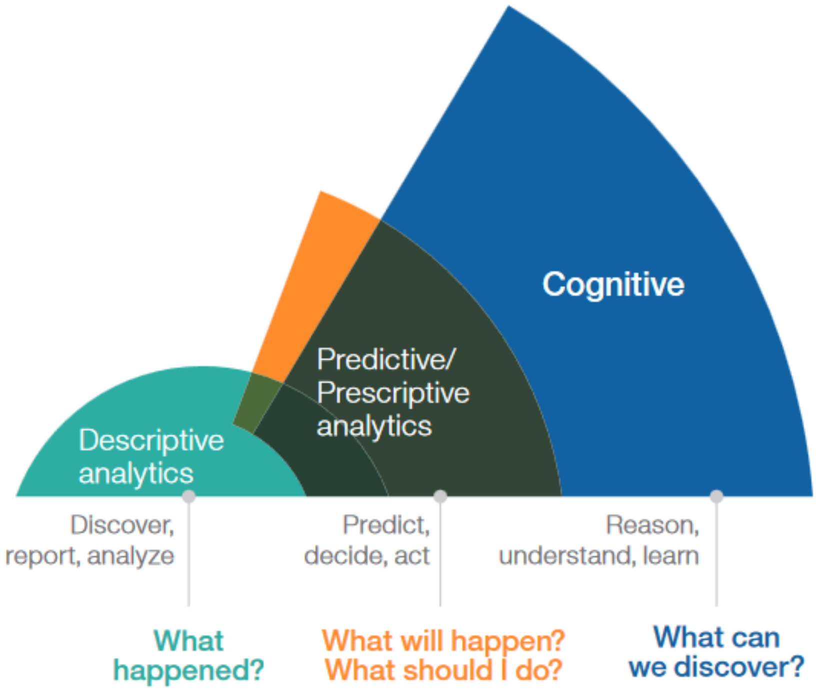

Figure 13: The analytics path to cognitive consists of multiple stages [source: (IBM Institute for Business Value analysis, 2016)]

Figure 13 illustrates that cognitive systems in combination with existing analysis methods have the potential to create an additional value for FIs. Therefore, the fundamental set of methods is descriptive analytics. Descriptive analysis approaches describe and visualize the available data in form of reports (Seiter, 2017, p. 25). However, descriptive methods only display the past and are not able to predict the future. Therefore, predictive analysis methods in combination with descriptive approaches can create forecasts of what could happen in the future under defined circumstances. Furthermore, prescriptive analysis methods can advise what the organization is supposed to do in the future (Seiter, 2017, p. 25).

Cognitive methods can add the abilities to reason, understand and learn to the existing analysis approaches to show the institution what it can discover from its data (IBM, 2016). In the following subsections, AI, data mining and machine learning are introduced as selected cognitive computing technologies that are particularly relevant for this research. Moreover, the thematic field of "regulatory technology" is presented.

2.5.1 Artificial Intelligence

An analysis of the topic-related literature has shown that there are several definitions of the term "artificial intelligence" with different levels of detail used to describe this thematic field (Stone et al., 2016, p. 12; Ginsberg, 1993, pp. 3-9). In the year 1955, John McCarthy, an American computer scientist, was the first person who gave a rough definition of this term. He explained that the goal of AI was to develop machines that behaved as if they were intelligent (McCarthy et al., 1956). This definition leads to the question how the word intelligence is defined in this situation. Therefore, it can be specified that intelligence systems are able to understand, reason, learn and combine (Ertel, 2011, p. 1; Duncan, 2010). In this context, human intelligence is often taken as a benchmark for the capabilities and progresses of AI systems (van de Gevel and Noussair, 2013, p. 9; Zahedi, 1991).

In 1950, Alan Turing (1950) designed a characterizing test of machine systems which act like humans (Hallevy, 2015, p. 7). The basic form of the Turing test is a modification of the imitation game (Li and Du, 2007, p. 4). The test proposes that a human being listens to a conversation between another human being and a machine.[14] The communication is suggested to be a written conversation. The test is passed if the listener is not able to clearly identify who the machine is and who the human is (Turing, 1950; French, 2000).

[14] In the original imitation game, a human being listens to a conversation between a man and a woman.

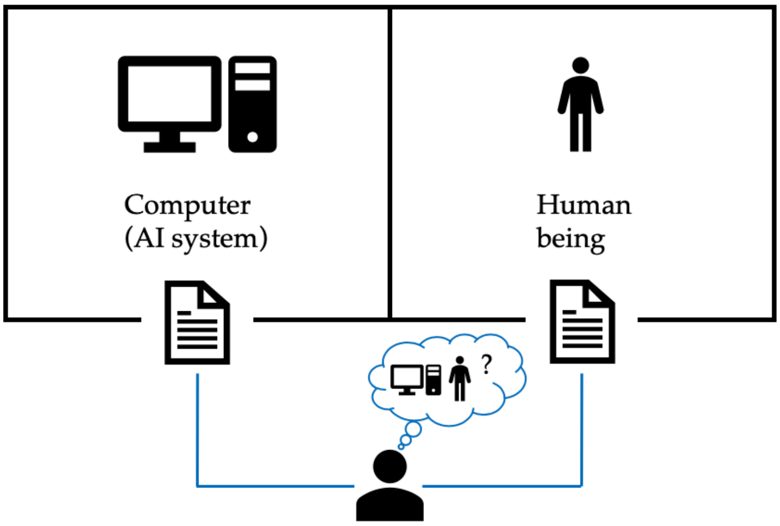

Figure 14: The Turing test for AI systems

[source: own presentation based on (Turing, 1950; Hallevy, 2015, p. 7)]

Figure 14 illustrates the basic form of the Turing test. This experiment has been modified and extended for several scientific researches over time (French, 2000). Nowadays, there are already several AI systems available that exceed the intelligence of humans, at least with regard to speed and accuracy. The subject of intelligence is examined by several different fields of research due to its various aspects. These fields of study include, amongst others, biology, economics, engineering, neuroscience, psychology and statistics. Consequently, these allied fields of research also benefit from progress made in the field of AI (Stone et al., 2016, p. 13 f.). In the year 1965, Hubert L. Dreyfus (1965) already realized the potential benefits of AI technologies for the financial sector. Dreyfus was convinced that AI solutions could improve, for instance, the investment banking activities of FIs in the future.

The first official workshop on the thematic field of AI was organized by John McCarthy. The workshop was called the "Dartmouth Summer Research Project on Artificial Intelligence" and was held in the summer of 1956. The aim of this project was to analyze how machines could be built to simulate different aspects of intelligence (McCarthy et al., 1956; Nilsson, 2010, p. 52 f.). In 1987, Winston (1987) defined AI as the investigation of ideas that allow computers to be intelligent. In a similar manner, Rich (1988) defined AI as the research field that has the goal to investigate how computers can perform tasks that are currently performed by human beings. A more recent definition of the term combined these two definitions by Winston and Rich and stated that AI is the scientific field to make computers perform tasks that require intelligence capabilities when executed by human beings (van de Gevel and Noussair, 2013, p. 11; Kurzweil, 1990; Minsky, 1966). In recent years, the increasing capabilities of AI systems have been accompanied by significant improvements of complementary hardware technologies to perform basic operations like object recognition and data processing. Moreover, new markets and products have also contributed to the increasing usage of AI technologies (Stone et al., 2016, p. 14).

However, when defining the term AI, it must be considered that AI is not one specific technology. It is rather a set of different technology systems that are highly specialized in particular tasks (Stone et al., 2016, p. 4). Therefore, Haun (2014, p. 113) defined AI as the interdisciplinary research field that uses technical systems, specific methods and technologies to create services that can be referred to as intelligent in a common understanding (Haun, 2014, p. 113). Furthermore, Haun defined capabilities and characteristics that are required for a system to be referred to as an AI system. Therefore, the main aspects are listed in the following (Haun, 2014, p. 114):

- the ability to operate with any symbols (not only figures)
- the ability to store and present knowledge
- the ability to process the stored knowledge appropriately to draw reasonable conclusions
- the ability to generalize (abstraction) and to specialize (application of general contexts to concrete circumstances)
- the ability to develop strategies to reach defined goals (problem-solving)
- the ability to learn and to evaluate partial progress or setback
- the ability to act in unclear and incomplete situations
- the ability to recognize patterns and to deal with the environment
- the ability to understand and process human language autonomously

The first three aspects of the list above are fundamental for any AI system because they are necessary conditions for the other abilities listed below them. The most important field of activity of most AI systems is knowledge processing. It is used as an instrument to present knowledge and as a method to handle and extend knowledge. Methods to extract knowledge from an available data base and approaches to use this knowledge target-oriented to solve defined tasks are therefore required (Haun, 2014, p. 114 f.).

One major risk regarding AI technologies is that they might not be accepted by human beings or society. Even though mistakes and errors of tasks that are carried out with the help of AI technologies may be less probable than those driven by humans, they will certainly attract more criticism and a loss of trust (Stone et al., 2016, p. 42). For this reason, it is critical to develop and implement AI systems that are reliable and therefore trustworthy for human beings.

2.5.2 Data mining and machine learning

Data mining describes an automatized, or semi-automatized, evaluation of high volumes of available data in order to discover specific patterns and connections (Witten et al., 2017, p. 9). For this purpose, data mining is a domain that is application-driven and integrates several techniques from other domains like machine learning, pattern recognition, statistics and others. An overview of common techniques that are used in combination with data mining is given in figure 15 (Han, Kamber and Pei, 2012, p. 23).

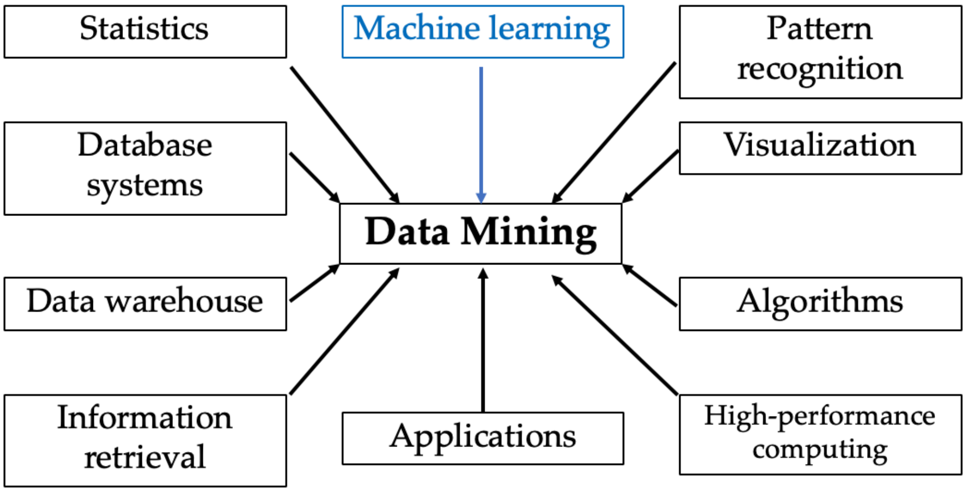

Figure 15: Common data mining techniques from different domains

[source: own presentation based on (Han, Kamber and Pei, 2012, p. 23)]

The wide-spread use of different disciplines contributes to the increasing relevance of data mining applications (Han, Kamber and Pei, 2012, p. 23). A detailed view on the single techniques is provided, for instance, in Han, Kamber and Pei (2012). This research focuses especially on machine learning and its connection to data mining (see chapter 4.1). Therefore, the term "machine learning" is highlighted in figure 15 through the use of a different font and frame color.

Machine learning technologies aim to identify relationships or specific patterns in a data sample and create a model that incorporates these relationships which lead to out-of-sample predictions (van Liebergen, 2017). Han, Kamber and Pei (2012, p. 24 f.) describe machine learning as a technology that investigates how computers are enabled to learn based on data. The field of machine learning has especially benefited from deep learning technologies, which are a form of trained adaptive artificial neural networks. The main method to train these networks is called backpropagation (Stone et al., 2016, p. 14). Machine learning technologies are able to analyze large sets of data in a comparatively short period of time. Therefore, machine learning technologies offer detailed and adaptive predictive analysis (Khandani, Kim and Lo, 2010; Shmueli, 2010).

Furthermore, data mining approaches that are based on machine learning technologies are capable of analysing and clustering large data-sets of structured and unstructured data, such as documents, E-Mails, spoken words or metadata. Therefore, machine learning and data mining capabilities enable the creation of accurate self-improving data analysis, modeling and forecasting approaches (Institute of International Finance, 2016c, p. 4; Sebastiani, 2002). Furthermore, these technologies enable FIs to deal with high volumes of multi-dimensional data (Shim et al., 2002).

For this reason, machine learning and data mining technologies are used in this research to improve the analytical capabilities of FIs in the areas of risk and regulatory compliance management (van Liebergen, 2017). For instance, newly developed risk and compliance management models that use machine learning and data mining approaches offer FIs deeper insights into risk data than previous models (Institute of International Finance, 2016c, p. 12). However, the increasing depth and granularity of predictive analysis can lead to an increased model complexity and result in a deficit of explanatory insight. This can cause issues when internal or external supervisors audit the applied models and therefore need to understand its functions. Supervisors demand risk models to be clear and understandable in order to be appropriate for validation purposes. Therefore, machine learning technologies that are used for risk and regulatory compliance management aim to combine the abilities of detailed predictive analysis with model simplicity in order to improve the auditability of the implemented systems (van Liebergen, 2017; Lin and Hsu, 2014).

A practice-oriented example for the usage of data mining approaches in the risk management environment of FIs is presented, for instance, by Groth and Muntermann (2011). They implemented data mining evaluation metrics to analyse unstructured, textual data like corporate disclosure statements or news articles to predict intraday market risk. In their research, they investigate the impact of information gathered from unstructured data on stock price volatilities. Groth and Muntermann evaluate that the analysis of textual data through text data mining approaches delivers valuable insights for the financial risk management of FIs (Groth and Muntermann, 2011). Furthermore, Saha, Bose and Mahanti (2016) present a data mining approach to implement an automated system-based compliance auditing scheme for the analysis of credit exposures for FIs. The developed applications are able to predict the risk level and risk impact of credit exposures and therefore ease the detection of fraudulent data. For this purpose, the models used text mining procedures to discover deviation pattern components from unstructured, textual data in credit exposures (Saha, Bose and Mahanti, 2016).

In chapter 3.1, a data mining approach in combination with a cluster analysis is presented to investigate the scientific literature that deals with cognitive computing technologies in the financial sector. Moreover, text mining and machine learning capabilities are used by the cognitive computing applications that are introduced in chapter 4.

2.5.3 Regulatory technology

Due to the increasing digitalization of the financial industry, financial technology, referred to as "FinTech", has become increasingly important for FIs. In recent years, especially payment systems, funding platforms and financing procedures have been impacted by FinTech systems (Gabor and Brooks, 2017). With regard to risk and compliance management demands, new technological solutions are designated as regulatory technology, or "RegTech" (Institute of International Finance, 2015, p. 2). The Institute of International Finance (2015, p. 2) defines RegTech as

"the use of new technologies to solve regulatory and compliance requirements more effectively and efficiently".

In a similar manner, Arner et al. (2017) define RegTech as

"the use of technology, particularly information technology, in the context of regulatory monitoring, reporting and compliance"

(Arner et al., 2017). According to Arner et al. (2017), FIs require RegTech solutions, for instance, to handle the rapid changes of regulations and regulatory requirements in the financial sector in a more efficient manner. An important requirement for the realization of RegTech solutions is that FIs create IT and risk management infrastructures that are able to integrate these new technological solutions (Arner et al., 2017). FIs have already started to apply initial RegTech solutions. However, compared to current innovations in the areas of FinTech and other technologies, RegTech is at an early stage of development (Institute of

International Finance, 2016c, p. 2 f.). Therefore, the Institute of International Finance (2016c, p. 3) expects

"that we are only at the early stages of a RegTech market, with more development of new solutions in the near future"

(Institute of International Finance, 2016c, p. 3). Currently, there are only few widely used and standardized RegTech solutions available. These applications mainly focus on digitalizing manual regulatory reporting and compliance management procedures (Arner et al., 2017; Baxter, 2016). One major reason for the hesitation of FIs to implement RegTech solutions is that there are repeatedly new and fundamentally revised regulatory requirements presented. These permanent changes make it difficult for FIs to choose a particular RegTech solution (Institute of International Finance, 2016c, p. 5). Therefore, FIs require RegTech applications that are able to immediately adapt to changes in regulatory requirements. As a result, FIs would not have to be concerned about being out-of-date regarding regulatory requirements and its implementation in the future. Figure 16 provides an overview of RegTech start-ups in Europe in the financial services industry between 2013 and 2017 (CB Insights, 2018).

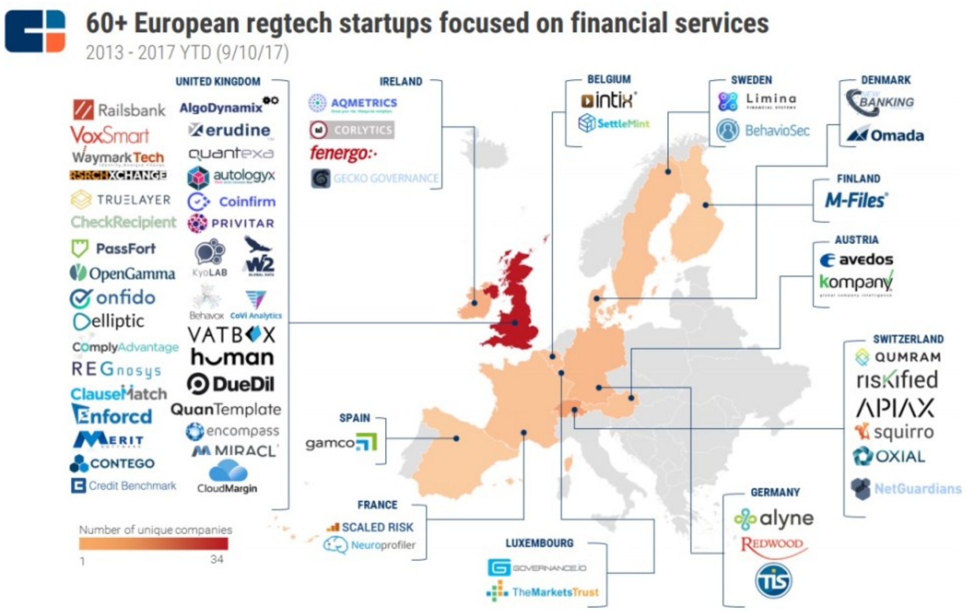

Figure 16: 60+ European regtech startups focused on financial services [source: (CB Insights, 2018)]

The map shows that most RegTech startups that were founded in Europe between 2013 and 2017 are located in the United Kingdom. Only three of more than 60 startups are situated in Germany. On the one side, this shows a significant backlog of the German IT industry in this sector in comparison with other European countries and on the other side, it shows a substantial market potential (CB Insights, 2018).

In order to regard this topic in further detail, the thematic fields of RegTech applications are analysed in the following section (see chapter 2.6).

2.6 FIELDS OF APPLICATION FOR REGULATORY TECHNOLOGY

One major reason for the increasing need for cognitive technologies in the financial sector is the exponential increase of data, which is referred to as "big data". A high amount of data can help AI-powered cognitive technologies to learn by examining new information and evaluating them to search for connections and specific patterns. Due to the exponential increase of available data and the development of new technological solutions that are capable of processing high amounts of data, the cost of collecting and processing digital information has declined over the years. This development made data processing technologies for institutions more affordable and therefore more useful (Institute of International Finance, 2016a, p. 3-6).

In March 2016, the Institute of International Finance published a research report called "Regtech in Financial Services: Technology solutions for Compliance and Reporting". The aim of this report is to estimate the development of the RegTech market to identify major fields of action for FIs and to discuss the question how FIs could benefit from RegTech solutions in these areas. The research report is mainly based on inputs from the members of the Institute of International Finance. According to their research, there are seven main issues that could especially benefit from RegTech solutions (Institute of International Finance, 2016c, p. 3):

1. Aggregation and management of risk data
2. Modeling, forecasting and scenario analysis for risk management and stress testing
3. Monitoring transactions of payments
4. Identification of legal persons and clients (know-your-customer principle)
5. Complying with customer protection requirements
6. Trading in financial markets
7. Identification and interpretation of new regulations

These seven issues can be classified into three different categories. Risk data aggregation and management (1), modeling, forecasting and scenario analysis for risk management (2) and identification of new regulations (7) can be classified as "risk and regulatory compliance management".

Monitoring of transactions (3), identification of legal persons and clients (4) and compliance with customer protection processes (5) are issues that deal with “security”. Finally, issues regarding trading in financial markets (6) belong to the “trade” category. The classification of these seven issues is visualized in figure 17 (Institute of International Finance, 2016c, p. 3).

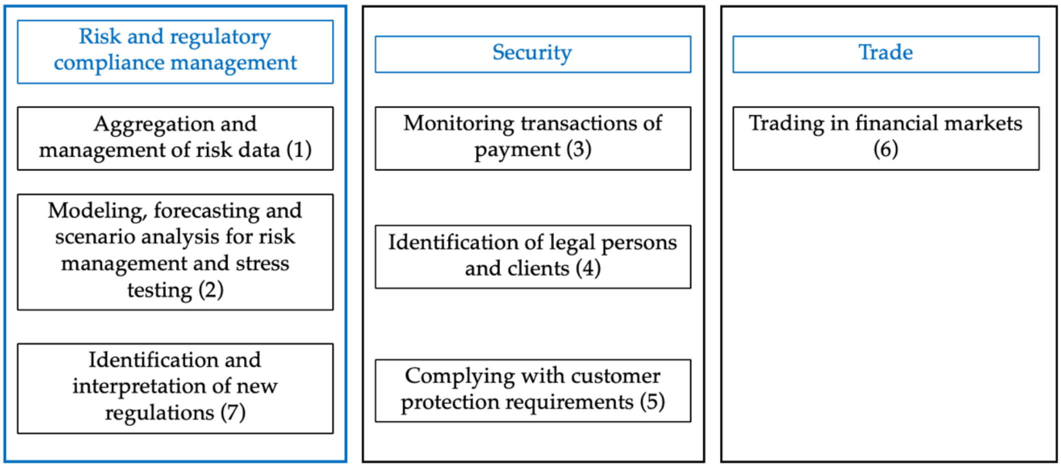

Figure 17: Classification of RegTech categories

[source: own presentation based on (Institute of International Finance, 2016c, p. 3)]

Since the aim of this research is to develop cognitive risk and regulatory compliance management strategies, the issues of the first category are analyzed in detail in the following sub-sections. Therefore, this category is highlighted by a thick frame in blue color in figure 17. The remaining two categories “security” and “trade” are framed in black color and are not examined in further detail in this research.

2.6.1 Aggregation and management of risk data

The term “risk data aggregation” is defined by the Basel Committee on Banking Supervision as

“defining, gathering and processing risk data according to the bank’s risk reporting requirements to enable the bank to measure its performance against its risk tolerance/appetite. This includes sorting, merging or breaking down sets of data”

(Basel Committee on Banking Supervision, 2013c). In the context of this research, this definition of risk data aggregation is applied for both banks and other FIs. Since supervisory agencies require large sets of granular data, it is critical for FIs that the sets of risk data are of a high quality. In particular, quantitative risk data need to be structured, consistently defined, accurate and complete (Institute of International Finance, 2016c, p. 6).

There are numerous regulations that are relevant to the aggregation of risk data. One major field of action are the capital requirements that are stated in Basel III for banks and Solvency II for insurance companies. They require a detailed reporting of risk data for the calculation of capital requirements. Besides, liquidity requirements demand FIs to evaluate large sets of risk data to perform various calculations (Institute of International Finance, 2016c, p. 7). Under Basel III, for instance, banks have to calculate several Liquidity Coverage Ratios (LCRs) and Net Stable Funding Ratios (NSFRs) on a regular basis (Basel Committee on Banking Supervision, 2013a; Basel Committee on Banking Supervision, 2013b). Some of these liquidity figures need to be reported even on a daily basis (Basel Committee on Banking Supervision, 2014; Ruozi and Ferrari, 2013, pp. 29-37). Moreover, the calculation of the LCRs and NSFRs requires the application of regulatory mandated assumptions and haircuts.

Another field of action that requires an extensive input of risk data is stress testing. FIs have to perform several stress test scenarios in order to determine their individual stability in different extraordinary situations (Institute of International Finance, 2016c, p. 7). The thematic field of stress testing is explained in the following chapter 2.6.2.

However, several banks and other FIs have difficulties to aggregate their risk data efficiently on an automated basis. Several internal IT issues and legal restrictions make the aggregation process a manual and labor-intensive task for the risk and regulatory compliance management departments. One major problem is that FIs normally use numerous different IT systems that have been built from different applications that are not always compatible. Besides, some risk management IT systems that are still in use are outdated and inefficient. One further issue is that data regulations complicate the aggregation of risk data for FIs. Regulatory requirements in terms of data localization, data security and data privacy force FIs to store specific data in decentralized data warehouses. This makes data consolidation activities within a financial group a difficult task. As a consequence, some risk data is under-analyzed and over-protected (Institute of International Finance, 2016c, p. 8).

These insights show that FIs require the support of new technological solutions in order to aggregate and manage their risk data more efficiently. Technical applications that are featured with cognitive capabilities enable FIs to gain deeper insights from their risk data. The following section covers the processing of risk data to perform several analysis tasks (see chapter 2.6.2).

2.6.2 Modeling, forecasting and scenario analysis for risk management and stress testing

There are also several regulations concerning the modeling, scenario analysis and forecasting of risk data for banks and other FIs (Kavassalis et al., 2017). For instance, Basel III and Solvency II include capital and liquidity frameworks that require model-based estimations of risks and capital needs. Besides, the analysis of stress test scenarios requires the modeling of defined external events, such as shocks in economic growth, on the sustainability, solvency and liquidity of a FI. Stress testing activities are one of the most demanding regulatory requirements in terms of modeling and forecasting. FIs need to use a selection of quantitative and qualitative techniques to simulate the effects of defined scenarios on their institutions (Institute of International Finance, 2016c, p. 8 f.; Basel Committee on Banking Supervision, 2009). For this purpose, the European Banking Authority (2018) published comprehensive "guidelines on stress testing and supervisory stress testing". The purpose of these documents is to guide FIs in Europe on how they are supposed to design and execute a stress testing programme within their institutions (European Banking Authority, 2018). These guidelines have been revised several times over the years. The current version was published in October 2017. Stress tests can be performed both by an institution itself and by external financial supervisory authorities. Failing a stress test can have a tremendous negative effect regarding the reputation of a FI. In June 2018, for instance, the American Federal Reserve Bank published the results of a stress test named "Comprehensive Capital Analysis and Review 2018". In this annual test, the Federal Reserve Board investigated the capital plans of the 35 largest banks that operate in the United States of America. As a result, one of the 35 institutions failed this stress test due to an insufficient crisis management (Board of Governors of the Federal Reserve System, 2018). The institution that did not pass the test, the Deutsche Bank USA Corporation, was in the news not only in the United States, but also in several further countries (e.g. Cuny, 2018; Egan, 2018; Teichmann, 2018).

With regard to credit risk management, banks and other FIs need to perform a detailed modeling and forecasting of the "expected credit loss" of their credit portfolio. In order to be capable of performing these analysis tasks, FIs require powerful technical applications that are capable of processing large amounts of data with millions of observations and forecasts. Therefore, data mining, AI and machine learning techniques are required to build cognitive prediction tools that are capable of performing these mandatory tasks more efficiently (Institute of International Finance, 2016c, p. 9).

2.6.3 Identification and interpretation of regulatory requirements

The identification of relevant new regulatory requirements, the estimation of their potential implications and the allocation of obligations are complex tasks that are traditionally difficult to automate and are therefore labor-intensive for the risk and regulatory compliance management departments of FIs. Moreover, world-wide operating FIs are challenged with local, regional and global regulations that differ and are constantly changing. Therefore, a significant capacity of human resources is required to keep track of the different regulatory requirements (Institute of International Finance, 2016c, p. 11).

Consequently, the analysis and implementation of regulations is a time consuming and cost-intensive task for FIs. Therefore, these institutions require the assistance of technical applications that are capable of supporting the experts of FIs to identify and interpret relevant regulatory requirements more efficiently. In chapter 4.1 of this research, selected applications of different technology companies are presented that aim to partly automatize and streamline this task. Moreover, a strategy is developed, how the use of cognitive technical capabilities can improve the management and processing of new and updated regulations (see chapter 4.1).

2.6.4 Implementation barriers

The presented report of the Institute of International Finance also identifies significant difficulties and barriers with regard to the implementation of RegTech solutions (Institute of International Finance, 2016c, p. 4 f.). One major concern affects IT and data protection regulations. Extensive IT requirements for FIs are responsible for an increasing complexity of IT systems. Besides, strict data protection regulations for regulatory data can result in an ineffective information sharing across financial groups and can lead to parallel bunkering of information. Therefore, the Institute of International Finance claims a revision of the regulations concerning the use and sharing of data for regulatory compliance purposes. This issue mainly concerns financial supervisor authorities. FIs have to adhere to the regulations published by these authorities. Therefore, this first issue is not regarded further in this research (Institute of International Finance, 2016, p. 4 f.).

The second concern is related to a lack of data harmonization within financial groups. According to the research of the Institute of International Finance, many FIs do not provide an integrated data taxonomy. This makes it difficult to aggregate risk data on an automated basis across financial groups. Another concern is that some regulatory agencies use reporting portals that are not up to date. This can lead to inefficiencies and errors in reports. Therefore, the institute recommends a review and an update of reporting portals and applications to enhance efficiency in the reporting processes for both FIs and regulators (Institute of International Finance, 2016c, p. 4 f.).

3 THE FUTURE OF RISK AND REGULATORY COMPLIANCE MANAGEMENT

The third chapter presents a systemic literature review, expert interviews and a survey on the past, present and future of risk and regulatory compliance management of FIs. The aim of these approaches is to answer the first RQ of this dissertation ("What are the major fields of action to improve the risk and regulatory compliance management of financial institutions?"). In the first part of this chapter, more than 2,000 papers are analysed using a text mining approach in combination with a cluster analysis. The goal of this method is to discover the content of papers that deal with cognitive computing technologies in the banking and finance environment. With regard to the purpose of this research, it is essential to analyse whether risk and regulatory compliance management are relevant topics (see chapter 3.1). A further approach to analyse the relevance of cognitive computing in the risk and regulatory compliance management environment is to carry out expert interviews and a subject-related survey. The purpose of both the expert interviews and the survey is to provide practical expert assessments on the subject matter. In the second part of this chapter, these two approaches are introduced and compared (see chapter 3.2). Afterwards, the objectives and the content of the interviews are explained. In addition, the preparation of the interviews is presented, and the interview participants are introduced. Furthermore, the outcomes of the interviews are stated (see chapter 3.3). The fourth section of this chapter deals with a topic-related survey. In a first step, the major objectives and the content of the survey are illustrated. Afterwards, the survey framework is explained. In detail, the creation of the survey form, the target audience and the timeline are discussed. The main part of this chapter is the presentation of the research results and a comparison to the scientific literature and to selected acknowledged surveys that cover similar thematic fields. Additionally, a critical view on the research results is stated (see chapter 3.4). Moreover, an interim conclusion is presented covering the results of the systemic literature review, the expert interviews as well as the survey (see chapter 3.5).

3.1 SYSTEMIC LITERATURE REVIEW

It is a critical task for banks and other FIs to deal with cognitive computing technologies to discover the most promising fields of application (see chapter 1). However, the available scientific literature tends to focus on individual applications of cognitive computing technologies rather than analysing a variety of possible application areas. For instance, the research of Bahrammirzaee (2010) is limited to the use of selected cognitive technologies for credit evaluation, portfolio management and financial forecasts. Also, Ngai et al. (2011) limit their research on financial fraud detection through the use of AI-featured cognitive technologies. On the other side, studies that analyse a variety of applications in banking, like Moro, Cortez and Rita (2015) are limited to a comparatively short time frame. For instance, Moro, Cortez and Rita limit their research on the period between 2002 and 2013. Consequently, there is a lack of a comprehensive overview of cognitive computing featured applications in the financial industry. Therefore, this section aims to provide the first holistic overview of the development of the scientific relevance of different application areas of cognitive computing technologies like AI at FIs. For this purpose, more than 2,200 abstracts of journal articles have been analysed through text data mining procedures in combination with cluster analysis techniques in order to discover further topics that were dealt with. This approach enables a holistic review of a high amount of publications that cover themes connected to cognitive computing and banking & finance. As a result, this section presents the first chronological distribution of the scientific development of the subject matter. Moreover, this approach enables to discover the main research areas of cognitive technologies at FIs. With reference to this research project, it is regarded whether risk and compliance management are relevant topics.

The first subsection presents the theoretical background of this part of the research. In particular, related studies are presented and the two major analysis methods text mining and cluster analysis are explained. Subsection three describes the design of this research approach. The following section covers a presentation and discussion of the research results.

3.1.1 Related studies

There are several scientific articles that cover related and comparable thematic fields as the systemic literature review in this research. An overview of selected comparable studies on the subject matter is presented in table 5.

Title	**Investigated articles**	**Research target**	**Method(s)**
Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation	219 articles	Analysis of trends in BI in the banking sector	Text mining and latent Dirichlet allocation modeling
The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature	49 articles	Analysis of the usage of Data Mining to detect financial fraud	Literature review and classification scheme
A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert systems and hybrid intelligent systems	about 200 articles	Analysis of AI applications in the financial industry	Comparative literature review
Financial crises and bank failures: A review of prediction methods	40 articles	Recommendation on further research to prevent future financial crisis	Review of empirical results

Table 5: Related systemic literature review studies

The research article "Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation", that was published by Moro, Cortez and Rita (2015) in the Expert Systems with Applications journal, searches for trends in BI solutions in the banking environment. Therefore, their paper presents an analysis of 219 journal articles published in the period from 2002 to 2013 by using text mining procedures in combination with a latent Dirichlet allocation modeling technique. The aim of their article is to identify relationships between topics regarding BI and banking and to develop hypotheses for further research directions. According to their study, credit business and risk management are the major topics of interest with regard to BI in the investigated time period. In particular, credit risk management and fraud detection are identified as the most relevant topics (Moro, Cortez and Rita, 2015).

A further article that deals with a similar subject matter is "The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature", published in Decision Support Systems by Ngai et al. (2011). This research article presents a systemic, comprehensive literature review and a classification scheme on the usage of data mining approaches in order to detect financial fraud. The paper analyses 49 journal articles that have been published between 1997 and 2008. Therefore, the thematic fields of the journal articles are classified into four different categories of financial fraud and six different classes of data mining methods. The literature review of their paper shows that data mining approaches have been applied predominantly to detect insurance, corporate and credit card fraud. Moreover, their paper also identifies research gaps between financial fraud detection and the needs of the financial industry (Ngai et al., 2011).

Another scientific article that can be compared to this research is "A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems", published by Bahrammirzaee (2010) in the Neural Computing and Applications journal. This article provides a comparative literature review of the three common AI techniques artificial neural networks, expert systems and hybrid intelligence systems in the financial sector. Therefore, the financial sector is classified into the three domains credit evaluation, portfolio management and financial forecast. For each of the three presented techniques, selected relevant researches are discussed in a comparative manner. Their evaluation of about 200 scientific articles shows that AI applications are superior compared to traditional statistical methods in evaluating financial issues. In particular, AI technologies enable FIs to deal with nonlinear patterns more efficiently (Bahrammirzaee, 2010).

The fourth article "Financial crises and bank failures: A review of prediction methods", published by Demyanyk and Hasan (2010) in the Omega journal, presents a review of empirical results to explain, predict and to suggest remedies for financial crisis or defaults. For this purpose, their paper analyses about 40 economics and operations research papers. The aim of their research is to recommend further empirical research to prevent bank failures and financial crisis from occurring again in the future (Demyanyk and Hasan, 2010).

These four studies have in common that they analyse existing journal articles with an explicit review method on a specific subject matter to derive new insights. This research goes one step further and uses text mining approaches in combination with cluster analysis techniques to be capable of analyzing a far higher amount of journal articles. The aim of this approach is to provide the first holistic overview on the development of the thematic field cognitive computing in the banking & finance environment and to discover current trend topics. In the following section, the text mining and cluster analysis techniques that are used in this research are introduced.

3.1.2 Research method

In this part of the research, text mining technologies are used to analyse a high amount of journal articles in order to discover specific terms and topics that are covered. In detail, an automated text categorization in form of a cluster analysis is applied to retrieve information from the set of documents that is analysed (Sebastiani, 2002).

There are two different ways to carry out this analysis. On the one hand, a "supervised learning" and on the other hand an "unsupervised learning" approach (Gampfer et al., 2018; Erskine et al., 2010; Gersten, Wirth and Arndt, 2000). The supervised learning approach requires that the model is taught to the computer. In general, supervised learning requires a guidance by the responsible researcher. Although the computer system fulfils defined tasks automatically, a human being is required to interact with it.

In contrast to that, unsupervised learning approaches mean that a computer is capable of detecting specific patterns in a set of documents on its own. For this purpose, the available documents are processed separately to detect patterns. In a first step, terms that describe a group of documents are identified by applying the inverse term frequency (IDF) function. To apply the IDF function, two types of information are required. At first, the number of documents in a predefined set of documents (n). Secondly, the number of documents that contain a specific term i (di).

$$IDF_i = 1 + log_2(\frac{n}{d_i})$$

The more often a term is included in a set of documents, the more relevant it is (Gampfer et al., 2018; Miao, Keselj and Milios 2005).

In a subsequent step, thematic clusters are identified by using cluster algorithms like k-means or by guessing the quantity of clusters and its centres. The thematic clusters are described by deriving a "friendly name" that contains the most descriptive terms for each cluster (Gampfer et al., 2018; Jain, Murty and Flynn, 1999). Furthermore, the ideal number of clusters can be identified by using the best splitting criteria. In this research, based on Gampfer et al. (2018), the Davies-Bouldin Index (DB) is applied to calculate the quality of a cluster algorithm (Davies and Bouldin, 1979).

$$DB = \frac{1}{N} \sum_{i=1}^{N} D_i$$

By using this method, the number of centres can be optimized. These unsupervised learning approaches are commonly used to determine specific patterns (Gampfer et al., 2018). The presented unsupervised learning procedure is applied to carry out the systemic literature review analysis that is described in the following subsequent sections.

3.1.3 Research design

The research design that is applied is based on the study by Gampfer et al. (2018). The first step is to search for appropriate English-written journal articles that cover the thematic fields cognitive computing and banking & finance. For the purpose of this research, the following seven literature research online portals were scanned in September 2018 to retrieve relevant publications:

- Web of Science (http://webofknowledge.com/)
- IEEE Xplore digital library (http://ieeexplore.ieee.org/Xplore/home.jsp)
- Science Direct – Elsevier (http://www.sciencedirect.com/)
- ACM digital library (https://dl.acm.org/)
- Wiley Online Library (http://onlinelibrary.wiley.com)
- Emerald Insight (http://www.emeraldinsight.com)
- Sage Journals (http://journals.sagepub.com)

These seven portals are selected due to their broad collection of high-impact journals in computer science, IT, economics and finance. The literature research online portal Web of Science offers high-class articles of more than 33,000 journals with more than two million articles (Clarivate, 2017). The Institute of Electrical and Electronic Engineers (IEEE) Xplore digital library provides more than four million publications in the fields of engineering, computer science and electronics. The IEEE library is specialized in scientific and technical content that is either published by the IEEE or its publishing partners. Articles of more than 195 different journals can be found there (Institute of Electrical and Electronics Engineers, 2017). The third literature research portal that is analysed is ScienceDirect, which is a platform of Elsevier. It offers millions of peer-reviewed scientific, technical and health publications from over 3,800 journals (Elsevier, 2017). Another platform is the Association for Computing Machinery (ACM) digital library. It provides millions of publications in the fields of computing and IT. The ACM library offers more than 50 high-impact and peer-reviewed journals of computing and IT disciplines (Association for Computing Machinery, 2017).

Besides, the research portal Wiley is analysed in this research. Wiley Online Library offers publications covering several scientific, technical and medical disciplines, including more than six million articles from over 1,500 journals (Wiley, 2018). One further relevant platform is Emerald Insight. This platform mainly covers the thematic fields business and management. Besides, publications in the areas health, education and engineering are presented. In total, Emerald covers nearly 300 journals (Emerald Publishing, 2018). The seventh scientific literature platform is Sage Journals. This platform covers more than 1,000 journals in the fields of humanities, social sciences, medicine, science and technology. Therefore, Sage is amongst the largest journal publishing platforms (Sage Publishing, 2018).

After selecting appropriate literature research portals, the next step is to define the search commands in order to identify and select suitable journal articles. Since the aim of this section is to evaluate articles that deal with the two subjects cognitive computing and banking & finance, each command line has to contain an "AND" expression between these two different elements. In detail, the following ten cognitive computing related search terms are defined:

- "Artificial Intelligence"
- "Artificial Neural Network*
- "Bayesian Network*
- "Business Intelligence"
- "Data Mining"
- "Deep Learning"
- "Expert System*
- "Machine Learning"
- "Pattern Recognition"
- "Robotics"

For the second part of each command line, the following seven banking & finance related terms are described:

- “Accounting”
- “Auditing”
- Bank*
- Financ*
- “Interest Rate*
- “Merger”
- (Portfolio AND Stock)

To form the individual command lines, each cognitive computing related term is combined with every banking & finance related expression. This equals a total of 70 different command lines. Please note that the exact syntax of a command is depending on the search engine and the required programming language (Buchkremer, 2016). For this research, the above-mentioned command lines could be used to explore information in all presented literature research online portals. For the first part of each command line, the term “Artificial Intelligence” or a related cognitive computing term is used. The quotation marks are necessary in order to find only articles that contain these two words adjacent to each other. Therefore, articles that randomly contain for example the two words “artificial” and “intelligence”, without dealing with the subject matter, are excluded from the results list. The selection of the related terms and synonyms is mainly based on the book “Artificial Intelligence and Machine Learning For Business” by Steven Finlay (2017). However, it must also be considered that only the most relevant cognitive computing terms are used in this research. In this context, the relevance of an expression is measured by the total number of hits in the seven literature research portals that are scanned. The second part of the command line contains a banking & finance related term. The star symbol after the last letter of the words “bank”, “finance” and “rate” is called a right-side truncation and means that the word has to start with this word fragment and can have either none or a different word ending (Gampfer et al., 2018).

For example, the two words “finance” and “financial” are both possible hits using the expression “financ*”. The banking & finance terms are derived from the Journal of Economic Literature classification categories. In particular, all category tags that deal with these subjects and are not ambivalent to other topics are selected for this research (American Economic Association, 2018).

As a result, 70 commands are typed into the search line of the presented literature research portals. The command search is restricted to titles and abstracts of journal articles. The content of the articles is deliberately not part of the command search because it would have also included articles in which cognitive computing and banking & finance are only marginal issues. Since title and abstract contain a summary of the main content of an article, it is ensured to find only articles where cognitive computing and banking & finance are presented as main topics (Schuemie et al., 2004). The results from the seven databases are exported in BibTeX format. Afterwards, the retrieved information is validated and complemented through the use of the Digital Object Identifier (DOI) lookup function.

An overview of the number of hits in titles and abstracts for the different commands is presented in figure 18.

		Banking and finance related term(s)						
#	AI related term(s)	accounting	auditing	bank*	financ*	"interest rate*"	merger	(portfolio AND stock)
1	"artificial intelligence"	135	21	89	221	9	12	19
2	"artificial neural network*"	119	25	77	337	21	5	10
3	"bayesian network*"	54	6	27	50	0	2	0
4	"business intelligence"	28	22	31	66	0	4	1
5	"data mining"	128	65	159	369	23	14	37
6	"deep learning"	29	4	19	47	1	0	2
7	"expert system*"	106	44	62	142	11	9	15
8	"machine learning"	136	25	111	305	22	7	28
9	"pattern recognition"	59	8	30	84	5	3	10
10	robotics	59	7	14	39	0	9	1
-	duplicates	-185	-37	-99	-219	-12	-13	-19
	Total per AI related term	**668**	**190**	**520**	**1,441**	**80**	**52**	**104**
	Intermediate total				3,055			
-	duplicates within one library				-502			
-	without abstract				-26			
-	manual sorting				-38			
-	duplicates between libraries				-210			
	Total				**2,279**			

Figure 18: Number of hits in titles and abstracts

The figure shows that most scientific articles are found for the command line ("Data Mining" AND Financ*) with 369 hits. The intermediate total of 3,055 articles is reduced by 502 duplicates within one library and 210 duplicates that appear in more than one research portal. Besides, 26 articles are sorted out as they did not provide an abstract and 38 articles are excluded through a manual sorting. The process of manual sorting is carried out in order to remove articles that did not match the research criteria. This deduction process is necessary to exclude articles that could corrupt the research results. As a result, 2,279 journal articles are analysed using the presented text mining and cluster analysis approaches (Gampfer et al., 2018).

3.1.4 Research results

The following section discusses the results of the systemic literature review. In the first part, the chronological distribution of the publications is presented. The second part covers a cluster overview for the overall time period from 1971 to 2018 and a more detailed view for the period between 2003 and 2018. In order to perform a more precise investigation of the literature, the third part of the subsequent section covers a period analysis for three selected time periods.

3.1.4.1 Chronological distribution

The chronological distribution of the identified research articles between the years 2003 and 2018 is visualized in figure 19. The years before 2003 were excluded in this chart since these years provide a significantly lower number of hits per year.

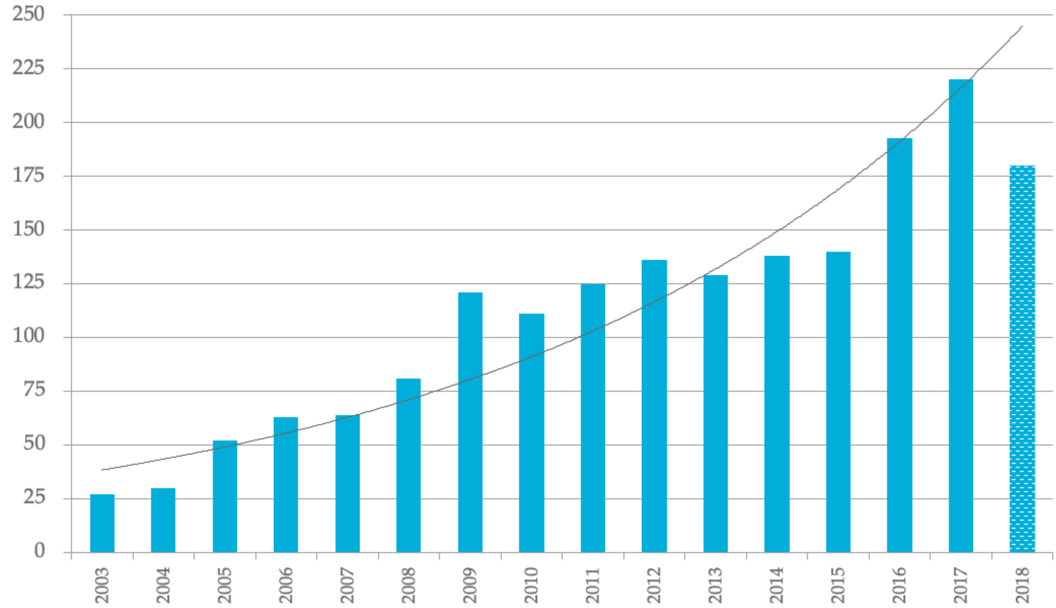

Figure 19: Chronological distribution of hits per year

The blue bars in figure 19 each represent the total number of hits in one year. The last bar that symbolizes the hits in 2018 has white dashes inside since this year has not been over when the research was carried out in September 2018. In addition to the single bars, the chart also shows a harmonized trend line for the overall time period. The black trend line visualizes an exponential increase of the number of hits per year between 2003 and 2017. This leads to the initial conclusion that cognitive computing technologies have become a significantly more important topic for banks and other FIs over time. The most significant bars can be observed in the years 2009, 2016 and 2017. In comparison to the previous year, the number of hits increased significantly from 2008 to 2009. However, between the years 2010 and 2015, the number of articles per year almost remained stable. The comparatively high number of hits in the year 2009 can be explained through the outcomes of the world-wide financial and economic crisis of 2007-2008. A detailed analysis of the individual articles shows that a variety of journal articles that were published in the year after the crisis deal with the negative impacts of the financial crisis and how to prevent it from happening again in the future. Many of these articles suggest AI or related cognitive computing technologies as possible solutions to identify indications of an upcoming crisis earlier and react more quickly than in 2007. These insights are in accordance to the study of Moro, Cortez and Rita (2015). In their study, the chronological distribution of articles also reveals a significant outlier in the year 2009. Moro, Cortez and Rita also explain this with a high number of articles that deal with the outcomes of the financial crisis of 2007-2008. Another significant growth can be observed in the time period between 2016 and 2017. The number of articles increased significantly in this period. One major reason for this development is that an increasing number of articles deals with the trend topic FinTech. Especially in the time period between 2015 and 2017, banks and other institutions invested heavily in FinTech companies.

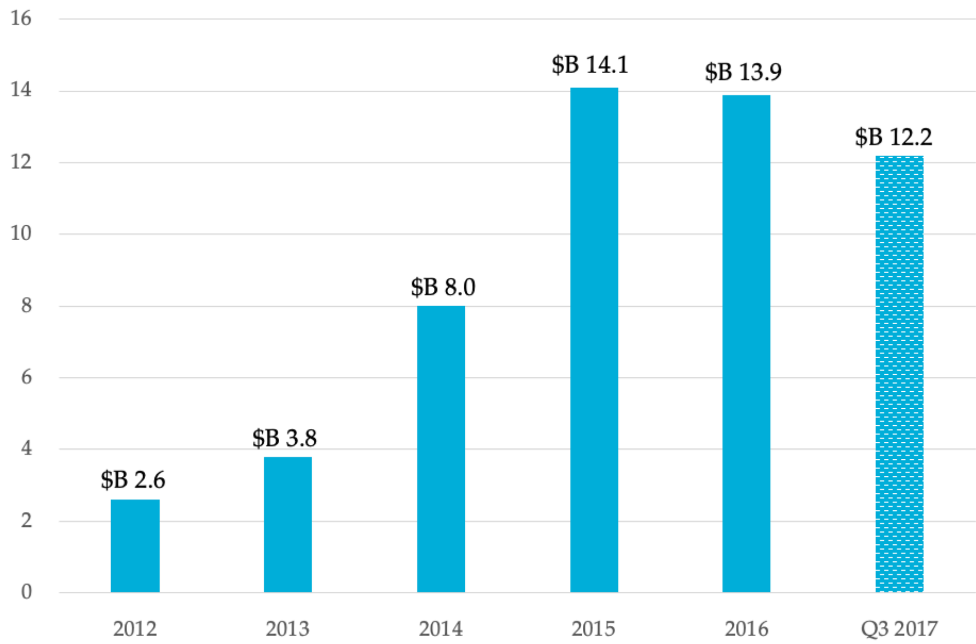

Figure 20: Global financing of venture capital backed fintech companies (in billion US-Dollars per year) [source: own presentation based on (CB Insights, 2017, p. 8)]

The bar chart in figure 20 shows the global amount of venture capital (in billion US-Dollars) invested in FinTech companies per year between 2012 and 2017. The last bar that visualizes the invested capital in 2017 has dashes inside since it does not contain the amount for the fourth quarter of 2017. An analysis of the single bars shows that there is a growth of more than 100 % between 2013 ($B 3.8) and

2014 ($B 8.0). Furthermore, the invested amount of venture capital increased by another 76 % between 2014 and 2015 ($B 14.1). This large increase of investments shows that FinTech has become a significantly more important topic for the financial industries in the years 2014 and 2015. In the year 2016, the amount of venture capital invested in FinTech companies declined marginally by 1.4%. The year to data number of $B 12.2 in the first three quarters of 2017 confirms that FinTech is still a highly-relevant topic for FIs (CB Insights, 2017, p. 8).

3.1.4.2 Overview

To determine the historical development and current trend topics regarding cognitive computing and FIs, 2,279 research articles are analysed with affection to the topics that they cover. For this purpose, the abstracts of these articles are fragmented through text mining methods and clusters are determined. The separation precision of the single clusters can be identified using a "Davies Bouldin" index (see chapter 3.1.2). The lowest average index in a range of 0 to 20 centers is set for nine cluster centers. Therefore, nine clusters are created. Besides, the ten most relevant descriptive terms of each cluster are named and exported to identify the superior topics of a cluster. Furthermore, a friendly name that describes the superior topic is found through a manual analysis of the ten terms of each cluster (Gampfer et al., 2018). Using this approach, the following nine clusters and their friendly names are identified (in alphabetical order):

- Auditing
- Bankruptcy prediction
- Credit risk measurement
- Customer services
- Digital advisory / Digital services / Pattern recognition
- Financial forecast
- Fraud detection
- Technology adoption
- Trading / Portfolio management

The overall number of hits for each cluster between 1971 and 2018 is visualised in figure 21.

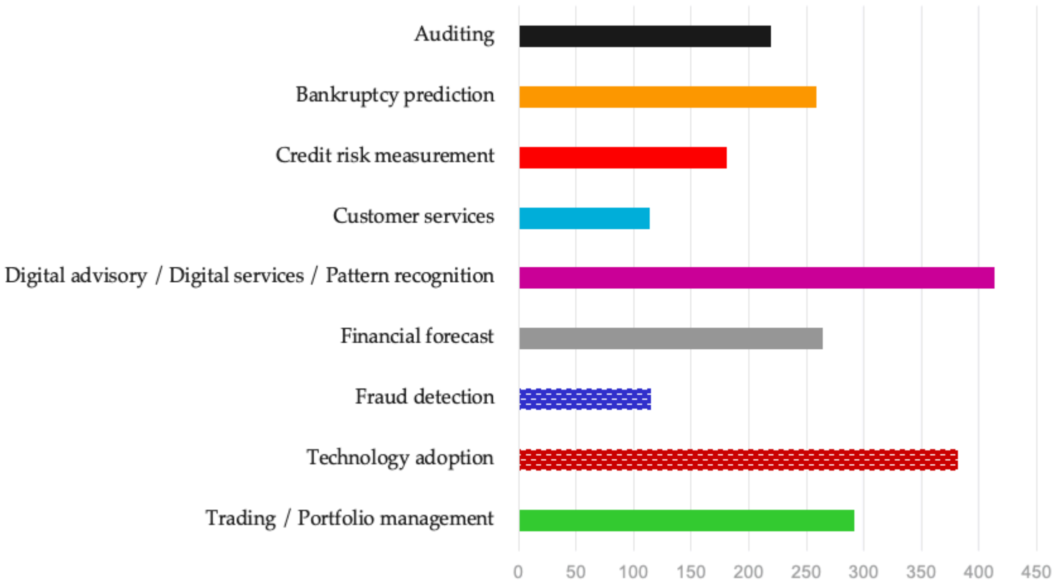

Figure 21: Number of hits per cluster

The bars presented in figure 21 show that "Digital advisory/ Digital services/ Pattern recognition", "Technology adoption" and "Trading/ Portfolio management" have been the most relevant topics regarding cognitive computing technologies and FIs between 1971 and 2018. Since this dissertation focuses on risk and compliance management activities, these clusters are not regarded in further detail in this research. Demyanyk and Hasan (2010) realized an increasing need for cognitive computing technologies to prevent bank failures and financial crisis in the future. These insights are therefore in accordance with the appearance of the clusters "Auditing", "Bankruptcy prediction", "Credit risk measurement" and "Fraud detection" since these tasks also aim to ensure (amongst others) the stability of FIs. Their study shows that statistical techniques are to be accompanied by cognitive computing technologies to increase model performance and better analyze and predict future defaults and potential crisis. According to Demyanyk and Hasan, artificial neural networks were the most widely used technique to perform these tasks (Demyanyk and Hasen, 2010).

However, it must be considered that only few articles have been published in the time period between 1971 and 2002. Therefore, the following analysis exclude this time period and start at the year 2003. The development of the clusters between 2003 and 2018 is visualized in figure 22 through the distribution of each cluster relative to the overall number of publications of each year (based on Gampfer et al., 2018).

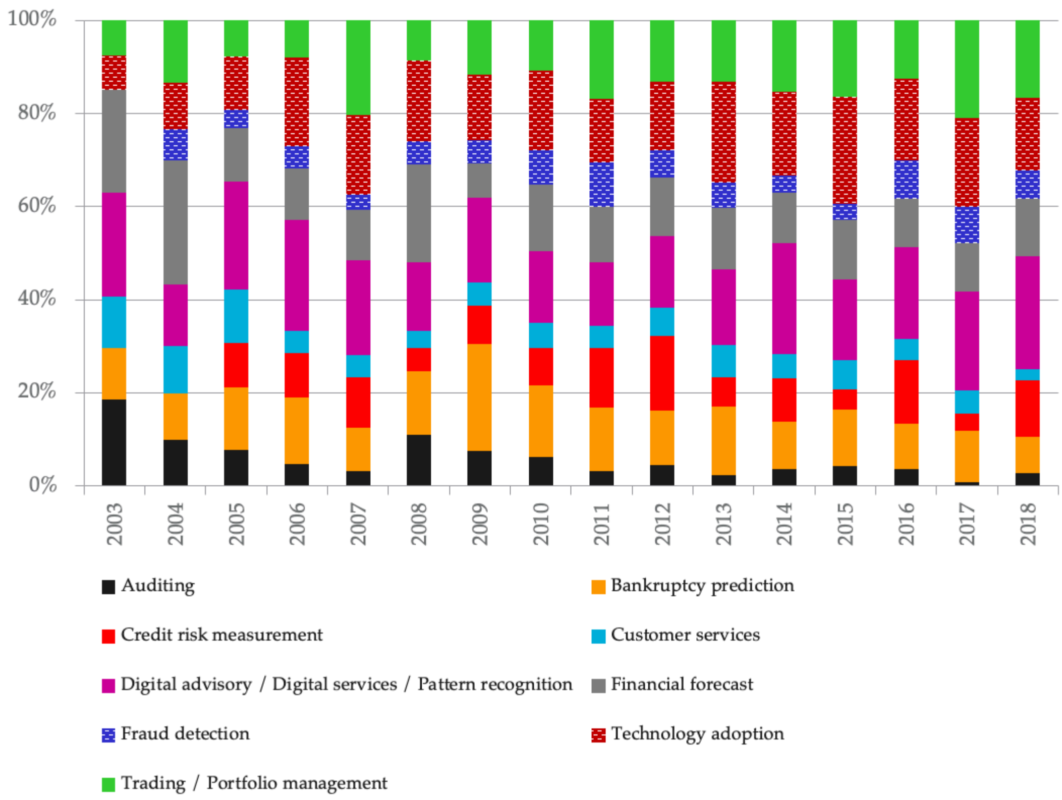

Figure 22: Distribution of clusters per year

Figure 22 shows the proportional distribution of the nine clusters per year from 2003 to 2018. Each cluster is represented by a different color. The bar chart shows that the cluster "auditing" had its highest share in 2003 and 2004. This insight is plausible since in the early 2000s, there have been several corporate accounting scandals that were covered in several scientific publications. Giroux (2008) provides an overview of the most important accounting scandals that occurred during that time. Besides, the cluster “financial forecast” also had its highest share between 2003 and 2004. According to Bahrammirzaee (2010) one major reason for this insight is that cognitive computing techniques are superior compared to traditional statistical methods to deal with financial forecasts, especially in terms of nonlinear patterns. The results of his study also show that capital market activities like portfolio management gained further relevance in this observation period, especially in the period between 2006 and 2010.

Besides, this study shows that the cluster “fraud detection” appears in each year, starting at 2004. According to the study carried out by Ngai et al. (2011), insurance fraud, corporate fraud and credit card fraud are the most relevant types of fraud for the implementation of AI-featured cognitive computing technologies. In combination with the clusters “auditing”, “bankruptcy prediction” and “credit risk measurement”, it must be considered that risk and compliance management activities cover four of nine clusters in this research. These insights are in accordance with Moro, Cortez and Rita (2015). Their study shows that risk and compliance management activities like fraud detection, bankruptcy prediction and credit risk management were the most relevant banking topics between the years 2002 and 2013. In detail, the cluster “bankruptcy prediction” has the highest share in the year 2009 as a response to the global financial and economic crisis of the previous years. The cluster “credit risk measurement” has a peak in 2012, which can be explained by the euro sovereign debt crisis that occurred in that period (Stracca, 2013).

With regard to the topic of this dissertation, it must be considered that risk and compliance management are highly relevant thematic fields for the application of cognitive computing technologies in the banking & finance environment.

3.1.4.3 Detailed period analysis

To display the recent development of the single topics in a more precise manner, a period analysis of 15 years from 2003 to 2017 is performed. Publications before 2003 are excluded since this part of the research focuses on current trends regarding cognitive computing and FIs. The three resulting time periods and the numbers of articles of each period are the following:

- 2003 to 2008: pre financial crisis period (317 articles)
- 2009 to 2015: financial crisis and post crisis period (900 articles)
- 2016 to 2017: new technologies/FinTech period (413 articles)

A separate cluster analysis is performed for each of the three periods. The procedures are similar as the ones described in chapter 3.1.4.2. In a first step, the abstracts of the articles of each period are fragmented and clusters for each period are determined. Secondly, the Davies Bouldin index is used to identify the separation precision of the single clusters. In line with the procedures described before, the next step is to name the ten most relevant terms of each cluster in order to identify the superior topics and to find a friendly name for these subjects. In some cases, the same clusters were found in each of the three periods. Moreover, four additional clusters were identified. This leads to the identification of 13 different clusters in the analysed 15-year period. The distribution of these clusters for each period is portrayed in the following chart (figure 23).

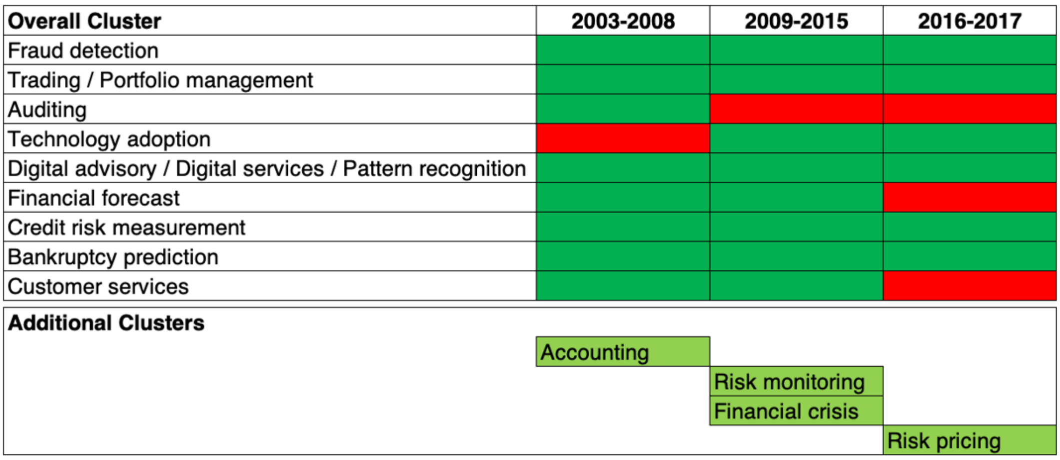

Figure 23: Detailed period cluster analysis

The table chart in figure 23 shows the distribution of each cluster through a colored box. The green color symbolizes that a cluster appears in the regarded period. Accordingly, the red color means that this cluster does not appear in a specific period.

This analysis shows that the clusters "Fraud detection", "Trading/ Portfolio management", "Digital advisory/ Digital services/ Pattern recognition", "Credit risk measurement" and "Bankruptcy prediction" appear in each of the regarded periods. In addition, "Accounting" is recognized as an additional cluster for the period between 2003 and 2008. As described in the previous section, the reason for the appearance of many accounting related articles is that there have been several corporate accounting scandals that were covered in numerous scientific publications in the early 2000s. As a further result, "Risk monitoring" and "Financial crisis" are two additional clusters that appear in the post financial crisis period between 2009 and 2015. The reason for the appearance of these additional clusters is that several journal articles investigated how financial crisis can be prevented from occurring again. The cluster analysis for the period 2016-2017 shows that the clusters "Auditing", "Financial forecast" and "Customer services" disappeared. However, this does not necessarily mean that these three topics were not dealt with in 2016 and 2017. It means that these thematic fields were not identified as individual clusters in that period. In contrast to that, the additional cluster "Risk pricing" occurred.

In consequence, it must be considered that recently published journal articles tend to focus on risk management topics rather than covering traditional banking & finance related themes like customer services and financial forecasts. This result is a further indicator for the increasing relevance of cognitive computing technologies for the risk and compliance management departments of FIs.

3.2 QUESTIONING APPROACHES

"Nothing seems easier than collecting information through asking questions"

(Atteslander, 2010, p. 109). This simple statement by Peter Atteslander refers to the problem statement, how information can be collected in an empirical research. Atteslander explains that there are different approaches to ask a question, depending on the information the questioner wants to receive. The basic form of structured questioning is an interview, where the questioner and the respondent are having a face-to-face conversation. Other forms of structured questioning are, amongst others, telephone interviews, group interviews and surveys. One characteristic that all these types of asking questions have in common is that they are target-oriented. The questioner has a defined interest and wishes information from the respondent (Atteslander, 2010, pp. 109-111). According to Atteslander (2010, p. 111), the major difference between scientific questioning and everyday questioning is the theory driven control of both the questions and the corresponding answers. The scientific character of questioning is therefore based on a systematic target orientation and theory. As a consequence, controlling each step of questioning is necessary to ensure that it is a scientific methodology (Atteslander, 2010, pp. 110-112). In this research, two different forms of questioning are performed to receive expert assessments regarding the future of risk and regulatory compliance management of German FIs. In a first step, face-to-face expert interviews are carried out to gather detailed insights on the subject matter. The outcomes of the expert interviews are then taken as a foundation to create a survey form and to carry out a survey with predominantly defined response options. A comparison of these two forms of structured questioning that are used in this research is presented in the following table (see table 6).

	Expert interviews	**Survey form**
Form of communication	semi-structured	strictly structured
Type of communication	verbal, face-to-face	written
Duration of the questioning	comparatively long	comparatively short
Evaluation effort	high	low
Type of results	mainly qualitative	mainly quantitative
Evaluation method	predominantly interpreting	predominantly measuring
Content, sequence and number of questions	partly flexible	predefined
Inquiries of the participant	possible	not possible
Possible insights	unrestricted	restricted

Table 6: Comparison of expert interviews and a survey form

[source: own presentation based on (Atteslander, 2010, p. 133)]

Please note that the content of this comparison refers to this research. It is not a general comparison of expert interviews and surveys. Table 6 shows that both forms of structured questioning have several different characteristics. When these two approaches are combined, the insights can be increased (Atteslander, 2010, p. 132).

In the following section, the creation and the execution as well as the outcomes of the face-to-face expert interviews are presented (see chapter 3.3).

3.3.1 Interview objectives and content

The main purpose of carrying out expert interviews in this research is to gather expert assessments on the future of risk and regulatory compliance management at German FIs. The insights of the interviews are taken as a foundation to create a survey with predominantly defined response options on the subject matter. The expert interviews in this research are semi-structured. The questions are prepared and phrased in advance, but the sequence of the questions and the exact phrasing are flexible. Therefore, the interviewer is given the chance to influence the cause of the interview depending on the answers of the respondent (Atteslander, 2010, p. 135). As a result, the interviewer has a direct influence on the course of conversation. On the one hand, this can lead to distortions and increases the evaluation effort, but on the other hand, it ensures that the interviewer can receive the information required from the respondent by reacting flexible on the individual situation (Atteslander, 2010, p. 136).

The content of the interview questions (IQs) covers four main thematic fields. The first topic is the current and estimated future relevance of different risk categories. Furthermore, the interviewees are asked to estimate the consequences of predicted future changes (IQ1-IQ3). The subsequent part of the interview refers to the current extent and complexity of regulations. The interview participants evaluate both the extent and complexity of regulations for FIs in general and of the MaRisk framework in particular. Moreover, they are invited to assess how FIs will deal with the increasing number of regulations in the future (IQ4-IQ7). In the third part of the interview, the potential use of new technologies in the risk and regulatory compliance management area is addressed. The participants are also invited to give suggestions for specific technologies that will be particularly relevant in the future (IQ8-IQ9). The last set of questions covers the current and estimated future role of AI-featured cognitive computing technologies to enhance the risk and compliance management activities and business processes of FIs (IQ10-IQ13).

The sequence of the questions is flexible and depends on the course of conversation. However, the presentation of the interview outcomes (see chapter 3.3.4) occurs in the predefined order.

The IQs were created based on a comprehensive topic-related literature research. The evaluation of the answers of the interviewees and the presentation of the results are in the form of aggregated information to ensure that the answers cannot be allocated to an individual participant. This approach is necessary to fulfil data privacy demands and policies of some of the interview participants and their institutions. For the evaluation purposes of this research, it is sufficient to present aggregated information that summarize the answers of the individual interviewees.

3.3.2 Preparation of the interviews

An expert interview needs to be prepared in advance in order to obtain the objectives that are defined. The preparation of the face-to-face interviews that were carried out in this research followed a guideline that is presented in table 7:

Step #	**Task**
Step 1	Definition of the interview objectives and content
Step 2	Searching for suitable interview participants
Step 3	Contacting the potential interviewees
Step 4	Arrangement of an appointment for the interview
Step 5	Preparation of the individual interview guideline
Step 6	Carrying out a face-to-face expert interview
Step 7	Writing an interview protocol
Step 8	Written elaboration of the interview outcomes

Table 7: Preparation guideline for the expert interviews

Table 7 shows that eight consecutive steps are required to carry out the expert interviews in this research. Steps 1, 2 and 8 had to be performed only once whereas the other five steps had to be repeated for each interview participant. The potential interviewees were contacted (step 3) via E-Mail or telephone. When the telephone number was known by the researcher, the potential interviewee was called directly and when the telephone number was unknown, the person was contacted via E-Mail. In total, ten potential interview participants were contacted through one of these approaches. As a result, six individuals were willing to arrange an appointment for the expert interviews (step 4). The interviews were carried out in October 2017.

For each of the interviewees, an individual interview guideline has been prepared (step 5). The guideline was aligned with the individual job role and specialist areas of the interview participant. For instance, the participating compliance officers were first asked about the extent and complexity of regulatory requirements (IQ4-IQ7), whereas the risk managers received the first questions with regard to the different risk categories (IQ1-IQ3). The main purpose of this approach is to ensure that the experts had enough time to answer the questions that directly relate to their job roles and specialist areas. Each face-to-face interview followed a defined timetable. According to Maynatz, Holm and Hübner (1999, p. 112), the duration of an interview has a significant impact on the willingness and motivation of a participant to answer questions. In general, Maynatz, Holm and Hübner (1999, p. 112) and Atteslander (2010, p. 135) suggest that the duration of a face-to-face scientific interview should be between 30 and 60 minutes. This time is long enough to receive information required for the research project and it is short enough that the receptivity of the respondent is at a high level during the interview.

Table 8 shows the suggested timetable for each face-to-face interview that was carried out in this research.

Estimated duration	Task
2-3 minutes	Personal introduction and presentation of the research project
5 minutes	Introduction of the interview participant (including job role, experience and responsibilities)
2-3 minutes	Information regarding data processing and data privacy
40 minutes	Interview questions and answers
5 minutes	Further remarks and explanations by the interview participant
2-3 minutes	Thanking the interviewee for participation

Table 8: Interview timeline

The estimated duration of each task is a guideline for the interviewer. The estimated overall time for each interview was one hour. In five cases, the timetable was met. In one case, the overall time was exceeded for the reason that the interviewee provided more detailed answers than expected beforehand. Since risk and compliance management related questions are sensitive information for most banks and other FIs, the interview participants were informed about the processing of their data before the first IQ was asked. This step is necessary to ensure that each participant knows beforehand what is supposed to happen to the information the participant provides during the interview.

3.3.3 Interview participants

One essential condition for an interview to be referred to as an expert interview is that the respondent has an in-depth understanding and extensive experience regarding the research object. The identification of appropriate interview partners is therefore an important task during the interview preparation phase (Atteslander, 2010, p. 141). In the following section, the interviewees and their job roles as well as their experiences are presented individually:[15]

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[15] Please note that the presented job roles and responsibilities refer to the time the individual interviews were carried out.

- Roland Bayer, Executive Risk Manager, IBM Credit Bank Germany

As the executive risk manager of the IBM Credit Bank, a credit institution situated in Ehningen in Germany, Roland Bayer is responsible for an adequate risk management and risk reporting to the supervisory authorities. Mr. Bayer has been working in the risk management environment for several years and has therefore a sufficient practical experience regarding risk management activities and procedures of FIs in Germany. Moreover, he has been involved in several digitalization projects within his institution. He is therefore an adequate interview participant regarding this research (Bayer, personal communication, October 2017).

- Julia Buedenbender, Compliance Officer, IBM Credit Bank Germany

Julia Buedenbender is responsible for the compliance management of both internal and external regulations. For this purpose, Mrs. Buedenbender is in contact with several departments within the IBM Credit Bank in Germany to ensure that their activities and business processes comply with internal requirements and external regulations. Due to her practical experience as an executive compliance officer at a credit institution in Germany, she is a suitable interviewee with regard to the purposes of this research project (Buedenbender, personal communication, October 2017)

- Andreas Burger, Regulatory Compliance Expert, Promontory Financial

Andreas Burger is a specialist for regulatory compliance management of FIs in Germany. As an executive consultant at the Promontory Financial Group, he advises banks and other FIs in Germany regarding regulatory issues. For this purpose, he has reviewed the compliance management activities and processes of several German FIs. His in-depth knowledge and practical experience regarding compliance management make Mr. Burger a suitable contact person and interview expert on the subject matter (Burger, personal communication, October 2017).

- Michael Grässer, Compliance Officer, Volksbank Ettlingen eG

As an executive compliance officer at a cooperative bank in Germany, Mr. Grässer is responsible for the observance of internal requirements and external regulations. Since the Volksbank Ettlingen eG is a credit union that acts according to the regional principle, Mr. Grässer is an expert for the specialities of regional banks regarding compliance management. He is therefore a suitable interviewee for this research (Grässer, personal communication, October 2017).

- Sabine Keller, Executive Risk Manager, Volksbank Ettlingen eG

Sabine Keller is an executive risk manager at a credit union in Germany. Therefore, she is an expert for the risk management activities and processes of a German regional bank. She provides expert assessments on regulations that affect the risk management departments of FIs in Germany. Moreover, Mrs. Keller provides an in-depth expertise concerning the specialities of regional banks regarding risk management activities. Therefore, she is a suitable expert for this research (Keller, personal communication, October 2017).

- Managing Director Financial Crime Investigation of a large German bank

The interview participant is the managing director for financial crime investigation at one of the German "big banks", one of the largest banks in Germany. His department therefore has a close cooperation with the risk and compliance management departments of the bank. The interviewee is responsible for the detection of fraudulent activities and deliberate deceptions of both internal and external parties. The managing director provides an in-depth knowledge regarding the interplay of fraud detection and risk and compliance management activities. He allowed that his statements are used for this research. However, the participant did not want his name mentioned in this dissertation (Managing Director Financial Crime Investigation, personal communication, October 2017).

The presented information about each interview participant were given by the interviewees at the beginning of the interview (see chapter 3.3.2).

3.3.4 Interview outcomes

In this section, the outcomes of the expert interviews are presented. For this purpose, each IQ is regarded individually. Please note that the answers given by the interview participants are presented as aggregated information that cannot be linked to one specific interview participant.[16] The main purpose of this approach is to comply with data privacy regulations of some interviewees and their institutions. For that reason, no direct or indirect quotes of statements of individual interview participants are presented.

The first set of IQs (IQ1-IQ3) deals with the current and expected future relevance of risk categories.

- IQ1: Banks and other financial institutions distinguish between different risk categories. In your opinion, which risk categories are currently particularly relevant for the risk management of financial institutions?

According to the interview participants, the risk categories that banks and other FIs have to deal with developed over time. Traditionally, most FIs perform credit business and therefore they have to deal with credit risk. When the institutions started to focus on trading at the capital market in the late 1990s and early 2000s, the risk category market risk became more important. During and shortly after the world-wide economic crisis of 2008, liquidity risk was put into focus to prevent bankruptcies of banks and other institutions. These three types of risk have in common that they are measurable and related to the core businesses of FIs. However, in recent years, mainly due to the digitalization of the industry, operational risk became significantly more important. For most interview

[16] In the following, the masculine form (he, his) is used when the statements of “one participant” or “one expert” are presented. It does not necessarily mean that the answer was provided by a male interview participant.

participants, credit risk and operational risk are nowadays the most relevant risk categories for the risk management departments of FIs. Besides, some participants recognized an increasing focus on non-traditional risk categories like regulatory risks and issues regarding cybersecurity and data privacy protection. Other risk categories that were mentioned by individual experts are counterparty default risk and reputational risk. In summary, the experts regarded traditional banking risks like credit risk, market risk and liquidity risk as particularly relevant as well as different kinds of operational risk. However, the experts also emphasized that each institution has to prioritize the risk categories individually depending on the individual situation (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ2: How will the relevance of the single risk categories change in the next five years?

The majority of interviewees were convinced that the relevance of operational risk will increase significantly in the following years. In general, they pointed out that since the world-wide economic crisis and its negative outcomes, banking supervisory authorities focus more on the management of risks at FIs. In particular, they focus on risks that are difficult to measure and are therefore challenging to manage and to regulate. For this reason, most of the participating experts were convinced that the management of non-financial operational risk will become a focus area for the risk management departments of financial organizations. Moreover, some of the experts also pointed out that they expect regulatory compliance management and data privacy protection to be on top of the agenda of several risk management departments (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ3: What will be the main consequences of these changes for the risk and regulatory compliance management departments?

According to the interviewed experts, banks and other FIs will have to change the way they measure and manage risks. Since operational risks tend to be more difficult to analyse and to model, financial organizations will have to implement new measurement and management procedures to be capable of handling these types of risk more efficiently in the future. Therefore, they will also need to revise their current business processes and applications. Besides, some interview partners also pointed out that the increasing importance of non-financial risks will have an impact on the capital buffers banks have to build. Moreover, the experts were convinced that FIs will need new system-based solutions to deal with operational risks in a more efficient and precise manner. An additional expectation of some experts was that FIs might struggle with increasing costs for their risk management activities in the future since they will have to invest in new, highly-skilled and specialized employees and external consulting firms to manage these types of risk. Furthermore, some of the interviewees predicted that banks and other FIs will have to establish stricter and more restrictive requirements regarding IT management activities in order to minimize IT-driven operational risks in the future. For this purpose, they will have to work very closely with their IT service providers to develop adequate solutions and regulations (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

The second part of the interview refers to the extent and complexity of regulations for FIs in general and in the risk management environment in particular (IQ4-IQ7).

- IQ4: In the second half of the year 2017, the German Federal Financial Supervisory Authority BaFin published a revised and extended version of the Minimum Requirements for Risk Management for financial institutions in Germany, known as MaRisk. How would you rate the extent of the latest version of this regulation?

The experts determined that every new version of the MaRisk causes significant implementation expenditure. The Federal Financial Supervisory Authority BaFin argues that the temporal expenditure is manageable since FIs only have to focus on modifications and extensions in the latest version of the MaRisk. However, according to the interviewees, it must be considered that these changes are getting more and more complicated with every release of the MaRisk. For instance, in the version of September 2017, there is a new chapter on the thematic field "risk culture" that needs to be investigated. The experts said that such an extension of the regulatory requirements causes a need for time-consuming internal coordination within the institution in order to develop an appropriate implementation concept. As an example, one expert explained that his institution needs approximately six months to implement the requirements of each new version of the MaRisk. Therefore, most of the experts were convinced that the current version of the MaRisk is too extensive. Besides, some interview participants also pointed out that it is very cost-intensive to implement the requirements of each new version of the MaRisk since their institutions require the advisory services of external experts. However, one expert was of the opinion that the extent of the MaRisk framework is large, but acceptable (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ5: How would you rate the degree of complexity of the current MaRisk framework?

In general, the experts considered that the complexity of the MaRisk increased in the last years. The experts explained that in some parts, the wording of the legal text is very vague and therefore, it is difficult to interpret the regulations correctly. As an example, an expert mentioned that the chapter regarding "capital requirements planning" is especially difficult to understand and to implement the necessary requirements for FIs. For this reason, some institutions refer to expert opinions of consulting firms that specialized on the subject matter. Some experts were of the opinion that it is more complex for small and regional organizations to understand and to implement the requirements of the MaRisk compared to large, international institutions. They explained that one major reason for this is that small institutions often only have a few employees that are responsible for the realization of the regulatory requirements stated in the MaRisk. In contrast to that, large global banks often have more than one hundred experts that can deal with the subject matter in a more detailed manner. In summary, the experts regarded the current version of the MaRisk as a complex framework for the risk management departments of FIs in Germany (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ6: In a broader context, how would you rate the extent and degree of complexity of the current overall regulatory framework for financial institutions in Germany?

At first, the experts pointed out that regulation always causes effort and costs for FIs. However, they have observed that since the world-wide financial and economic crisis of 2007-2008, the implementation effort increased significantly. Therefore, they said that nowadays, FIs are overcharged by the regulatory framework. It is not possible for an individual person to understand all requirements. Therefore, FIs need to have experts for the single aspects of different regulations. For instance, one expert explained that more than 3 % of the employees of his institution engage full time in the implementation of regulatory requirements. Moreover, the experts were convinced that this development will continue in the future. For this reason, the experts concluded that the extent and complexity of regulations is a burden for FIs in Germany (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ7: How will financial institutions deal with the increasing number of regulatory requirements in the future?

There is no alternative to the practical implementation of regulatory requirements. Laws have to be respected at all times. In the expert's opinion, FIs especially need to invest in specialized employees that have the required skills to deal with these tasks in an efficient manner and they need to invest in new technological solutions that can assist them to manage regulatory requirements. Moreover, some of the experts were convinced that, in the near future, one of the most critical fields of action will be to ensure compliance of business processes within the risk management environment of FIs. One expert pointed out that nowadays, several regulatory compliance management processes are ineffective and cost-intensive. Therefore, according to the expert, new information technologies featured with AI capabilities are required to ensure compliance of business processes in this area (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

The third set of questions deals with technological solutions that aim to assist FIs with their risk and regulatory compliance management tasks (IQ8-IQ9).

- IQ8: In recent years, the financial industry has been disrupted by new business models and technologies, referred to as Financial Technology, or FinTech. In terms of risk and regulatory compliance management, new technological solutions are referred to as Regulatory Technology, or RegTech. How would you rate the future potential of RegTech solutions?

The participants estimated that RegTech solutions have great potential. According to the risk and compliance management experts, the two major potential advantages of RegTech solutions are streamlining of regulatory compliance management activities and processes as well as reduction of costs. Therefore, the main field of action of RegTech technologies is the automatization of manual tasks to ensure a standardization of execution and to improve the quality of business processes. Therefore, according to the experts, these technologies will be a major support for the employees in this area. Moreover, one expert was convinced that RegTech has the potential to transform financial regulation and reporting completely. Some experts also mentioned that their institutions already use RegTech applications to monitor and prevent fraudulent activities like money laundering (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ9: Which new information technologies will be particularly relevant to improve the risk and regulatory compliance management of financial institutions in the future?

There are several new information technologies available that have the potential to support FIs in this area. In summary, the experts named six different types of technologies: AI, big data, blockchain, cloud computing, cybersecurity and machine learning. Most experts were convinced that AI technologies will have a high impact on risk and regulatory compliance activities in the future. In particular, the experts estimated that AI can assist FIs to reduce the manual workload in the risk and compliance management environment, make risk management activities more accurate and reduce costs. Moreover, some of the experts said that AI solutions in combination with machine learning capabilities will have the potential to automatize several business processes and risk management activities that are executed manually at the moment. However, one expert determined that AI and machine learning technologies are challenging to implement in some parts of the risk and regulatory compliance management environment due to the paradigm of transparency. FIs are legally bound to understand and to trace every step of some parts of their risk management activities. This mandatory requirement might be challenging to fulfil with some AI and machine learning applications in use. For this reason, the expert recommended that FIs verify in advance if they can use AI and machine learning solutions for the purposes they want. One other technology that was named by the interviewees is blockchain. According to the experts, blockchain can assist ensuring transparency of risk management activities. For instance, blockchain can ensure a safe and reliable exchange of data between FIs and banking supervision authorities. However, one expert pointed out that the benefits of blockchain have to be regarded in the context of implementation costs. Besides, big data was named as an umbrella term for technologies that are capable of processing large sets of data like data mining technologies (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

The last part of the interview deals with the implementation of cognitive computing technologies like AI in the risk and regulatory compliance management environment of FIs (IQ10-IQ13).

- IQ10: In your opinion, how can Artificial Intelligence solutions in particular improve the risk and regulatory compliance management of financial institutions?

According to the experts, AI technologies have the potential to change large parts of the risk and compliance management activities. Therefore, they were confident that the possible fields of application for AI technologies are not limited. Most of the interview participants were convinced that AI solutions will be especially relevant for the automatization of business processes and risk management activities with the aim to improve process quality and save costs for FIs. Besides, some experts pointed out that AI can help FIs to increase the accuracy of their risk reports. However, some experts also mentioned that a human being will remain the critical factor. Therefore, AI cannot replace human beings completely, but it can assist them and reduce their workload. Moreover, according to the experts, it must be considered that AI solutions can only add a value if the data quality is sufficient. Otherwise, even the best technology will not bring any improvements (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ11: When did your institution officially start to deal with the field of Artificial Intelligence?

The answers provided by the experts differed significantly. Three experts explained that their institutions have not started to get involved with this subject yet. Two further interviewees said that their FIs have been dealing with this topic for two to three years. The remaining two experts stated that their institutions have begun to deal with the field of AI more than three years ago (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ12: In your opinion, when will Artificial Intelligence solutions be implemented and used in the risk and regulatory compliance environment of your institution?

With regard to this IQ, the answers of the experts also differed significantly. Some experts said that AI featured solutions are already in use in their institutions and other participants expected that their institutions will implement the first AI applications in the next one to two years. Further interviewees estimated that AI solutions will be in use in the following two to five years (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

- IQ13: How will your institution mainly develop and implement Artificial Intelligence solutions?

The individual experts provided significantly different answers to that question. Some interviewees estimated that their institutions will develop and implement AI solutions with both internal capabilities and external specialists like AI experts and technical consultants. Other interview participants were convinced that their institutions will mainly implement AI applications that are developed by their IT service providers. One other expert said that his institution does not have employees with the necessary skills to develop AI solutions. Therefore, he expected that his FI will need the support of external resources like consulting firms (Bayer, Buedenbender, Burger, Grässer, Keller and Managing Director Financial Crime Investigation, personal communication, October 2017).

The answers provided by the six interview participants were taken as a foundation to create the survey form that is presented in chapter 3.4. In particular, some of the predefined response options to the questions were based on the outcomes of the expert interviews. Moreover, the results presented in chapter 3.4.3 are compared to four topic-related surveys and are regarded in the context of the scientific literature.

3.4 SURVEY

3.4.1 Objectives and content of the survey

The overriding aim of the presented survey is to present expert assessments regarding the future of risk and regulatory compliance management of German FIs. Selected aspects of this survey have been published by the researcher in the journal "The Review of Finance and Banking" (Becker and Buchkremer, 2018b).

The survey form covers four main topics and additionally a set of survey questions (SQ) to receive statistical information about the surveyed (SQ1-SQ5). The first thematic field is the current and estimated future significance of selected risk categories. The participants are invited to rate the current relevance of risk categories in a range from "very low" to "very high". Additionally, they are requested to create a ranking of both the current and the estimated future significance of predefined risk categories (SQ6-SQ8). The subsequent questions cover the extent and degree of complexity of regulations. In this part of the survey, the participants are requested to assess the provided legal regulations for their institutions (SQ9-SQ11). The third thematic field covers an estimation of the future relevance of selected new technologies for the risk and regulatory compliance management of the participating institutions. The surveyed are requested to create a rating as well as a ranking of the relevance of selected new technologies for their individual FIs in the following five years. In a broader context, they are also requested to give the major reason to invest in new technologies for German FIs (SQ12-SQ14). In the last part of the survey, the participants evaluate the current and estimated future role of AI technologies for risk and regulatory compliance management departments of their organizations (SQ15-SQ17).

The presented SQs were created based on three consecutive steps. The first part is a subject related comprehensive scientific literature research. The aim of this first step is to build a theoretical foundation to create initial SQs. In addition, four acknowledged surveys on the subject matter have been analyzed. An overview of the assessed existing surveys covering similar thematic fields is presented in table 9. This research focused on studies that were carried out in the years 2016 and 2017 (Becker and Buchkremer, 2018b).

Survey title	**Topic(s)**	**Issuer(s)**	**Geographic area(s)**	**Year**
AI and you: Perceptions of Artificial Intelligence from the EMEA financial services industry	The implementation of AI and further cognitive technologies in the financial industry	Deloitte in cooperation with Efma	Europe, Middle East and Africa (EMEA)	2017
Restore, rationalize and reinvent: A fundamental shift in the way banks manage risk	Transformation of risk management in the financial sector	Ernst & Young in cooperation with the Institute of International Finance	World	2017
The future of risk management in the digital era	Technological solutions to improve the risk management in the financial sector	McKinsey in cooperation with the Institute of International Finance	World	2017
European Banking Barometer - 2016: Seeking stability in an uncertain world	Risk and regulatory compliance management activities are the focus areas in the financial sector	Ernst & Young	Europe	2016

Table 9: Surveys covering similar thematic fields in 2016 and 2017

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The survey named “AI and you: Perceptions of Artificial Intelligence from the EMEA financial services industry”, that was executed by Deloitte in cooperation with the Efma organization, deals with the usage of AI and further cognitive technologies in the financial sector. In this survey, more than 3,000 business as well as technical executives of financial organizations gave their estimations regarding the current and estimated future relevance of AI technologies for FIs in the geographic areas of Europe, Middle East and Africa (EMEA). Furthermore, the main fields of application for the implementation of AI technologies in the financial environment are presented (Deloitte, 2017).[17]

The survey presented by Ernst & Young and the Institute of International Finance has the title "Restore, rationalize and reinvent: A fundamental shift in the way banks manage risk". It is a global research that investigates the significance of several risk categories and the potential impact of new information technologies on risk management activities. Therefore, executive risk managers of 77 institutions across 35 different countries were surveyed (Ernst & Young, 2017).

Besides, McKinsey & Company and the Institute of International Finance carried out a survey that deals with a similar topic and is entitled "The future of risk management in the digital era". In addition, the study by McKinsey also deals with the potential impacts of digital risk on FIs. Therefore, executive risk managers and chief executive officers of 30 selected FIs were surveyed (McKinsey & Company, 2017).

The survey with the title "European Banking Barometer - 2016: Seeking stability in an uncertain world" was executed by Ernst & Young and the Institute of International Finance. Their study evaluates the business outlook of 250 selected FIs in Europe. The results of their research show that risk and regulatory compliance management are the main focus areas for a majority of participating experts (Ernst & Young, 2016).

The results of the survey that was carried out in this research are compared to the insights of the four acknowledged surveys and to the content of selected articles (see chapter 3.4.3) in order to discover similar research results and possible discrepancies (Becker and Buchkremer, 2018b).

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17 Efma is a globally operating non-profit organization that was founded by banks and insurance companies in the year 1971. Efma has the goal to encourage networking between decision-makers in the financial industry. Therefore, this institution provides insights to help financial organizations to reach the best possible decisions to encourage innovation and lead transformation (Deloitte, 2017).

As a third step, the insights gathered from the expert interviews with risk managers and compliance officers as well as external experts of selected financial organizations in Germany (see chapter 3.3) were taken as a foundation to specify the SQs. These three steps are built on one another. In summary, the process to design the survey form is exemplified through the pyramid scheme that is presented in figure 24 (Becker and Buchkremer, 2018b).

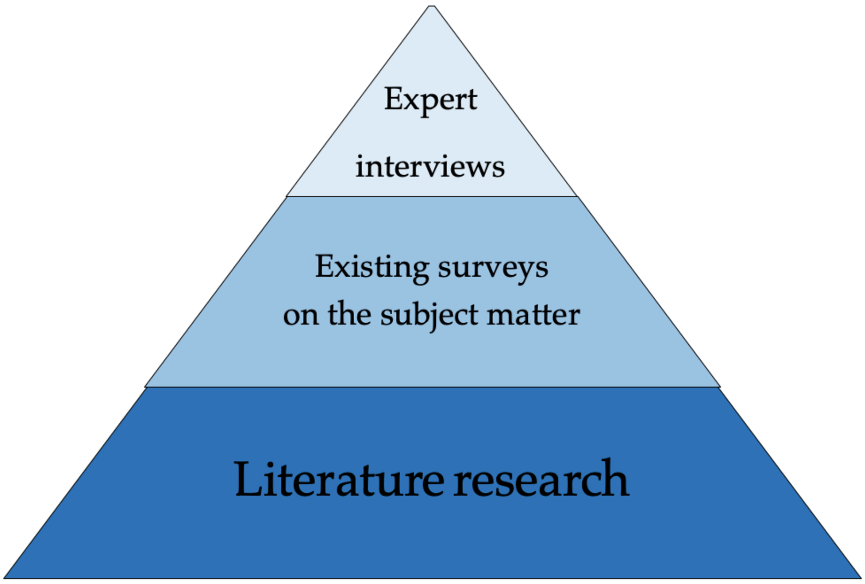

Figure 24: Procedure to create the questionnaire

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The created initial survey form has been tested by three executive risk and compliance management experts from different FIs in Germany to ensure an appropriate quality of the survey form. For this purpose, the individual questions and the predefined response options were reviewed with regard to completeness, comprehensibility, significance and uniqueness (Atteslander, 2010, p. 295 f.; Becker and Buchkremer, 2018b). In a subsequent step, the feedback of the experts was evaluated to revise the survey form. The final version of the survey includes 17 questions (see annex 1). The majority of SQs contains predefined response options.

In addition, in some parts, the participating experts were given the opportunity to write complementary answers in text boxes (Becker and Buchkremer, 2018b).

The response options of each question are presented in the third part of this chapter (see chapter 3.4.3). The results of this survey are presented as aggregated data that cannot be linked to one specific participant. The purpose of this approach is to ensure data privacy and anonymity of the individual survey participants (Becker and Buchkremer, 2018b).

3.4.2 Survey framework

3.4.2.1 Creation of the survey form

The survey form was created through two different approaches. On the one side, the survey was generated in the Portable Document Format (PDF) both in German and in English. PDF documents can be opened on a personal computer (PC) with the use of software tools such as the free software Adobe Reader (Adobe Reader, 2017). The participants were invited to either print the survey and fill it out handwritten or edit the PDF document directly on the PC screen. Either way, they were asked to return the completed survey via E-Mail. On the other hand, the survey was also created on the internet using the online services of umfrageonline.com. This website belongs to the enuvo GmbH in Switzerland (enuvo GmbH, 2017). The online survey can be accessed directly with a unique link, without a specific user identification or password. The main reason for this approach is to ensure the anonymity of the participants. However, possible disadvantages of this approach are that a multiple participation and a contribution of an unauthorized third party are theoretically possible. Due to the limited target audience and the selective distribution of the survey, the occurrence of this scenario is unlikely and regarded as a minor risk factor. Besides, the questionnaires that did not meet with predefined criteria were sorted out manually to ensure a high quality of data (see chapter 3.4.2.2). The online survey was also created both in German and in English versions. The estimated time to complete the survey is approximately ten to 15 minutes.

By using these two approaches, the individual participant is given the chance to decide whether to fill out the survey either online or offline. According to Bethlehem (2010), one major methodological problem of web-based surveys is that specific groups of the target audience might be under-represented as they might have less access to the internet than other groups of participants. With regard to this survey, in some FIs, the internet access of employees might be limited, and several websites cannot be accessed due to the internet security policy of the institutions. In this case, the recipient of the survey has the alternate option to participate in the survey using the PDF document. The data of both kinds of survey forms were reviewed and consolidated after the submission deadline. For the evaluation of the survey data, it was not relevant whether the survey was completed offline or online.

3.4.2.2 Target audience

The target audience of this survey are experienced executive risk managers and compliance officers of banks and other FIs in Germany. The participants had to meet all of these criteria (Becker and Buchkremer, 2018b):

- business operations in Germany
- job role: compliance officer or risk manager
- more than five years of professional experience in this job role
- middle level management ("executive") or higher

The aim of this selective approach is to ensure a high quality of evaluation data. The survey forms of participants, who did not meet all of the above-mentioned criteria were not considered in the survey evaluation (see chapter 3.4.3.1). To make sure that the participants of the survey have an adequate level of experience, they are required to have more than five years of professional experience. In addition, the participants are required to be executives or chief executives at their practiced profession. Since this survey focuses on the geographic region of Germany, it is also demanded that the respondents perform business operations in Germany. The distribution of the survey form was carried out through two different approaches. At first, a cover letter and the survey form have been sent via E-Mail to 164 selected addressees both in German and in English language. The contact information of the recipients was gathered from the websites of selected FIs, as well as from the network of IBM Germany (ger. IBM Deutschland

GmbH) and suitable job descriptions at XING (2017), a social network for professionals. It must be considered that only one person of each selected bank or other FI has been contacted (Becker and Buchkremer, 2018b).

Moreover, the survey form was distributed via E-Mail by the German banking association Bankenfachverband e.V. to 54 selected executive compliance officers and risk managers in Germany.[18] The aim of this second approach is that the willingness to participate in the survey might be higher when the survey is distributed through an established association. Each selected bank or other FI has only been contacted through one of these two approaches. As a result, a total of 218 individuals has been contacted (Becker and Buchkremer, 2018b).

The target proportional distribution of the survey audience was based on the German report of bank branches in the year 2016. The publisher of this report is the German Federal Bank (Deutsche Bundesbank, 2017c). For this purpose, the total number of FIs and the total number of branches of each individual sector were used as a benchmark to define a target share of participants for the banking sector in Germany (see chapter 2.1) (Becker and Buchkremer, 2018b).

The calculated target audience is presented in table 10.

Target audience	**Total number of FIs**	**Total branches**	**Participants target (%)**
Cooperative banks	976	11,145	39.1 %
Private banks	381	9,825	26.0 %
Public savings banks	412	11,351	29.6 %
Other FIs	119	1,593	5.2 %
Total	**1,888**	**33,914**	**100.0%**

Table 10: Target survey participants

[source: own presentation based on (Deutsche Bundesbank, 2017c; Becker and Buchkremer, 2018b)]

18 The Bankenfachverband e.V. is an association that aims to represent the concerns of selected credit banks in Germany (Bankenfachverband e.V., 2017).

The percentage distribution of the overall number of FIs in Germany and the number of total branches were taken as a foundation to calculate the target distribution of participants for each bank sector. The following formula was used to calculate the target proportion of each bank sector (Becker and Buchkremer, 2018b):

$$Target\ audience\ (\%) = \frac{number\ of\ FIs}{\sum number\ of\ FIs} * \frac{1}{3} + \frac{number\ of\ branches}{\sum number\ of\ branches} * \frac{2}{3}$$

In the first part of the formula, the total number of FIs in one bank sector is divided by the number of all FIs (1,888). The result of this division is multiplied by the factor one third. In the second piece of the formula, the individual number of branches is divided by the overall number of branches of all sectors (33,914). This initial result is then multiplied by the factor two thirds. To get the percentage target audience, the two partial results have to be added up. The formula shows that the proportion of the number of branches is weighted higher than the proportion of the number of FIs. This approach is necessary since the number of branches is regarded as a more significant indicator for the proportional share of a bank sector than the number of FIs (Deutsche Bundesbank, 2017c). For this reason, several different proportional splits of these two factors have been tested (Becker and Buchkremer, 2018b).

As a result, the distribution list for the survey of this research was based on the target percentage distribution of participating experts (see table 10) (Becker and Buchkremer, 2018b).

3.4.2.3 Timeline

From November 15 to November 17, 2017, the survey form was sent via E-Mail including a personalized cover letter. The distribution mail contained the link to the online survey as well as the PDF documents of the survey in German and in English. About two weeks later, the German bank association Bankenfachverband e.V. sent the survey form via E-Mail on November 28 (Becker and Buchkremer, 2018b).

On December 10, the preliminary number of evaluable survey forms was analyzed with respect to the target number of participants. If the actual number of participants had been below 30 on this date, an E-Mail reminder would have been sent out to the same distribution list.[19] However, since 56 executive risk managers and compliance offices completed the survey until this date, the E-Mail reminder was not sent. The deadline for submission was December 22, 2017 (Becker and Buchkremer, 2018b).

3.4.3 Survey results

3.4.3.1 Survey participants

In total, 32.6 % of contacted individuals have participated in the survey. This equals a total number of 71 survey forms that have been returned. To ensure a high quality of data, each form was revised individually and anonymously. A filled-out survey form that did not meet all criteria presented in chapter 3.4.2.2 was sorted out by the researcher (Becker and Buchkremer, 2018b). Figure 25 illustrates the total number of submitted surveys and the deduction due to defined criteria. The review of the data was carried out in descending order. If a survey form did not meet with a specific criterion, it was sorted out without further examination of the other criteria. A total of nine survey forms were sorted out through this approach. Two of them were rejected because the participants did not complete the survey. In both cases, the concerning addressees processed only about 50 % of the survey.[20] The survey form of one participant was excluded since the person belonged to the same institution as another participant (SQ1). In this case, the survey form that was submitted secondly was sorted out. Two further questionnaires were rejected as the participants did not work as risk managers or compliance officers (SQ3). The reason for the refusal of three additional survey forms was that the participants did not have more than five years of professional experience (SQ5). Furthermore, the submitted survey of one participant was excluded since that person was not an executive at the mentioned occupation (SQ4).

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[19] The number of 30 survey forms was defined as the minimum quantity for the evaluation of the survey (Becker and Buchkremer, 2018b).

[20] A survey form is considered complete when at least 15 of 17 questions were edited. This equals a processing quota of 88.2 %.

Preliminary total number of participants	71
Participant did not finish the survey	-2
Participant(s) from the same institution	-1
Participant is not a Risk Manager or Compliance Officer	-2
Participant does not have more than 5 years of professional experience	-3
Participant is not an executive	-1
Participant has no business operations in Germany	0
Adjusted total number of participants	62

Figure 25: Number of survey participants

As a result of the review process, an adjusted total of 62 survey forms was taken for the evaluation procedures and the presentation of the survey results. This equals an adjusted quota of 28.4 % compared to the total number of persons contacted. In table 11, the actual percentage proportion of survey participants is presented and compared to the target survey audience that was illustrated in chapter 3.4.2.2.

Target audience	Total numb. of FIs	Total branches		Participants target (%)	Participants actual (%)
Cooperative banks	976	11,145		39.1 %	27.4 %
Private banks	381	9,825		26.0 %	32.3 %
Public savings banks	412	11,351		29.6 %	29.0 %
Other FIs	119	1,593		5.2 %	11.3 %
Total	**1,888**	**33,914**		**100.0 %**	**100.0 %**

Table 11: Target and actual survey participants

[source: own presentation based on (Deutsche Bundesbank, 2017c; Becker and Buchkremer, 2018b)]

Table 11 shows that the target share of cooperative banks (39.1 %) is significantly higher than the actual proportion of 27.4 %. In contrast to that, the quota of participants from private banks (32.3 %) is considerably higher than the target share of 26.0 %. Furthermore, the actual quota of other FIs (11.3 %) is also remarkably higher than the target portion of 5.2 %. With regard to the sector of public savings banks, the actual quota (29.0 %) only differs slightly from the target quota of 29.6 %. These deviations of target and actual quotas are caused by divergent return quotas for the individual bank sectors. The surpassing return quotas of private banks and other FIs might be explained by the fact that they were mainly contacted by the German bank association Bankenfachverband e.V. Since the request to participate in the survey came from an official German association, the acceptance and the potential willingness to fill out the survey form might have been higher (Becker and Buchkremer, 2018b).

Regarding the occupation of the survey participants, it has to be considered that about one third (32 %) responded that they work as executive compliance officers and about two thirds (68 %) work as executive risk managers (SQ3). The results of the two professions are not presented individually since the purpose of this survey is to derive aggregated results from both compliance managers and risk managers. The survey participants provide an average professional experience of 11.1 years at their indicated occupation (SQ5). Therefore, the participants provide an adequate level of experience. With regard to the management level, 95 % of the survey participants indicated that they are executives and 5 % specified that they are chief executives (Becker and Buchkremer, 2018b). In the context of this survey, an executive is defined as a person in a high position, given the responsibility to manage the affairs and to make decisions within defined boundaries. A chief executive is defined as the person with the most powerful and influential position at an organization. Therefore, executives are in the management level below chief executives (Cambridge University Press, 2017; eds. Wehmeier et al., 2005).

3.4.3.2 Evaluation of risk categories

In this first thematic field, the survey participants created a rating and a ranking of the current relevance of predefined types of risk. In this situation, the term “relevance” is used to describe to what extent a FI is concerned by a specific risk category. In a further question, the surveyed experts estimated the potential future relevance of the predefined risk categories by the year 2022 (Becker and Buchkremer, 2018b).

In a first step, the participants were requested to rate the current relevance of risk categories on a scale ranging from "very low" to "very high". The scale for this SQ was based on Atteslander (2010, pp. 227-243). To visualize the answers to this question in figure 26, the terms of this scale had to be described by a numeric value. For this purpose, the term "very high" is described as the value one, the term "high" is defined as the numeric value two, the word "middle" is defined as number three, "low" equals the value four and the term "very low" is defined as the numeric value five. As a consequence, a risk category that shows a high average rating is regarded to be less relevant than a risk category that shows a low average rating. The illustration in figure 26 presents the average rating of the individual categories in ascending order (Becker and Buchkremer, 2018b).

- SQ6: How would you rate the current relevance of the following risk categories for the risk management of your institution?

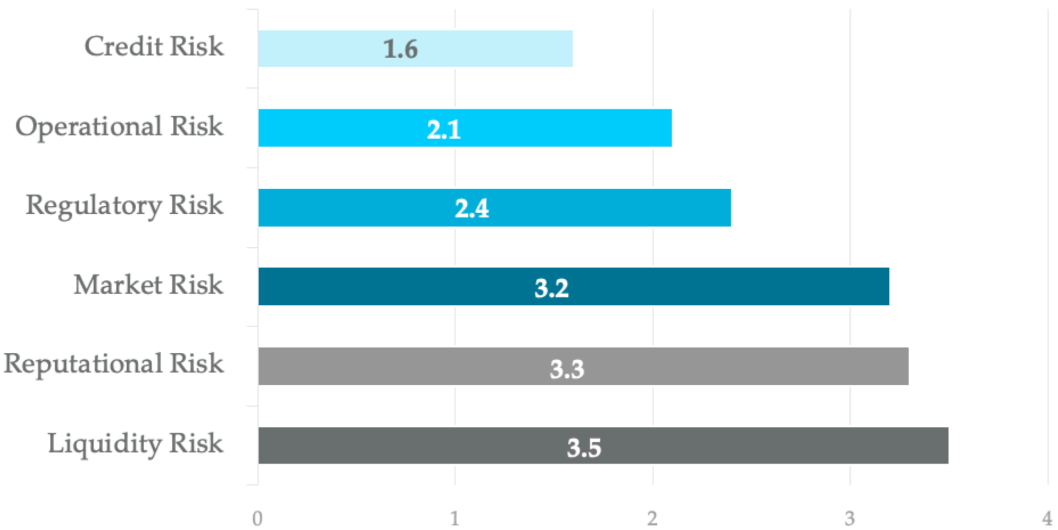


Figure 26: Rating of the current relevance of predefined risk categories

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The usage of the six predefined categories is based on the answers provided in the expert interviews (see chapter 3.3) and Hull (2010). It must be considered that the selected risk categories can be defined differently depending on the background of the chosen definition (Becker and Buchkremer, 2018b). Therefore, a common definition of each risk category is provided for the survey recipients to ensure that the experts have a common understanding of the terms.

In this survey, credit risk describes the risk that a borrower or other counterparty may default and fail to meet obligations that are in line with predefined terms, e.g. the risk that a borrower is not able to pay back a loan (Hull, 2010, p. 289; Bank for International Settlements, 1999). The term operational risk describes the risk of losses caused by insufficient internal processes and systems or by external events like natural disasters (Hull, 2010, p. 368 f.; Basel Committee on Banking Supervision, 2001). Regulatory risk is an integral part of operational risk and describes the risk of losses caused by the lack of regulatory compliance. However, since regulatory risk has become significantly more important since the world-wide economic crisis of 2007-2008, it is stated as a risk category of its own. The category market risk describes the risk of losses caused by adverse market price movements (European Banking Authority, 2017). Furthermore, reputational risk describes the risk of losses caused by negative perception of an institution. It must be considered that reputational risk is explicitly excluded from operational risk by the Basel Committee on Banking Supervision. The sixth risk category is liquidity risk. This term is defined as the risk of being unable to meet liabilities and make payments as they become due (Hull, 2010, p. 385; Nikolaou, 2009).

The bar chart in figure 26 shows that the category credit risk is regarded as the most significant risk category with an average rating of 1.6. With 0.5 points behind, the category operational risk (2.1) is at the second position. With an average rating of 2.4, regulatory risk is rated on position three. Figure 26 also indicates that the three further risk categories market risk (3.2), reputational risk (3.3) and liquidity risk (3.5) are considered to be considerably less significant for the risk management of German FIs (Becker and Buchkremer, 2018b).

The following section provides a comparison of the results of question six and question seven. The main difference between these questions is that in question six, an individual rating of the risk categories is required and in question seven, a ranking of the risk categories on a scale from one to six is created. Therefore, with regard to question six, the survey participants are given the opportunity to provide two or more risk categories with the same rating. However, in question seven, the participants have to define a descending order of the relevance of risk categories and cannot rank two or more factors as equally relevant (Becker and Buchkremer, 2018b).

The current ranking of the relevance of predefined risk categories is illustrated in figure 27. The scale reaches from one to six. In this context, the numeric value one defines the most relevant category and the value six defines the least relevant risk category (Becker and Buchkremer, 2018b). The bar chart in figure 27 illustrates the average ranking of the individual categories in ascending order.

- SQ7: Please create a ranking of the current relevance of selected risk categories for the risk management of your institution on a scale from one to six.

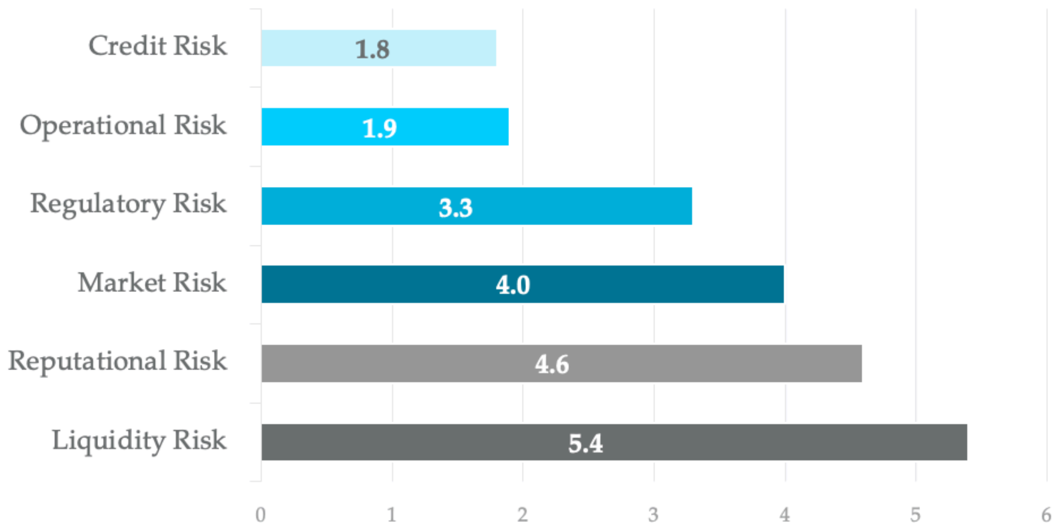


Figure 27: Ranking of the current relevance of predefined risk categories

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The results of questions six and seven show that the descending order of categories is equal in both questions. One major difference is the gap between the individual risk categories. The results of both questions show that, according to the survey participants, the category credit risk is the most significant risk category for German FIs with an average ranking of 1.8. According to Azzollini and Pacelli (2011), in the past years, credit risk has been the most significant risk category for the risk management of a majority of FIs.

Closely behind, the category operational risk is on position two with an average of 1.9. In accordance to that, Power (2005) and Jobst (2007) also discovered the increasing relevance of the risk category operational risk and regarded it as an important factor for the regulation of banks and other FIs since the International Convergence of Capital Measurement and Capital Standards document, known as Basel II, was introduced in the year 2004. The measurement and management of operational risk became even more relevant for banks and other FIs in the EU when the Basel II reforms were extended by the current regulatory framework Basel III in December 2010 (Bank for International Settlements, 2017; Ames, Schuermann and Scott, 2015). The significant gap between these two risk categories and the other four categories illustrates that credit risk and operational risk are the main fields of interest for the risk management departments of FIs in Germany (Becker and Buchkremer, 2018b).

The third position is held by the category regulatory risk with an average ranking of 3.3. As a result, it must be considered that regulatory risk is above traditional banking risks like market risk (4.0), reputational risk (4.6) and liquidity risk (5.4). An explanation for the bad ranking of the category liquidity risk in both questions six and seven can be the current loose monetary policy carried out by the ECB. Banks and other FIs in the EU were enabled to get large amounts of money at a comparatively low interest rate at the time this research was executed. As a result, the risk of being not able to meet obligations on time is small (Becker and Buchkremer, 2018b). These insights are in accordance with the survey called the "European Banking Barometer of 2016", that was carried out by the consulting company Ernst & Young and the Institute of International Finance. The results of their study also show that banks and other FIs tend to focus more on non-traditional risks like operational risk than on basic banking-related risks (Ernst & Young, 2016). Moreover, Lemieux (2012, p. 47 f.) also realized a major shift from focusing on traditional financial risks towards non-financial risk categories since the financial and economic crisis of 2007-2008 (Lemieux, 2012, p. 47 f.; Becker and Buchkremer, 2018b).

The following SQ deals with the estimated future relevance of predefined risk categories by the year 2022. The results of this question are presented in figure 28.

- SQ8: In your opinion, how will the ranking of the above-mentioned risk categories look like in five years from now? Please create a ranking of the estimated relevance of the risk categories for the risk management of your institution in five years from now on a scale from one to six.

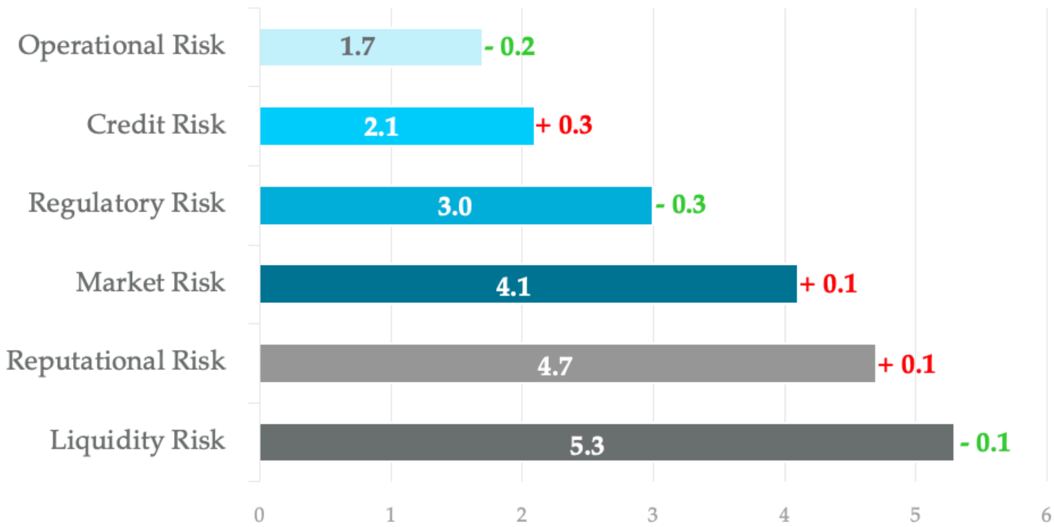


Figure 28: Ranking of the estimated future relevance of predefined risk categories [source: own presentation based on (Becker and Buchkremer, 2018b)]

The figures in green and red colors behind each bar show the deviation of the results of this question from the ranking of the current significance of the categories in question seven. It is noticeable that the category operational risk is ranked as the most important risk category by the end of the year 2022 with an average ranking of 1.7. In comparison with the insights of question seven, this is equivalent to a deduction of 0.2 points. In contrast to that development, the average ranking of the category credit risk is 0.3 points higher (2.1) than at the previous question. This switch between the first and the second rank illustrates that the survey participants estimate that operational risks will be more significant for the risk management departments of German FIs than credit risk by the year 2022 (Becker and Buchkremer, 2018b). This finding is in accordance with the study of Ernst & Young of the year 2016. The participants of this study also evaluate that the category operational risk will become considerably more relevant for FIs in Europe in the near future (Ernst & Young, 2016). Furthermore, Lemieux (2012, p. 47 f.) also estimated that operational risk is going to be the most significant risk category for the risk management of FIs in the future. Regulatory risk is also expected to become considerably more relevant in comparison with the results of question seven. The average ranking of regulatory risk is 3.0, which equals a reduction by 0.3 points (Becker and Buchkremer, 2018b). According to Cohn (2016), an explanation for this development is the complex relation between the aspects risk and regulation. Cohn evaluated that the regulation of risks that are identified and estimated reshapes and generates new risks for banks and other FIs. As a result, an increasing extent of regulations directly causes an increase in regulatory risk. Figure 28 also shows that the results of the three additional categories market risk (4.1), reputational risk (4.7) and liquidity risk (5.3) each vary by 0.1 points in comparison with the results of question seven (Becker and Buchkremer, 2018b).

3.4.3.3 Evaluation of regulatory requirements

In the following section, the extent and degree of complexity of regulations for FIs in Germany are regarded. The aim of this set of questions is to determine if the current overall framework of regulations is seen as a burden for the risk and compliance management of German FIs. The response options to these questions are based on Atteslander (2010, pp. 227-243) (Becker and Buchkremer, 2018b).

- SQ9: How would you rate the current extent of regulatory requirements for your institution?

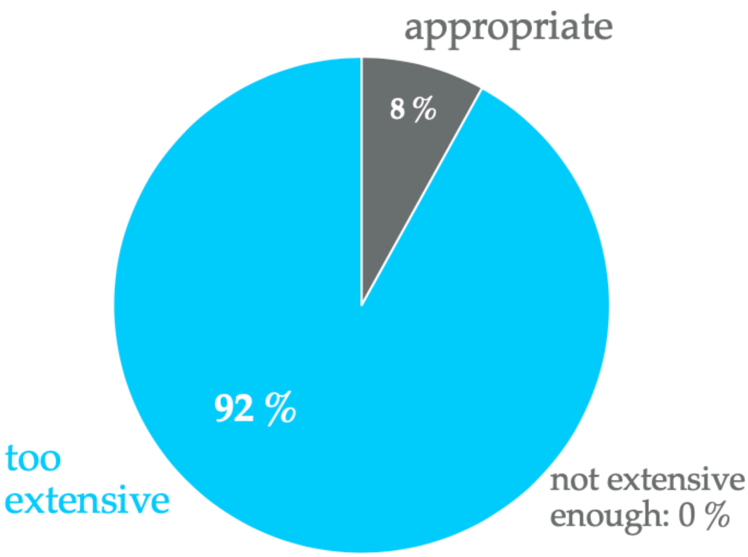


Figure 29: Rating of the current extent of regulatory requirements

[source: own presentation based on (Becker and Buchkremer, 2018b)]

Figure 29 illustrates that more than 9 of 10 (92 %) of the surveyed risk managers and compliance officers claim that the current regulatory framework is too extensive for their institutions. This finding represents a first indication that FIs in Germany might feel overloaded by the large extent of regulations. In addition, the other 8 % of the survey participants say that the current number of regulatory requirements is appropriate. It is noticeable that not one of the 62 participating experts answered that the current extent of regulations is not extensive enough. In a further step, the insights of this question are compared to the insights of the following questions (Becker and Buchkremer, 2018b).

- SQ10: How would you rate the degree of complexity of the current regulatory requirements for your institution?

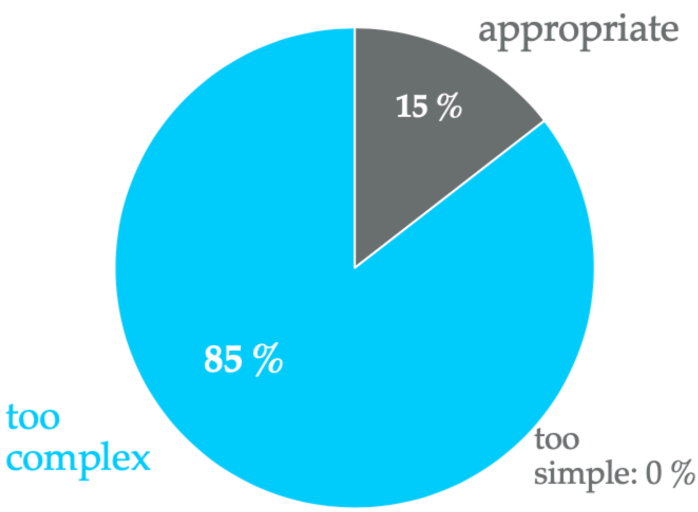


Figure 30: Rating of the degree of complexity of the current regulatory requirements [source: own presentation based on (Becker and Buchkremer, 2018b)]

The pie chart in figure 30 illustrates that 85 % of the surveyed experts claim that the regulatory framework for German FIs is too complex. Therefore, this insight is an additional indicator that German FIs might feel overloaded by the current regulatory requirements. Additionally, the other 15 % of the participants answered that the complexity of the current regulations for FIs is acceptable. It must be considered that no one of the participants said that the current regulations are too simple (Becker and Buchkremer, 2018b). The third question of this section combines the two thematic fields regulations and new technologies. The participating risk managers and compliance officers are asked to evaluate if their organization will be required to implement new solutions in order to deal with the growing number of regulatory requirements in the following five years (Becker and Buchkremer, 2018b).

- SQ11: Since the world-wide financial and economic crisis of 2008, the number of regulatory requirements for financial institutions increases steadily. Do you think that your institution will need to implement new technological solutions in order to manage the increasing number of regulatory requirements in the next five years?

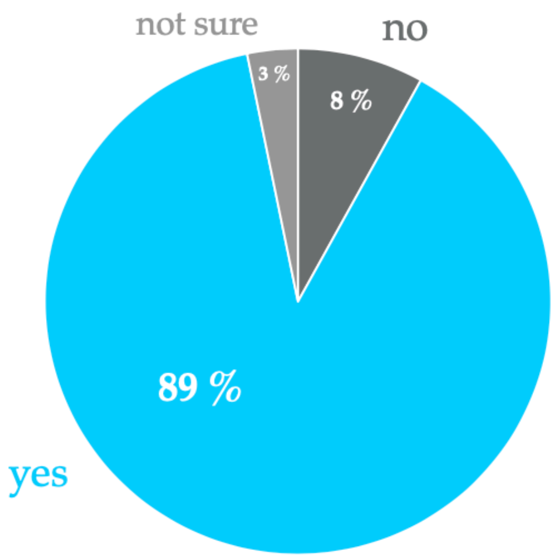


Figure 31: The need of technical solutions to manage regulations in the future

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The answers provided to this question show that 89 % of the surveyed experts estimate that their institutions will be required to deal with new technologies in the area of regulatory compliance management in the following five years. This insight is a further indicator that German FIs feel overloaded by the current and estimated future regulations. Another 8 % predict that their organizations will not need to deal with the implementation of new technologies in the regulatory compliance environment. The remaining 3 % of the participants are not sure about this thematic field (Becker and Buchkremer, 2018b).

The results of this set of questions are in line with the insights of the study that was carried out by McKinsey & Company in the year 2017. Their research shows that 97 % of the participants are convinced that the thematic fields of digitalization and new technologies are critical factors to deal more efficiently with an increasing regulatory burden. Moreover, 100 % of the European respondents of the McKinsey survey see new technologies as an essential factor to cover this topic in the future (McKinsey & Company, 2017). One reason for the minor differences between the insights of the study carried out by McKinsey and this research is that the target survey audiences are slightly different. The survey carried out in this research provides no restriction of the size of the organizations of the participants, whereas the McKinsey study regards G-SIFIs. Global banks and other FIs might tend to rank the relevance of new technologies higher than smaller regionally operating banks since the business actions and structures of G-SIFIs are often more complex than those of comparatively small regional banks (McKinsey & Company, 2017; Becker and Buchkremer, 2018b). In general, the evaluation of scientific literature also shows that an increasing demand for new technological solutions is expected to deal with the increasing number of regulations. In particular, Agarwal et al. (2017) introduce a cognitive computing platform that uses new technologies like AI and machine leaning with the aim to achieve and ensure compliance with regulations. Furthermore, Arner, Barberis and Buckley (2017) and Weber (2017) identify a huge potential of RegTech solutions.

To draw a conclusion, the evaluation of the three questions covering the thematic field of regulatory requirements shows that the current overall regulation is too extensive and too complex for most of the surveyed FIs in Germany. Therefore, a large portion of the contributing risk managers and compliance officers estimate that their organizations will be required to deal with new technological solutions to be capable of dealing with this topic more efficiently in the future (Becker and Buchkremer, 2018b).

3.4.3.4 Evaluation of new technologies

In this section, the experts are requested to both rate and rank the expected future relevance of selected new technologies for the risk and compliance management departments by the year 2022. In a further step, they are asked to identify the main reason for FIs in Germany to invest in new technological solutions (Becker and Buchkremer, 2018b).

The bar chart in figure 32 visualizes the answers provided to the first SQ of this topic. In particular, the surveyed rate the estimated future relevance of predefined new technologies on a scale ranging from “very low” to “very high”. The illustration of the bar chart is generated in accordance to the methodology used for SQ6. Therefore, an average rating of each technology on a scale from one to six is presented (see chapter 3.4.3.2).

Accordingly, a technology that received a higher average rating is regarded as less relevant than a technology that received a lower average rating by the survey participants (Becker and Buchkremer, 2018b).

- SQ12: How would you rate the relevance of the following new technologies for the risk and regulatory compliance management of your institution in the next five years?

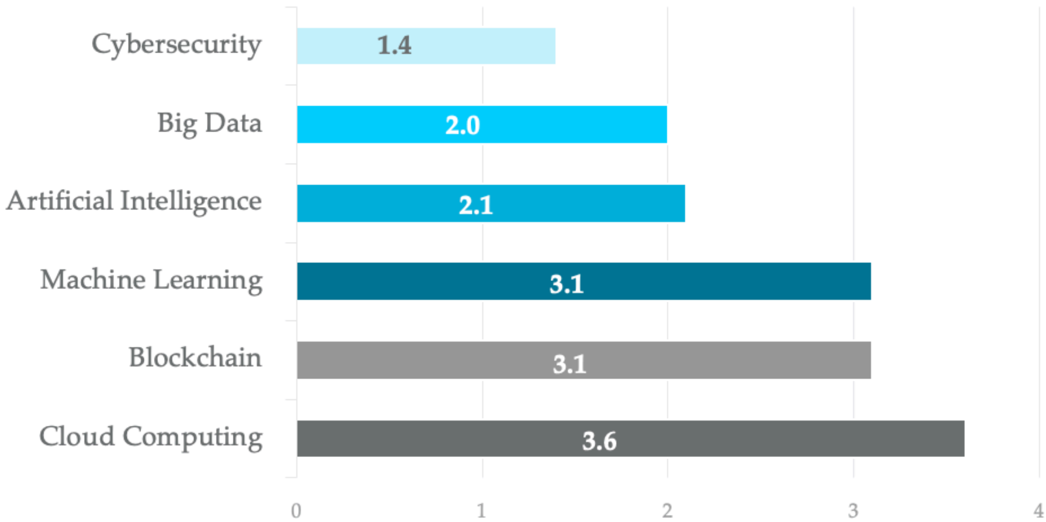


Figure 32: Rating of the estimated future relevance of predefined new technologies [source: own presentation based on (Becker and Buchkremer, 2018b)]

The selection of the presented technologies is based on the insights of the expert interviews (see chapter 3.3) and on the study "Regtech in Financial Services: Technology solutions for Compliance and Reporting", which was executed by the Institute of International Finance (2016c).

It must be considered that the technologies presented in figure 32 are defined differently in the available literature. Therefore, each presented technology is defined in a particular way for this survey to ensure that the participants have a common understanding of the terms (Becker and Buchkremer, 2018b).

The term Cybersecurity describes technological ways of protecting computer systems against threats (Cambridge University Press, 2017). In general, Big Data is defined as a large set of data, which is difficult to process with the use of a standard computer or server (Finlay, 2017, p. 123). AI is defined in a broad perspective as the replication of biological, mainly human, capabilities to understand, reason, learn and combine (Ertel, 2011, p. 1; Finlay, 2017, p. 123). Another technology that is defined in a specific manner in this survey is Machine Learning. This term describes technologies to identify relationships or specific patterns in a data sample to create a model that incorporates these relationships which lead to predictions. In the literature, Machine Learning is often regarded as a part of AI. However, since specific Machine Learning solutions become significantly more important for FIs, it is stated as a category of its own (van Liebergen, 2017; Marr, 2016). The term Blockchain describes distributed immutable ledger technologies to share information in and between institutions (Institute of International Finance, 2016c, p. 4; IBM, 2017c). The commonly used term Cloud Computing describes the use of IT capabilities that are on the internet rather than on a PC or server (Cambridge University Press, 2017).

Figure 32 illustrates that Cybersecurity is regarded as the most significant new technological field in the risk and compliance management environment. It received an average rating of 1.4. Big Data technologies are on position two with an average rating of 2.0 and AI solutions are close behind with a rating of 2.1. The three further technologies Machine Learning (3.1), Blockchain (3.1) and Cloud Computing (3.6) are rated considerably less significant than the first fields of technology (Becker and Buchkremer, 2018b). In a further step, the insights of SQ12 are compared to the answers provided to SQ13. The differences between questions twelve and 13 are like the differences between questions 6 and 7 (see chapter 3.4.3.2).

Accordingly, the bar chart in figure 33 illustrates the rank of the relevance of the predefined new technologies on a scale ranging from one to six. Similar to the prior section, the numeric value one equals the most relevant field of technology and the numeric value six equals the least significant field of technology (Becker and Buchkremer, 2018b). The bar chart shows the ranking of the predefined technologies in ascending order.

- SQ13: Please create a ranking of the estimated relevance of the above-mentioned new technologies for the risk and regulatory compliance management of your institution in the next five years on a scale from one to six.

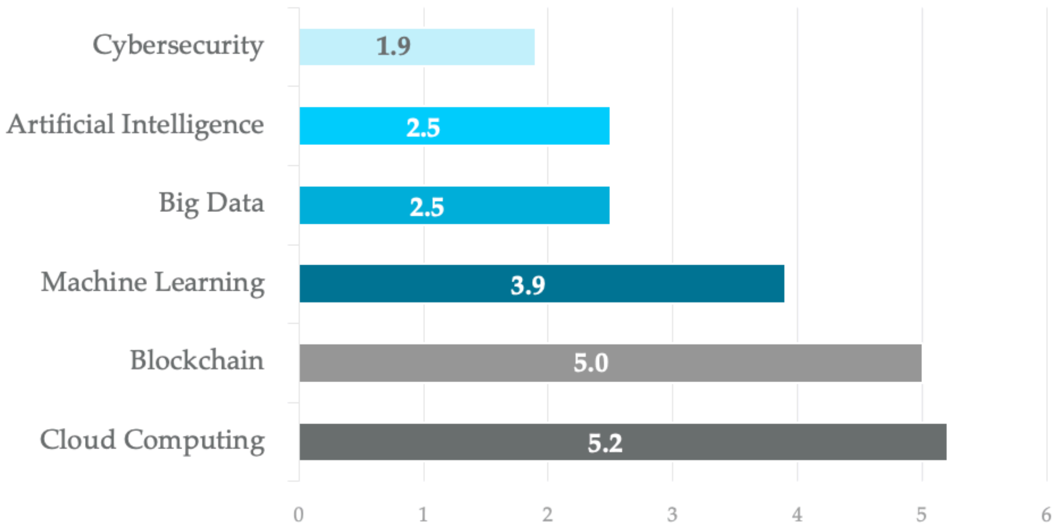


Figure 33: Ranking of the estimated future relevance of predefined new technologies [source: own presentation based on (Becker and Buchkremer, 2018b)]

The results of SQ13 show that the ascending order of ranked technologies differs from the order presented for SQ12. In figure 33, AI technologies are ranked marginally above Big Data solutions. The sequence of the other technologies did not vary. However, a comparison of the results shows that the gap between the single technologies also differs (Becker and Buchkremer, 2018b).

The results of both question twelve and 13 show that Cybersecurity technologies are highly relevant for the risk and compliance management departments of German institutions with an average rank of 1.9. According to Lemieux (2012, p. 47 f.), one explanation for this outcome is that issues regarding Cybersecurity are not only expensive, but also a significant risk regarding the reputation of an organization. Besides, Johnson (2015) explains that concerns of FIs regarding Cybersecurity issues are arising. Johnson evaluated that concerns regarding Cybersecurity of G-SIFIs could lead to a shock or debilitation of the global financial sector that could have a tremendously negative impact on the overall global economy. For this reason, Johnson explains that technologies ensuring Cybersecurity are important to prevent such an undesirable scenario from happening in the future. These results are also in accordance with the study by Ernst & Young that was carried out in cooperation with the Institute of International Finance (2017). Their study evaluates that 77 % of the included risk managers regard Cybersecurity as the top agenda item for the risk management activities of FIs.

AI technologies and Bis Data solutions are regarded as almost equally relevant with an average ranking of 2.5. With regard to the survey carried out by Ernst & Young, almost every second (45 %) participant expects that AI technologies will have a considerable impact on future risk functions of financial organizations in the next years. These insights are a first indicator for the significant future demand of AI technologies in the risk and regulatory compliance management environment (Becker and Buchkremer, 2018b). Furthermore, Stone et al. (2016) are convinced that AI solutions and Cybersecurity will be significant factors in order to ensure public and corporate safety by the year 2030.

Machine Learning technologies are on position four with an average ranking of 3.9. The two further technologies Blockchain (5.0) and Cloud Computing (5.2) are regarded as less significant than the other technologies. The comparatively poor rank of Cloud Computing technologies is consistent to the positive rank of Cybersecurity. In general, data that is available and processed in a cloud-based environment that is hosted externally tends to be more probable to be affected by possible cyber threats than data that is stored locally at the servers of an organization (Becker and Buchkremer, 2018b). The study that was carried out by McKinsey & Company (2017) indicates that 83 % of the European participants claim that a potential shift from locally installed to cloud-based technologies is inhibited by security concerns. Moreover, their study shows that half of the participants also regard extensive regulation of the financial sector as a major reason to prefer locally installed applications rather than environments in a cloud system (Mc Kinsey & Company, 2017). An overview of potential security concerns with reference to cloud computing is provided by Aich, Sen and Dash (2015) and Kulkarni et al. (2012).

In the next part, the main reasons for investing in new technological solutions for German FIs are investigated. Please note that this question (SQ14) is not restricted to the risk and compliance management activities of FIs. For this reason, further aspects that might be relevant for the surveyed are also considered (Becker and Buchkremer, 2018b).

- SQ14: In your opinion, what is currently the main reason for investing in new technologies for financial institutions in Germany?

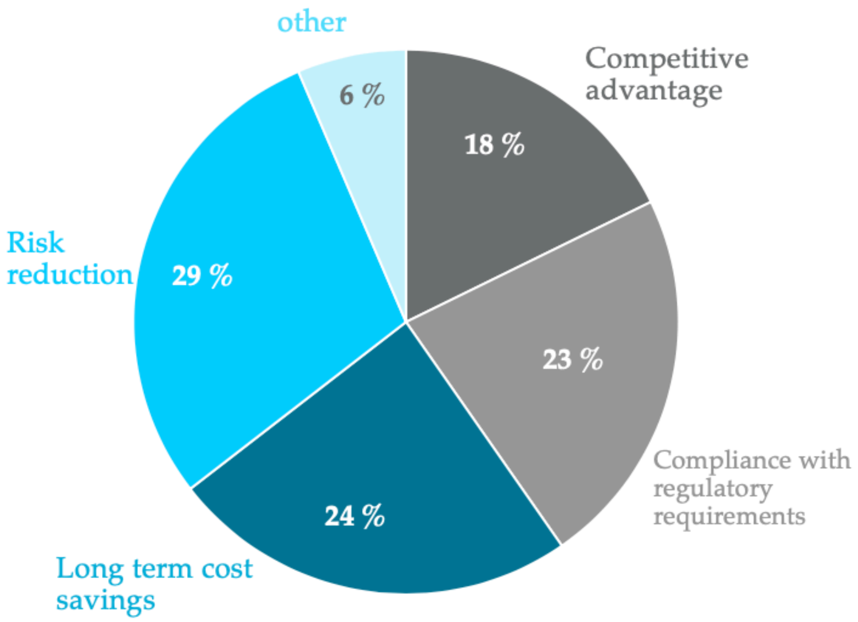


Figure 34: Overview of the main reasons for investing in new technologies [source: own presentation based on (Becker and Buchkremer, 2018b)]

The predefined response options presented in figure 34 are mainly based on the study regarding AI at the financial services environment, which was executed by Deloitte (2017) and Efma. The chart illustrates that the reduction of risk is the main reason to invest in new technologies for 29 % of the participants. A possible explanation for this large proportion is that the surveyed experts are risk manager and compliance officers of German FIs. For this focus group, risk reduction is likely to be of significant importance. About one quarter (24 %) of the surveyed estimate that long term cost savings are the main reason to invest in new technologies. For 23 % of the surveyed experts, compliance with regulations is the main aspect and a further 18 % regard competitive advantage as the major reason (Becker and Buchkremer, 2018b). A portion of 6 % of the participants used the additional text box to provide different answers. In particular, the following responses are given:

- creation of new products
- usage of online distribution channels
- strategic digitalization
- changing customer behaviour

Each of these four answers was provided by one participant (Becker and Buchkremer, 2018b).

3.4.3.5 Artificial Intelligence technologies

The last part of the survey deliberately focuses on the implementation of AI solutions rather than on cognitive computing technologies in general. The reason for this limitation is that the expert interviews showed that the participating experts are more familiar with the term AI than with the more general term cognitive computing. Therefore, the following SQs deal with the implementation of AI applications. The overriding goal of this approach is to identify to what degree the risk and compliance management of FIs in Germany are engaged in this thematic field. In a further step, the surveyed experts are invited to predict when AI-featured solutions will be in use in the future. The purpose of the last SQ is to determine how FIs will predominantly develop AI applications in the following years. The questions presented in this section and the individual response options are based on the insights of the expert interviews (see chapter 3.3) and on the study entitled "AI and you: Perceptions of Artificial Intelligence from the EMEA financial services industry" that was executed by Deloitte and Efma (Deloitte, 2017; Becker and Buchkremer, 2018b). Since the Deloitte study was carried out in the same year (2017) as the survey presented in this research, the results are comparable. However, the target audience of this research are risk managers and compliance managers of German FIs, whereas the Deloitte study focuses on business and technical executives in the geographic region of EMEA.

In the first question of this thematic field, the surveyed are asked when the risk and compliance management departments of their organizations have started to get involved with AI-featured solutions. It needs to be considered that the answers refer to the time the survey was executed in late 2017 (Becker and Buchkremer, 2018b). Figure 35 visualizes the answers to this question.

- SQ15: When did the risk and regulatory compliance management department(s) of your institution officially start to deal with the field of Artificial Intelligence?

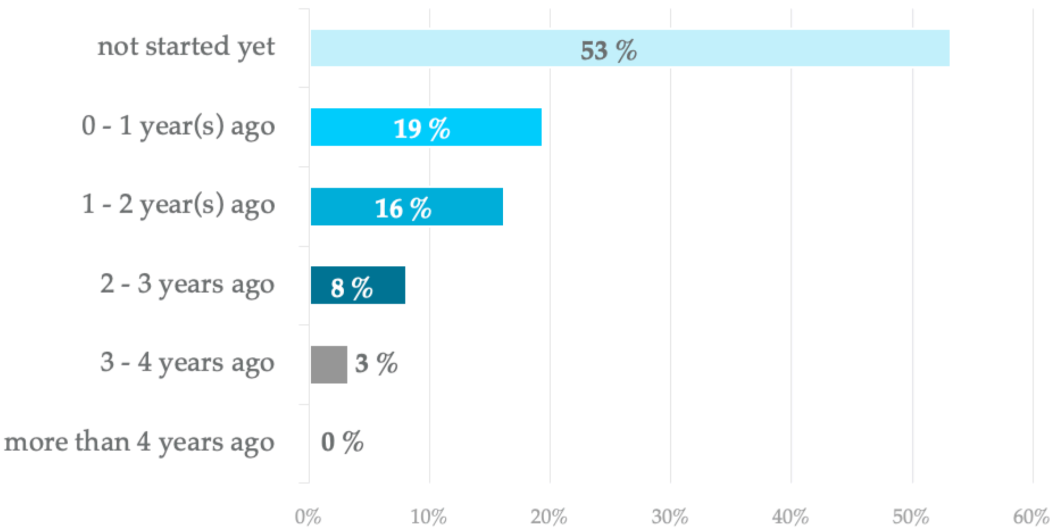


Figure 35: Official starting point for Artificial Intelligence technologies

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The bar chart in figure 35 shows that 53 % of the risk and regulatory compliance management departments of the participating German FIs have not started to get involved with the subject matter yet. Furthermore, 19 % of the surveyed say that their institution has begun to deal with AI technologies in the last twelve months. Another 16 % point out that their institutions have started to get engaged in this field one to two years ago and 8 % of the survey participants emphasize that they have already commenced two or three years ago. The other 3 % say that they have even started three or four years ago. No one of the participants said that their institution has already started to deal with this subject more than four years ago. These results show that AI is a comparatively young field of research. Therefore, the risk and compliance management environments of several FIs have not started to engage in this field of action yet (Becker and Buchkremer, 2018b)

In comparison with the study by Deloitte and Efma (2017), it must be recognized that there are substantial deviations in the statements of results. According to the study carried out by Deloitte, only about one of ten (11 %) of the interview partners has not commenced to cope with AI solutions yet, compared to 53 % of the respondents of this survey. An explanation for these deviations is that the studies have different target groups. This study is limited to risk and compliance managers that operate in Germany, whereas the study by Deloitte focuses on business and technical executive experts in the EMEA region. In other parts of banking activities and services, AI-featured solutions have already been developed further than in the risk and compliance management environment. For this reason, executives of other departments might estimate the situation in a different way (Deloitte, 2017; Becker and Buchkremer, 2018b). With regard to the topic-related scientific literature, Moro, Cortez and Rita (2015) evaluated the literature on the thematic field of BI in the financial industry from 2002 to 2013 by using a text data mining approach with the aim to discover the most significant fields of BI-featured solutions in the financial sector (see chapter 3.1). The insights of their research show that credit business was the main field of action for the financial industry between 2002 and 2013. Furthermore, Moro, Cortez and Rita point out that special risk management tasks like bankruptcy prediction and fraud detection are also relevant fields for BI applications. The insights of their study confirm the importance of new technologies like BI and AI for the risk management departments of financial organizations (Becker and Buchkremer, 2018b).

In a subsequent step, the survey participants are requested to predict when AI solutions will be applied and used with the aim to enhance the risk and compliance management activities of their individual institutions (Becker and Buchkremer, 2018b). The corresponding results of this question are visualized in figure 36.

- SQ16: When do you think Artificial Intelligence solutions will be implemented and used to improve the risk and regulatory compliance management processes of your institution?

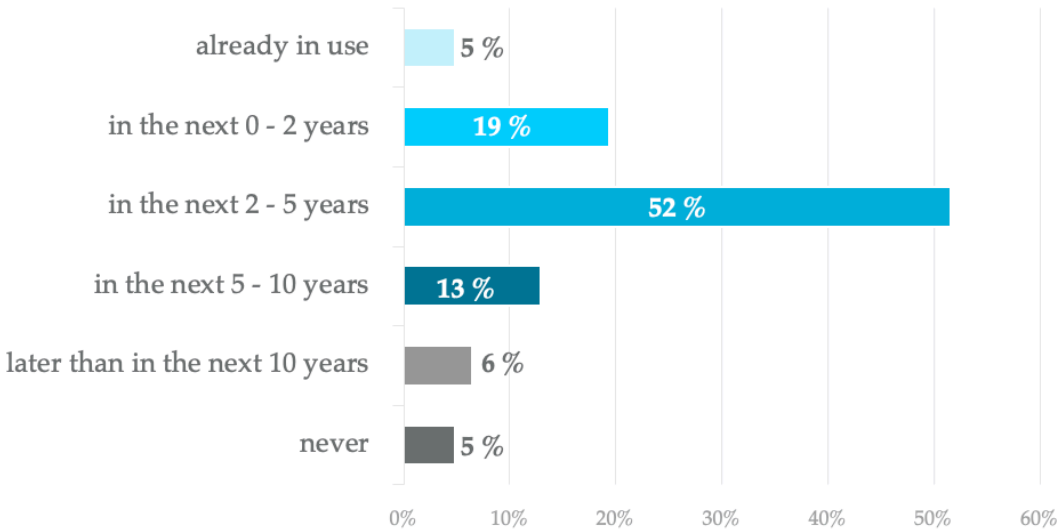


Figure 36: Implementation and usage of Artificial Intelligence technologies

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The bar chart in figure 36 illustrates that more than every second participant expects AI-featured technologies to be implemented and in use in the next two to five years (52 %). A further 19 % are of the opinion that AI-based solutions will already be in operation in the following two years. Consequently, a majority of 71 % of the surveyed experts estimate AI to be applied by the end of the year 2022. In addition, 5 % of the participants say that AI solutions are already in operation in their individual institution. Besides, 13 % think AI will be implemented in the next five to ten years. Another 6 % expect that it will even take more than one decade. 5 % of participating experts estimate that AI solutions will never be used in the risk and compliance management environment of German FIs (Becker and Buchkremer, 2018b). These insights are similar to the insights of the study that was carried out by Deloitte and Efma. Their study evaluates that 42 % of the participating experts of financial companies are convinced that AI-featured solutions will be mainstream in the next two to five years. Additionally, the Deloitte survey highlights that 88 % of the participants estimate that AI-featured solutions will be in use by the end of the year 2022. Only 3 % estimate that AI applications will never be in use (Deloitte, 2017). With regard to risk and compliance management activities, FIs in Europe are challenged by restrictive regulations of IT systems (Basel Committee on Banking Supervision, 2013c). For this reason, several FIs still hesitate with the investment in AI-based technological solutions. However, a majority of risk and compliance managers that participated in this survey expect AI-powered solutions to be in operation by the end of the year 2022 as a consequence of a rising business need (Becker and Buchkremer, 2018b).

The final question of this survey identifies how German FIs will mainly develop AI applications in the future. It must be considered that the participating experts who estimated that AI solutions will never be used at their individual institution (SQ 16) were not included in the assessment of this question (Becker and Buchkremer, 2018b). Figure 37 visualizes the results.

- SQ17: In your opinion, how will your institution mainly develop Artificial Intelligence solutions for the risk and regulatory compliance management in the future?

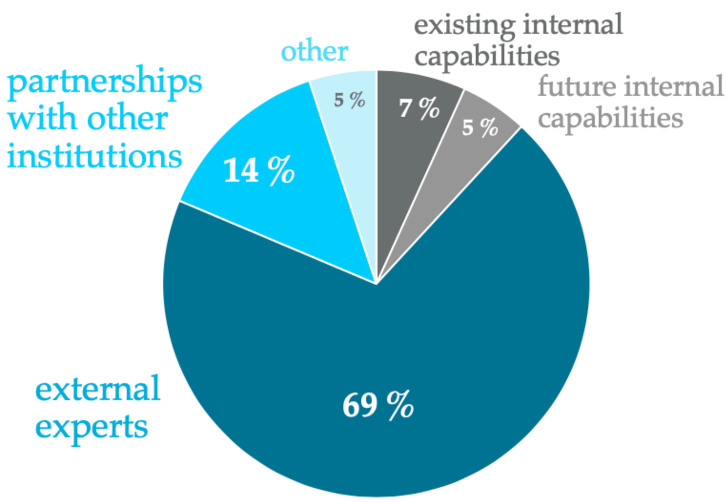


Figure 37: Development of Artificial Intelligence applications

[source: own presentation based on (Becker and Buchkremer, 2018b)]

The pie chart in figure 37 illustrates that 69 % of the survey participants believe that their FIs will predominantly develop AI applications through the expert knowledge of external parties. Another 14 % respond that their FIs will partner with other organizations to reach this objective. A sum of 12 % are of the opinion that their FIs will predominantly develop AI-featured applications with existing (7 %) or potential future (5 %) internal resources. 5 % of the surveyed provided a response using the text box (Becker and Buchkremer, 2018b). The following answers were submitted:

- within the financial group
- existing network of institutions
- within the group of German public savings banks

In general, the three additional answers that were provided can be assigned to the predefined option "partnership with other institutions". As a result, the share of this response would be increased to 19 %. With regard to the AI-related study by Deloitte, the results are comparable. The insights of the Deloitte study show that 49 % of the participating experts estimate that AI solutions will be developed through external consultants and technical experts. In addition, more than one quarter (26 %) of the participants are of the opinion that they will cooperate with other institutions and another 15 % believe that the implementation of AI applications will mainly be done by internal resources (Deloitte, 2017; Becker and Buchkremer, 2018b).

3.4.4 Critical view on the survey results

One major risk factor of the presented survey is the size of the sample group. It is nearly impossible to include all 1,888 FIs in Germany in a survey (reporting date: December 31, 2016). For this reason, it is a mandatory task to create a sample group that aims to reproduce the statistical population. Therefore, the risk exists that the theoretical statistical population is not reflected accurately. This may lead to incorrect assumptions (Atteslander, 2010, p. 163; Bethlehem, 2010; Becker and

Buchkremer, 2018b). In this research, the sample group is based on the proportional distribution of the banking sector in Germany. The aim of this approach is to reproduce the allocation of the banking sector based on the total number of institutions and the number of bank branches. However, deviations of the target and the actual survey audience occurred due to different response quotas of the single banking sectors and due to the relatively small sample group in comparison to the number of FIs. In total, 62 of 1,888 (3.3 %) FIs in Germany participated in this survey. Since the main purpose of this survey is to derive general statements to the subject matter from the survey results, errors in the composition of the sample group are regarded as a minor factor. Other potential risk factors are the questionnaire and the participants of the survey. The recipients edited the survey forms independently without an opportunity to raise questions to single subjects or to the response options. Therefore, the wording of the questions and a restriction of the given response options can lead to distortions of the opinions of the participants. Moreover, the wording may also lead to misinterpretations and different assumptions of the recipients (Atteslander, 2010, p. 163; Bethlehem, 2010). To reduce possible errors and misinterpretations, the first draft of the questionnaire has been tested by three different experts on selected factors. The feedbacks of the specialists have been included in the revision of the questionnaire. Besides, the respondents were given the opportunity to add individual answers to selected questions if they did not agree with the predefined response options. In detail, four respondents used the additional text box to provide their answers to question 14 and three participants wrote an individual answer to question 17 (Becker and Buchkremer, 2018b).

Moreover, the distribution through online channels may also lead to errors due to technical issues that could lead to a distortion of results (Bethlehem, 2010). It may occur that recipients who are willing to participate in the survey may not have access to the online version of the survey due to technical difficulties or internet access restrictions of their institutions. To reduce this source of error, the survey form was distributed in two different versions. One of them offered the opportunity to edit the survey form offline using a PDF document. For this reason, the potential for errors caused by the online distribution is regarded as marginal.

As a consequence, the survey results do not allow to draw general conclusions for each risk and compliance management department of German FIs due to the above-mentioned risks of errors and misinterpretations. This essential aspect has to be considered when the survey results are interpreted. For this reason, the statements of this survey are compared to the topic-related literature and to four acknowledged existing surveys that cover similar thematic fields. Therefore, the results of this survey in combination with the evaluation of the literature and the four reference surveys allow the derivation of initial general conclusions (Becker and Buchkremer, 2018b).

3.5 INTERIM CONCLUSION

In this chapter, the major fields of action to enhance the risk and compliance management of FIs were regarded from both a theoretical and a practical perspective to answer the first RQ. The theory-based approach is to analyse more than 2,200 scientific articles that deal with the use of cognitive computing technologies in the financial sector. For this purpose, seven literature research online portals are scanned to find suitable journal articles that deal with the subject matter. These papers are analysed using a text data mining approach in combination with a cluster analysis with the aim to discover the thematic fields of the articles (see chapters 3.1.2 and 3.1.3). As an initial result, the chronological distribution of the number of hits per year shows that cognitive computing technologies like AI have become a significantly more relevant topic for FIs over time. In detail, especially the years 2016 and 2017 show a considerable increase in the number of articles compared to the previous years. One reason for this significant growth is that a large proportion of journal articles deal with the implementation of FinTech or related subjects (see chapter 3.1.4.1). With regard to the thematic fields that the articles cover, the technical analysis leads to the identification of nine subject clusters. The evaluation of these clusters shows that four of these clusters deal with topics that are related to risk and compliance management activities of financial organizations. In particular, these clusters are entitled "auditing", "bankruptcy prediction", "credit risk measurement" and "fraud detection". Consequently, the systemic literature review shows that risk and compliance management are highly relevant topics with regard to the application of cognitive computing technologies in the financial environment. The additional clusters mainly cover the integration of new technologies and typical banking activities like "customer services" and "portfolio management" (see chapter 3.1.4.2). In a further step, an additional cluster analysis is performed for three predefined time periods in order to discover the recent development of the topics that deal with cognitive computing in the financial sector. The evaluation of the pre financial crisis period from 2003 to 2008 shows that "accounting" appears as an additional cluster in that time. The main reason for this result is that several articles deal with the occurrence of numerous corporate accounting scandals in the early 2000s. In the financial crisis and post crisis period from 2009 to 2015, the additional clusters "risk monitoring" and "financial crisis" are detected because several journal articles investigated the development and the outcomes of the financial crisis and how new technologies can assist to prevent such a crisis from occurring again in the future. The third period from 2016 to 2017 is entitled new technologies / FinTech period. In this time, the additional cluster "risk pricing" is detected whereas other clusters like "financial forecast" and "customer services" disappeared. With reference to this research, the systemic literature review shows that a significant share of recently published journal articles regards risk management related subjects rather than focussing on traditional banking tasks (see chapter 3.1.4.3).

The aims of both the expert interviews and the survey that were carried out in this research are to provide expert assessments regarding the future of risk and compliance management at German FIs. On the one hand, these approaches aim to analyse how FIs handle the increasing number and complexity of regulations. On the other hand, they purpose to identify perspectives on new cognitive computing technologies like AI applications to increase the effectiveness and efficiency of the risk and regulatory compliance management activities of FIs in Germany (Becker and Buchkremer, 2018b). For these purposes, six experts were interviewed, and 218 selected executive risk managers and executive compliance officers were asked to participate in the survey. In total, 71 recipients submitted a survey form and 62 of these forms were considered in the assessment of the survey. The insights of the study in this research were compared to four reference surveys and to the topic-related scientific literature in order to identify conformities and possible differences to existing researches (see chapters 3.4.1 and 3.4.3). The insights of the survey show that credit risk is currently ranked as the most important risk category for FIs in Germany. However, risk and compliance managers expect operational risk to become the most important risk category by the end of 2022. This result is in accordance with the results of comparable studies and to the existing literature (see chapter 3.4.3.2). This development is a major challenge for the risk management of FIs. The possible impact of operational risk is significantly more difficult to measure than the risk resulting from the credit portfolio of an institution. Therefore, FIs will have to deal with new technological solutions that provide innovative approaches to manage these non-financial risk factors. With regard to the current framework of regulations, a vast majority of respondents complained that the regulatory requirements are too extensive (92 %) and too complex (85 %).

Moreover, almost nine of ten participants (89 %) estimate that there is a requirement for new technological solutions to deal with the increasing number of regulations in the future. This statement matches the results of the referencing surveys and the topic-related literature. The survey entitled “The Future of Risk Management in the Digital Era”, that was executed by McKinsey & Company and the Institute of International Finance (2017), determines that 97 % of the participating banks are convinced that solutions based on new technologies are critical tools to manage an increasing regulatory burden (see chapter 3.4.3.3). The research results of these two thematic fields show that there is a high demand for new technologies in order to increase the risk and regulatory compliance management activities of FIs in Germany. In particular, the risk and compliance managers expect Cybersecurity, AI and Big Data to be the most relevant technologies by the end of the year 2022 for the risk and compliance management environment of German FIs. These results are in line with the topic-related scientific literature and four related surveys on this thematic field (see chapter 3.4.3.4). When the survey was executed in late 2017, there have already been a variety of technological applications on the market regarding Cybersecurity and Big Data. However, AI-based solutions have been at a comparatively early stage of implementation in 2017. As a result, more than every second (53 %) participant says that his or her institution has not started to get involved with the thematic field of AI in the risk and regulatory compliance management area yet. This considerable divergence between a realised need for AI-featured applications and a comparatively low engagement in this area shows that German FIs have a significant backlog with regard to this subject. A vast majority of 71 % of the participating experts estimate that AI applications will be implemented and in use to enhance the effectiveness and efficiency of the risk and compliance management activities by the end of the year 2022. These results are comparable to the insights of the acknowledged surveys. The presented insights are consequently an indicator for the enormous potential of AI-based solutions in the risk and compliance management area of FIs. A vast majority of 69 % of the survey participants estimate a need for external parties to develop AI-featured cognitive solutions (Becker and Buchkremer, 2018b). This result is in accordance to the AI study by Deloitte (2017). In this study, almost half of the participating experts (49 %) are of the opinion that AI solutions will mainly be developed by external experts (see chapter 3.4.3.5).

These insights show the business opportunities for both technology companies that provide AI-featured applications as well as for consulting organizations that specialize in the field of AI. As a result, the insights of the expert interviews and the survey in combination with four comparable studies and the available scientific literature show that there is a substantial business demand for new technologies to be capable of managing the increasing extent and complexity of regulations for German FIs (Becker and Buchkremer, 2018b).

4 DEVELOPMENT OF COGNITIVE RISK AND REGULATORY COMPLIANCE MANAGEMENT STRATEGIES

The insights of the systemic literature review, the expert interviews and the survey regarding the future of risk and regulatory compliance management at FIs in Germany are taken as a foundation for the development of cognitive risk and compliance management strategies (see chapter 3). The main goals of the newly-developed approaches are to increase both the efficiency and the effectiveness of selected risk and compliance management activities and processes. In this chapter, two different strategies are presented. The first strategy aims to answer the second RQ ("How can the management of regulatory requirements be improved by cognitive computing technologies?") and deals with the implementation of regulatory requirements at banks and other FIs. In a first step, several RegTech tools from selected international technology companies are analysed with regard to their features and one specific tool is selected and used for the purpose of this research (see chapter 4.1.1). Secondly, a strategy is presented that uses an iterative procedure model to process legal documents using the solution IBM Watson Regulatory Compliance (WRC) (see chapter 4.1.2). The approach of this strategy is then compared to a traditional procedure to implement regulations at a selected FI in Germany (see chapter 4.1.3). The second strategy that is presented in this chapter deals with the implementation of process mining procedures to optimize business processes in the risk management of FIs. The aim of this analysis is to answer the third RQ ("How can risk and compliance management business processes be enhanced by cognitive computing technologies?"). In chapter 4.2.1, selected process mining tools are introduced and one application is used for the purpose of this research. Besides, a strategy is developed to use a process mining tool in the risk management department of FIs. For this purpose, the process management lifecycle is analysed (see chapter 4.2.2). Additionally, a specific risk management process is presented (see chapter 4.2.3) and the procedures to implement a process mining tool are explained (chapter 4.2.4). Besides, the selected business process is evaluated using the process mining tool Disco (chapter 4.2.5).

4.1 IMPLEMENTATION STRATEGY FOR REGULATORY REQUIREMENTS

Ensuring the adherence of regulations has to be regarded from two different perspectives. On the one side, it is required that banks and other FIs are aware of all relevant regulatory requirements. On the other side, FIs have to ensure and control the implementation of these regulations. These two aspects need to be considered when an implementation strategy for regulatory requirements is developed (Becker and Buchkremer, 2018a). In this section, an iterative procedure model for the implementation of legal requirements using a RegTech solution is developed. Selected aspects of this implementation strategy have been published by the researcher (see Becker and Buchkremer, 2018a). First of all, selected RegTech applications are introduced that can assist banks and other FIs with this task. Since the presented RegTech solutions have different functionalities, one specific application is selected for the practical development of the strategy.

4.1.1 Analysis of Regulatory Technology applications

There are several RegTech solutions available that can assist banks and other FIs to manage the increasing number and complexity of regulations. In this section, selected applications from five experienced, international technology companies are introduced and compared (Becker and Buchkremer, 2018a). Table 12 provides an overview of the selected technological solutions.

Provider	**Application**
IBM	Watson Regulatory Compliance
MetricStream	Regulatory Intelligence and Content Management
Oracle	Financial Services Crime and Compliance Management Analytics
RSA	Archer Regulatory and Corporate Compliance Management
SAP	Process Control

Table 12: Selected existing Regulatory Technology applications

[source: own presentation based on (Becker and Buchkremer, 2018a)]

These five applications are selected as they have comparable functionalities and they all intend to facilitate the management of regulatory requirements for banks and other FIs. They have the common overreaching goal to support FIs with the recognition, analysis and implementation of relevant regulatory-driven obligations (Becker and Buchkremer, 2018a). The scope of application of the technical solutions presented in table 12 is therefore comparable. Please note that the selection of these applications took place in June 2018. At a later point in time, there might have been different or extended solutions available from these technology companies or from other firms.

IBM WRC[21] is an integral part of the IBM OpenPages GRC platform. This platform combines eight individual applications that aim to cover the whole range of GRC management activities of FIs. Moreover, it is possible to use single applications of the OpenPages platform individually (IBM, 2018b). This solution from IBM combines regulatory compliance management with cognitive computing technologies like AI, data mining, machine learning and language processing to automate the assessment of legal documents and to accelerate the understanding of its content and impact. Therefore, IBM WRC uses these cognitive computing capabilities to help compliance officers to streamline the identification and prioritization of obligations and controls arising from regulations. The web-based tool can be trained by regulatory compliance experts to improve the automatically generated evaluations over time through machine learning capabilities (IBM, 2018d).

The web-based solution MetricStream (MS) Regulatory Intelligence and Content Management (RICM) enables FIs to organize and manage regulations in a centralized repository. For this purpose, MS RICM can automatically access legal documents from various external sources. Furthermore, this application supports FIs with the creation of a workflow for a consistent regulatory change management. Therefore, changes of regulatory requirements can be identified and processed directly. The system can help to ensure that all relevant stakeholders are informed

21 The original name of the application is IBM Regulatory Compliance Analytics with Watson. In March 2018, the application was renamed IBM Watson Regulatory Compliance.

of regulatory changes. Compliance officers can also distribute regulatory requirements to affected departments, business units and product lines. For this purpose, multiple users across departments can access and work on the development of obligations simultaneously. This application is an integrated part of the MS GRC platform (MetricStream, 2018).

The application Oracle Financial Services Crime and Compliance Management Analytics (CCMA) enables FIs to monitor their compliance management performance and financial crime prevention activities. Therefore, Oracle CCMA provides customizable analysis and reporting functions to measure the effectiveness of compliance and fraud prevention programs. In particular, this solution can help to identify operational inefficiencies that can lead to non-compliance and fraud. Furthermore, this application enables an analysis of historical information to identify trends and patterns related to regulatory compliance and fraud detection. The compliance management and fraud detection reports can also be accessed by relevant stakeholders. The application is an integral part of the Oracle Financial Services Analytical Applications and therefore a part of a holistic GRC platform (Oracle, 2018).

The RegTech solution RSA Archer Regulatory and Corporate Compliance Management (RCCM) enables FIs to create and manage an integrated, individual control framework for the compliance of an institution with regulatory requirements. This framework aims to increase transparency of the compliance management activities and to reduce the risk of violations of legal regulations. It allows the compliance officers to prioritize and link regulatory impacts to business units and departments within the organizational structure. Therefore, regulatory data is consolidated from multiple sources into a centralized repository. Besides, RSA Archer RCCM enables FIs to establish a workflow for managing changes in regulations. This application is an integral part of the RSA Archer GRC platform (RSA, 2018).

One further technical solution is SAP Process Control (PRC). This application is an integral part of the SAP GRC platform and enables FIs to automatize compliance management for both internal, and external requirements. SAP PRC can help FIs to streamline their control activities by identifying, analysing and prioritizing key business processes that are affected by regulations. It provides a single repository for multiple internal and external regulations and compliance procedures. Furthermore, the application enables compliance officers to perform comprehensive control evaluations and to streamline the issues management. Besides, compliance management workflows can be created to ensure that all relevant stakeholders are involved. This solution can be deployed both on-premise and in a private cloud environment (SAP, 2018).

Despite the comparable scope of application, the specific features and characteristics of these five technical solutions differ. In order to select one application to develop an implementation strategy, the characteristics of the RegTech solutions are compared. For this purpose, table 13 shows an overview of the characteristics and features of the presented solutions. Please note that the comparison of characteristics was carried out in June 2018. It includes the features of the applications that were available at that point in time. New or extended functionalities that might have been added after June 2018 are not included in this overview.

Characteristic / feature	IBM WRC	MS RICM	Oracle CCMA	RSA RCCM	SAP PRC
Automated identification of obligations	yes	-	-	-	-
Centralized repository for regulations	yes	yes	-	yes	yes
Cloud / Web-based solution	yes	yes	-	-	yes
Cognitive computing capabilities	yes	-	-	-	-
Compliance reporting functions	yes	yes	yes	yes	yes
Configurable compliance management workflow	yes	yes	yes	yes	yes
Integral part of a GRC platform	yes	yes	yes	yes	yes
Link to control framework	yes	yes	yes	yes	yes
On premise installation	-	-	yes	yes	yes
Regulatory change management	yes	yes	yes	yes	-
Role-based functions	yes	yes	yes	yes	yes

Table 13: Comparison of selected Regulatory Technology applications

The list is created based on the characteristics and key features of the five applications. The descending order of characteristics in table 13 was generated alphabetically. The term "yes" means that a characteristic is provided by an application. In some cases, each of the five investigated RegTech solutions contains a specific feature or characteristic. However, in other cases, only one of the five applications has a specific functionality or characteristic. In particular, IBM WRC is the only RegTech solution that uses cognitive computing capabilities like AI and data mining for the identification and initial technical analysis of obligations.

Based on the comparison in table 13, one of these five RegTech applications is selected for the development of an implementation procedure. For this purpose, a scoring system is created. The existence of each characteristic or feature equals one point. If an application does not provide a specific feature, it does not receive a point. In total, a RegTech solution can have a maximum score of eleven points since table 13 contains eleven characteristics or features. The application that has the highest score is selected for the strategy development. The scores of the individual applications is presented in alphabetical order in table 14:

Application	**Score**
IBM WRC	10 points
MetricStream RICM	8 points
Oracle Financial Services CCMA	7 points
RSA Archer RCCM	8 points
SAP PRC	8 points

Table 14: Score of selected Regulatory Technology applications

Table 14 shows that the RegTech solution IBM WRC has the highest score with 10 points. The three applications MS RICM, RSA Archer RCCM and SAP PRC each provide a score of 8 points. Closely behind, the solution Oracle Financial Services CCMA has a total score of 7 points. Based on this evaluation process, the IBM application is selected for the development of the implementation procedure that is presented in the following section (see chapter 4.1.2).

4.1.2 Implementation procedure

Since regulations are constantly changing, it is required to implement a flexible approach to manage regulatory requirements in a more efficient manner. There are numerous descriptions of several flexible procedure models in the literature (Kuster et al., 2011, p. 29). One essential characteristic that most flexible methods have in common, is an iterative procedure model (see for instance Eisenhardt and Tabrizi, 1995; Boehm and Turner, 2004; Highsmith, 2004; Schwaber, 2004; Augustine, 2005; Cohn, 2005). In this context, iterative means the repeated execution of processes or a process chain with the aim to optimize the outcomes (Vijayasarathy and Turk, 2012). Some methods use synonyms to describe this iterative approach. For instance, in the agile project management method SCRUM, the term "sprint" is used to describe an iteration (Kuster et al., 2014, p. 29; Schwaber and Beedle, 2001). In this research, the common terms iterative or iteration are used.

This flexible approach is one essential aspect that distinguishes iterative from traditional project management methods (Becker and Buchkremer, 2018a). At first, figure 38 exemplifies a traditional project management cycle (Project Management Institute, 2017):

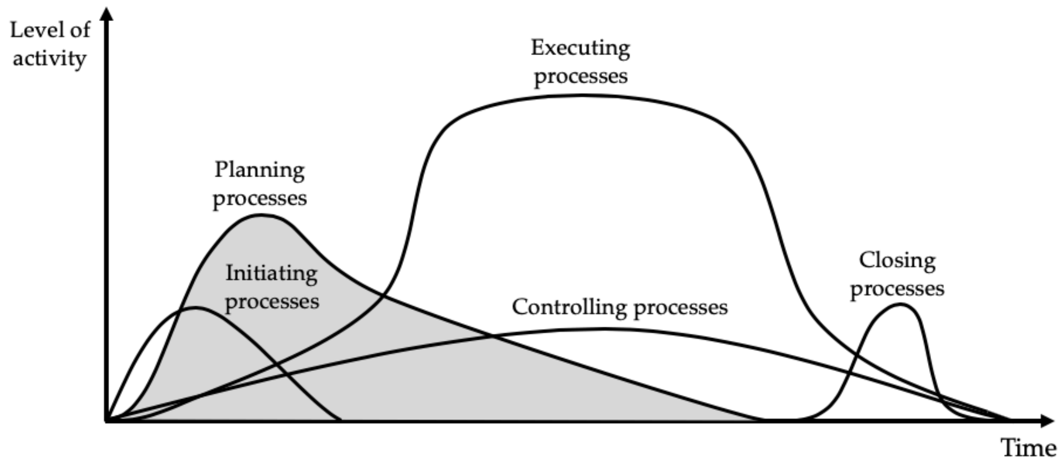


Figure 38: Traditional project management cycle

[source: own presentation based on (Project Management Institute, 2017; Griffiths, 2006; Becker and Buchkremer, 2018a)]

Figure 38 illustrates that each process group is normally executed once during a traditional project management cycle. Therefore, the cycle starts with the execution of initiating processes. In this first step, the required framework for the project is created. This framework includes, for instance, the identification of the project stakeholders and shareholders. The following steps are planning, executing, controlling and closing processes. It must be considered that the execution of these individual steps is not necessarily carried out sequentially. Therefore, controlling processes are normally executed parallel to the other process groups. Controlling processes are required to ensure an appropriate quality of the project or a project phase. Planning processes define the way the project is executed. In this phase, a detailed timetable for the project is determined. In figures 38 and 39, planning processes are highlighted through a grey background color. During the execution phase, the predefined steps are executed. The last part of the project management cycle is characterized by closing processes, which are required to end a project or a project phase. In case of a software implementation project, typical closing processes are, for instance, the acceptance of the final product by the client and the documentation of the project outcomes (Project Management Institute, 2017; Becker and Buchkremer, 2018a). As a comparison to this traditional approach, figure 39 exemplifies an iterative procedure for the execution of a project or a strategy:

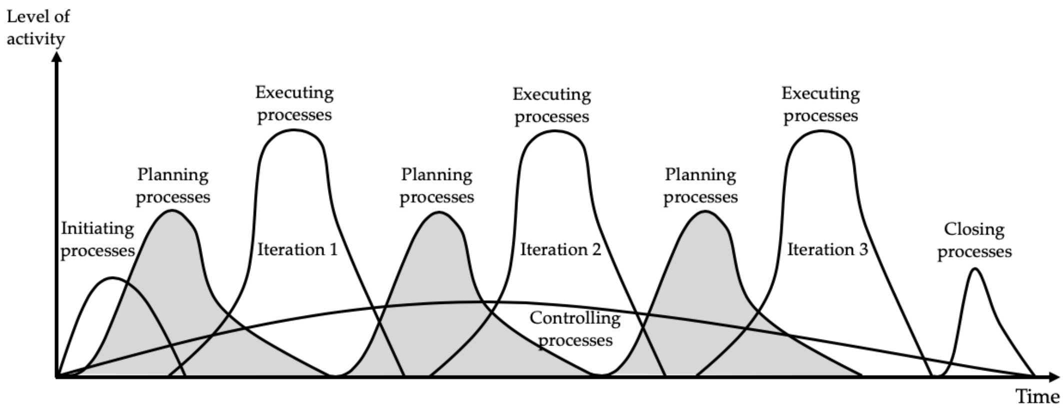


Figure 39: Iterative project management cycle

[source: own presentation based on (Griffiths, 2006; Becker and Buchkremer, 2018a)]

Figure 39 shows an exemplary presentation of a project management cycle with three iterations. At first, it must be considered that the iterative cycle also begins with the one-time execution of initiating processes. In contrast to the traditional project management cycle, the planning and executing processes are executed more than once. The execution of a planning phase and a corresponding executing phase is referred to as an iteration. Figure 39 illustrates that the planning of a new iteration already begins before the currently executed iteration has ended. This approach aims to prevent possible waiting times between two consecutive iterations. The project or a project phase also ends with the one-time execution of closing processes following the last iteration. Controlling processes also run parallel to other project phases during the whole cycle (Griffiths, 2006; Project Management Institute, 2017; Becker and Buchkremer, 2018a).

The following development of an implementation strategy for regulatory requirements is based on an iterative cycle with several iterations as presented in figure 39. A major goal of the presented procedures is an increase in the efficiency of the identification, management and controlling of obligations resulting from regulatory requirements for banks and other FIs. First of all, it is a mandatory task to define all regulations that are relevant for an individual institution (Becker and Buchkremer, 2018a). The selected technical solution offers a comprehensive library of current national and international legal requirements that is updated on a daily basis (IBM, 2018d). The compliance officers of the individual institutions select all relevant regulations and ensure that the list of legal documents is complete. If relevant legal texts are not included in the library, they need to be complemented by the compliance experts or the producer of the library application. This first step needs to be executed once at the beginning of an implementation project and repeatedly during the operation of the application when new or extended regulatory requirements are published by the supervisory authorities (Becker and Buchkremer, 2018a). To facilitate this task, the website Global Regulation offers an alert system when new or extended regulations are published by supervisory agencies. In this case, the compliance management expert receives an E-Mail alert as soon as new relevant regulations are available (Global Regulation, 2018).[22] With regard to the iterative cycle, this step equals the initiating phase. In the planning phase of each iteration, the responsibilities and the timetable for the following project execution phase are defined. For this purpose, the compliance management experts identify the departments and individuals that are affected by a certain regulation. These experts are required to participate in the following execution phase of an iteration. For instance, when a legal document that affects the risk management environment of an institution is analysed, it is required that the risk management department gets involved in the execution processes and that the risk managers provide their expertise. Besides, a timetable for the execution phase has

22 The website Global Regulation can be accessed using the following URL: https://www.global-regulation.com/alerts.php

to be created to ensure that the mandatory tasks are executed at the right time (IBM, 2018d; Becker and Buchkremer, 2018a).

The next step is the initial technical analysis of the individual legal texts. The application IBM WRC analyses and evaluates the single words and sentences of each regulation through the usage of data mining procedures in combination with AI technologies. The result of this procedure is an automatically generated list of potential obligations that are derived from a legal document. The relevance and the corresponding prioritization of the individual obligations is illustrated probability-weighted. The completeness of the list of obligations and the determined prioritization needs to be reviewed by the regulatory compliance experts of the institution or by external experts (IBM, 2018d; Becker and Buchkremer, 2018a). Figure 40 illustrates the analysis of the obligations with the IBM application.

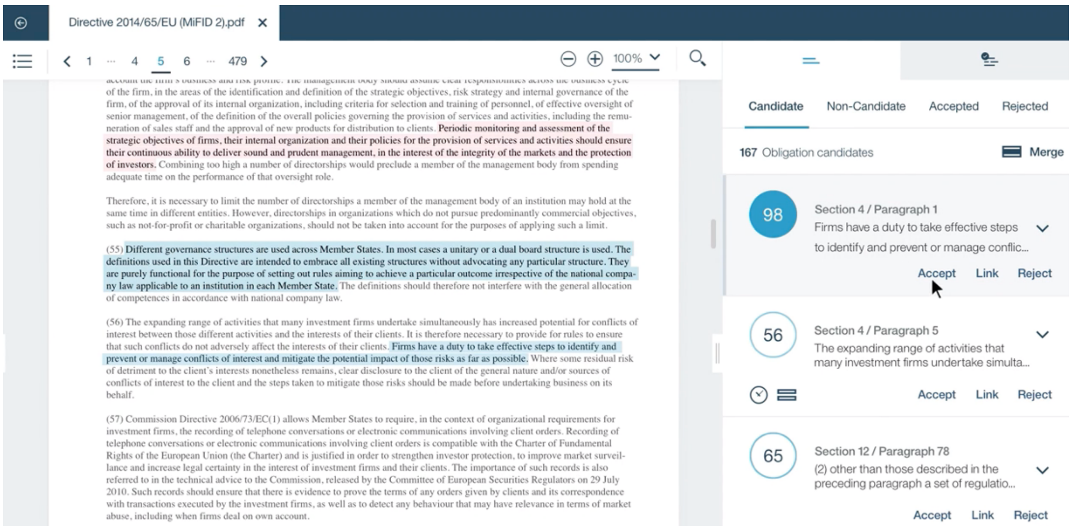


Figure 40: Analysis of obligations

[source: (IBM, 2018d; IBM, 2017b)]

The screenshot shows the obligations from the legal text Markets in Financial Instruments Directive (MiFID) 2. On the left side of the figure, the legal text is presented with coloured markings of the obligations that have been identified by the application. On the right side, the individual obligations and the corresponding probability-weighted relevance are presented. Selected experts of the institution evaluate whether an obligation is relevant and is therefore accepted or rejected (IBM, 2018d; Becker and Buchkremer, 2018a). In a further step, it has to be considered that not all identified obligations are considered as regulatory requirements. Obligations that result from legal texts might also be identified as a guidance on how to address an obligation. For this reason, the experts of an institution are required to review the initial analysis of the system and to define whether an obligation is defined as a requirement or a guidance element (IBM, 2017b). This consecutive task is illustrated in figure 41.

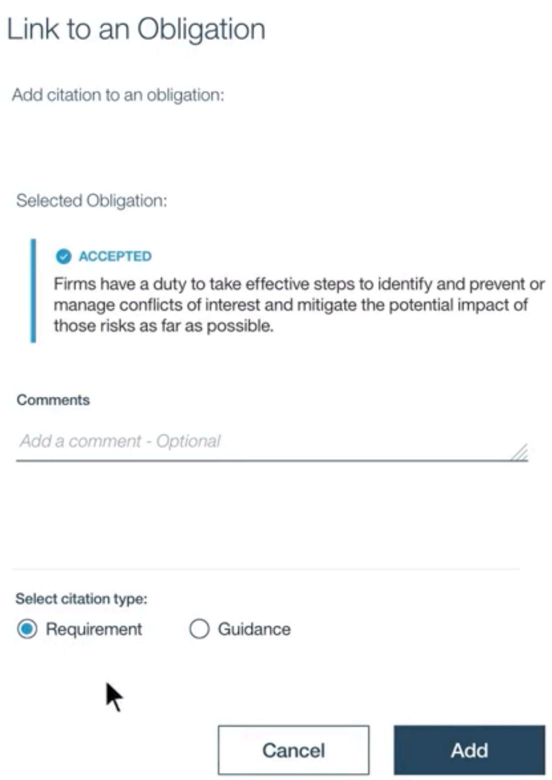


Figure 41: Linking of obligations

[source: (IBM, 2018d; IBM, 2017b)]

When the expert is clicking on the "link" button next to a specific obligation, the pop-up window "Link to an Obligation" opens as presented in figure 41. The expert for the regulation decides whether the potential obligation is defined as a legal requirement or a guidance on how to address an obligation. The expert is also given the opportunity to add a comment on his choice. An element that is defined as a guidance can be linked to a specific requirement (IBM, 2018d). In the example illustrated in figure 41, the obligation is initially defined as a requirement.

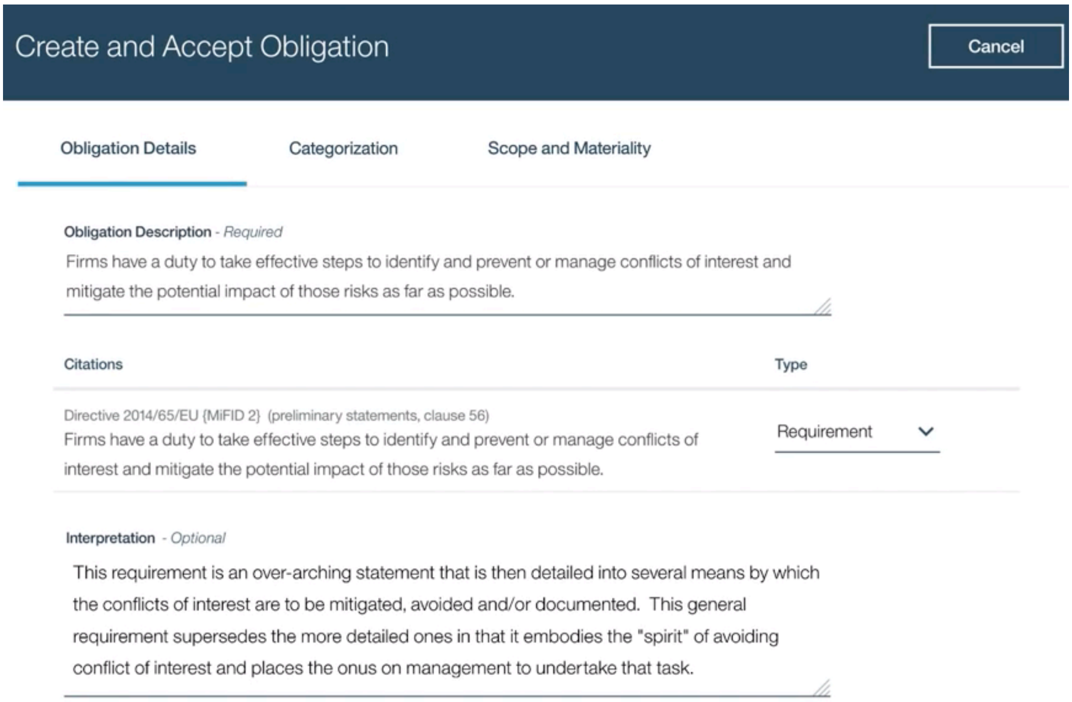


Figure 42: Customizing obligations

[source: (IBM, 2018d; IBM, 2017b)]

The screenshot of the IBM WRC application in figure 42 shows that the user is required to add a description of an obligation. In this example, the citation of the legal text is also taken as the description of the obligation. Moreover, the user is given the chance to write an initial interpretation based on what the obligation means to his institution (IBM, 2017b).

When further obligations are analysed, it might occur that a citation is defined as a guidance on how to address a specific requirement. The screenshot in figure 43 shows that the expert identified a citation as a guidance element addressing the requirement that was defined previously.

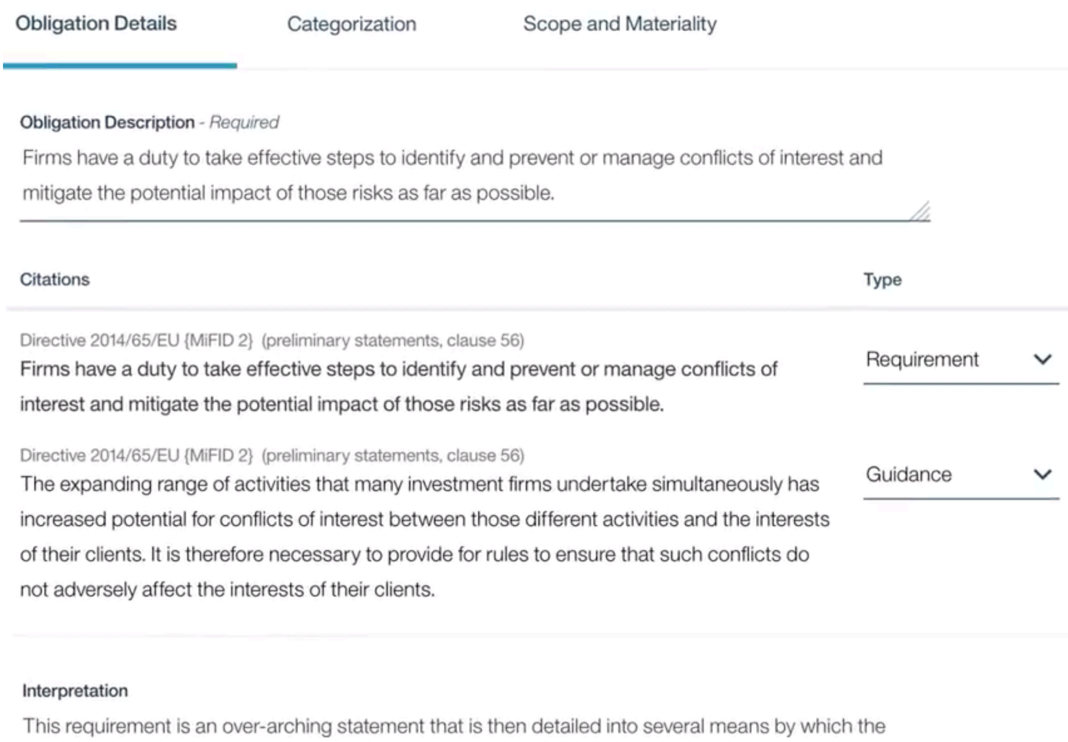


Figure 43: Storage of obligations

[source: (IBM, 2018d; IBM, 2017b)]

In the "obligation details" tab, an overview of an obligation requirement and the corresponding guidance is presented (see figure 43). The obligations that are identified for a legal framework including the institution specific context are stored in a centralised, dedicated repository. Furthermore, individual obligations can also be linked to multiple legal documents. The aim of this step is to avoid duplicative storage of obligations that affect more than one regulation (IBM, 2018d).

When the individual list of relevant obligations is complete for a legal text, the individual obligations are linked to the related jurisdictions, business lines, products, processes and compliance themes. The experts that were determined in the planning phase of the current iteration are required to analyse the areas that are affected by certain obligations and maintain the corresponding links in the application. Therefore, IBM WRC presents an initial categorization and offers two different ways to perform this task. On the one hand, the user can add category tags to categorize an obligation. On the other hand, the expert can link an obligation to specific jurisdictions, business lines, processes and products of the individual institution (IBM, 2018d; IBM, 2017b; Becker and Buchkremer, 2018a). Figure 44 shows an example for a categorization of an obligation by using category tags.

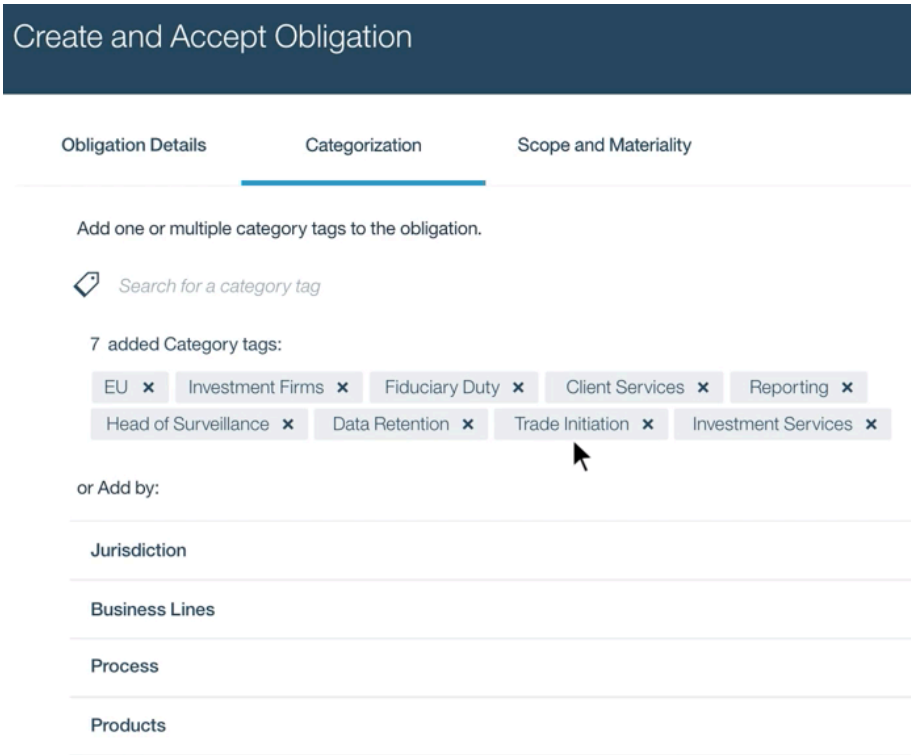


Figure 44: Categorization of obligations

[source: (IBM, 2018d; IBM, 2017b)]

The categorization in figure 44 illustrates that the system identified two tags automatically and the expert of the institution added seven category tags. In total, the nine category tags “EU”, “investment firms”, “fiduciary duty”, “client services”, “reporting”, “head of surveillance”, “data retention”, “trade initiation” and “investment services” are used (IBM, 2017b).

After the categorization of an obligation is complete, the scope and materiality of an obligation for different divisions and segments are defined. In a first step, the compliance management expert analyses the relevant segments that are affected by an obligation. Besides, the user is given the opportunity to add one or more business segments if the list of segments is not complete. Secondly, the expert rates the materiality of an obligation for individual business segments on a scale ranging from "very low" to "very high". This indication is required to prioritize the obligations of a legal text for different segments (IBM, 2018d; IBM, 2017b; Becker and Buchkremer, 2018a). In figure 45, an example is presented for the materiality of four segments.

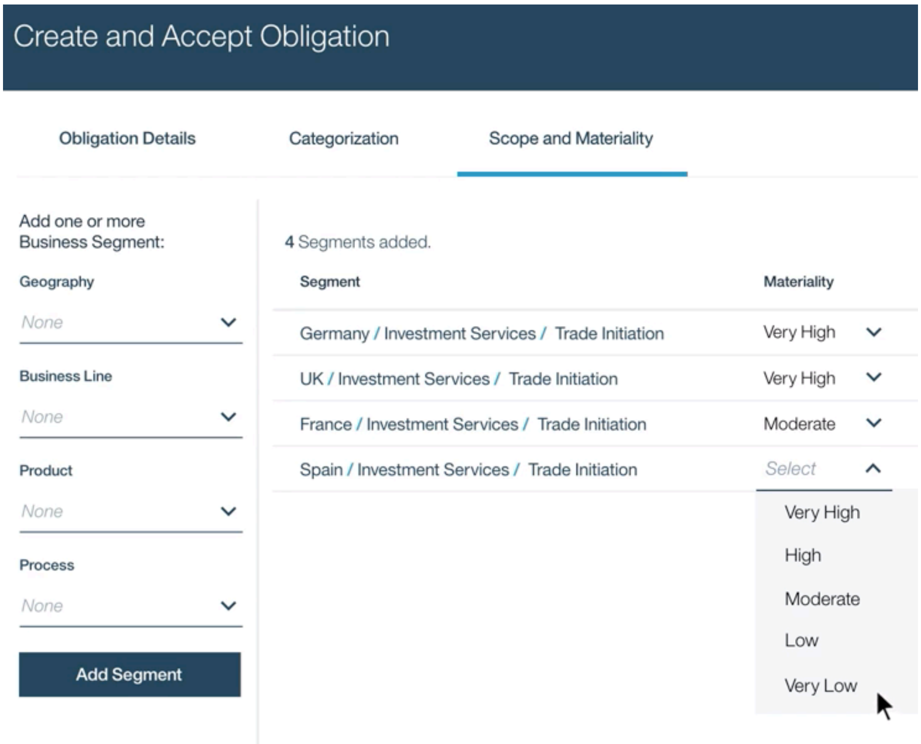


Figure 45: Scope and materiality of obligations

[source: (IBM, 2018d; IBM, 2017b)]

On the left side of figure 45, the expert can add a segment that is affected by an obligation. For this purpose, the geography, business line, product and process of a business segment can be defined. When the list of relevant segments is complete, the expert rates the materiality of each segment. In the example in figure 45, the geographic regions Germany, United Kingdom, France and Spain are rated by using a drop-down menu. The user is given the opportunity to rate the materiality for each segment as "very low", "low", "moderate", "high" or "very high" (IBM, 2017b).

One further task is the definition of instructions and controls that can be used to address the identified obligations. Controls are required to ensure that the institution complies with the obligations that result from the legal framework (IBM, 2017b). The screenshot in figure 46 exemplifies a recommended potential control for an obligation.

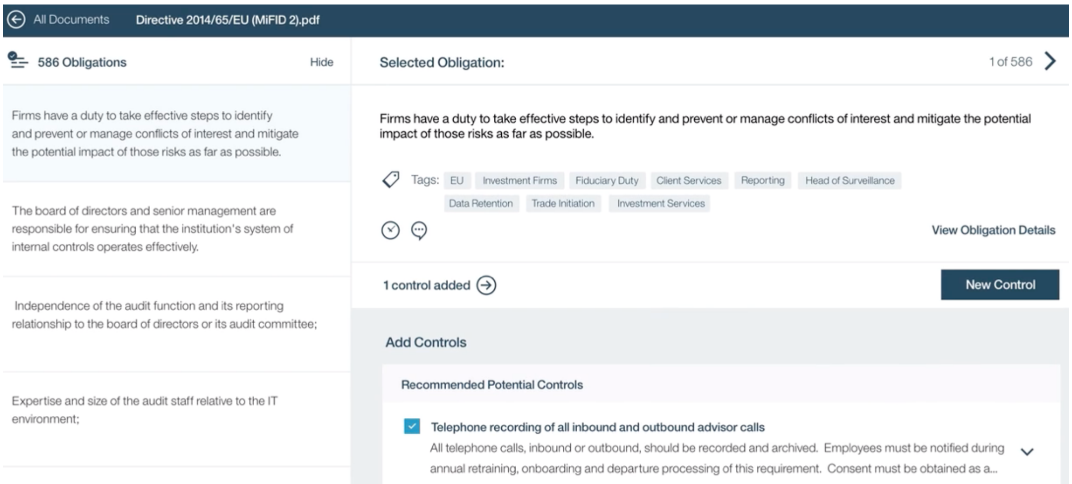


Figure 46: Creation and mapping of controls

[source: (IBM, 2018d; IBM, 2017b)]

On the left side of the screen, all obligations for a specific legal document are presented. At first, the user is required to select an obligation. In a further step, the application recommends potential existing controls that might be relevant for the selected obligation. In this example, "telephone recording of all inbound and outbound advisor calls" is a recommended potential control for the obligation presented above. The expert can accept the recommended control by ticking the box next to the individual control. When the user ticks the box, a white coloured check mark appears with a blue background color (IBM, 2017b).

Besides, the user is given the opportunity to search for other existing controls that may be relevant for a specific obligation and select them. Figure 47 shows the search function for existing controls.

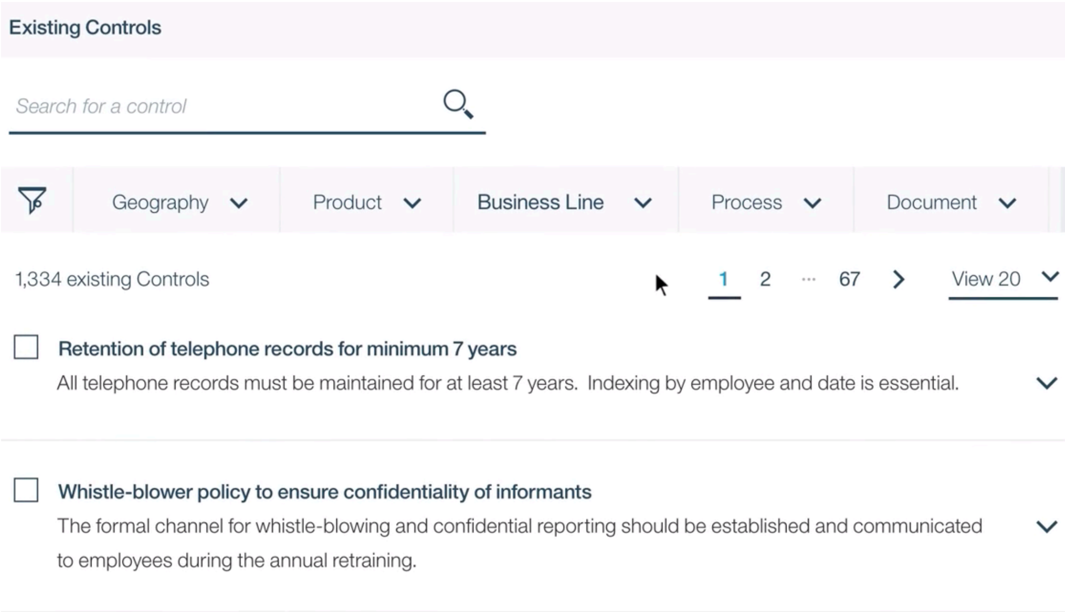


Figure 47: Search function for existing controls

[source: (IBM, 2018d; IBM, 2017b)]

The user can search for specific controls by entering words at the search bar presented in figure 47. Besides, the expert can filter the list of existing controls by geography, product, business line, process or document. In this example, the list of controls has 1,334 elements that can be mapped to an obligation. In addition, the expert is given the chance to insert new control objectives that are not in the list. When the mapping of all obligations of a legal document is complete, the institution is provided with an enriched repository that contains both the obligations and the control objectives that are used to address individual obligations (IBM, 2017b).

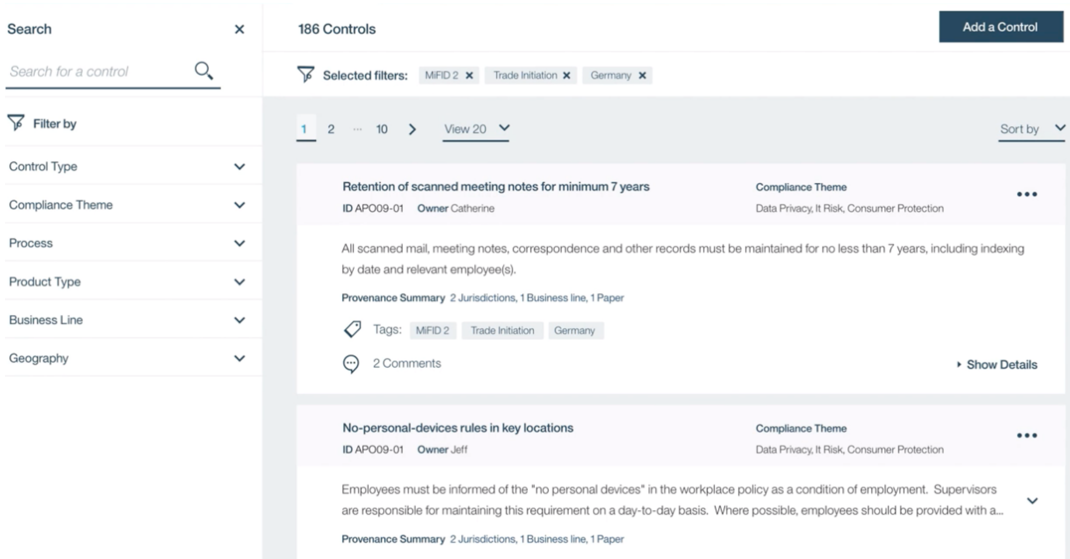


Figure 48: List of controls

[source: (IBM, 2018d; IBM, 2017b)]

The "controls" tab in the application presents a list of controls that can be filtered by control type, compliance theme, process, product type, business line and geography or by entering words in the search box on the left side of the screen. In this example, 186 controls are identified when the filters "MiFID 2", "Trade initiation" and "Germany" are used. Figure 48 also shows that the owner of each control is presented. Therefore, responsibilities for controls can also be managed (IBM, 2017b). As soon as the review process for one document is complete, the tool analyses the results using data mining and machine learning approaches and extends its system-based knowledge based on the answers provided by the experts of the institution. When a further legal text is analysed by the system, the application refers to the stored insights of the previous answers and improves the identification of obligations by comparing the new regulation to past responses in similar legal texts. The application is therefore able to optimize the automatic evaluation of obligations. The experts of the FI analyse in a new iteration the systemically provided obligations and review the correctness of the assessments. This iterative procedure allows the application to learn and to enhance the initial technical analysis of the obligations (IBM, 2018d; Becker and Buchkremer, 2018a).

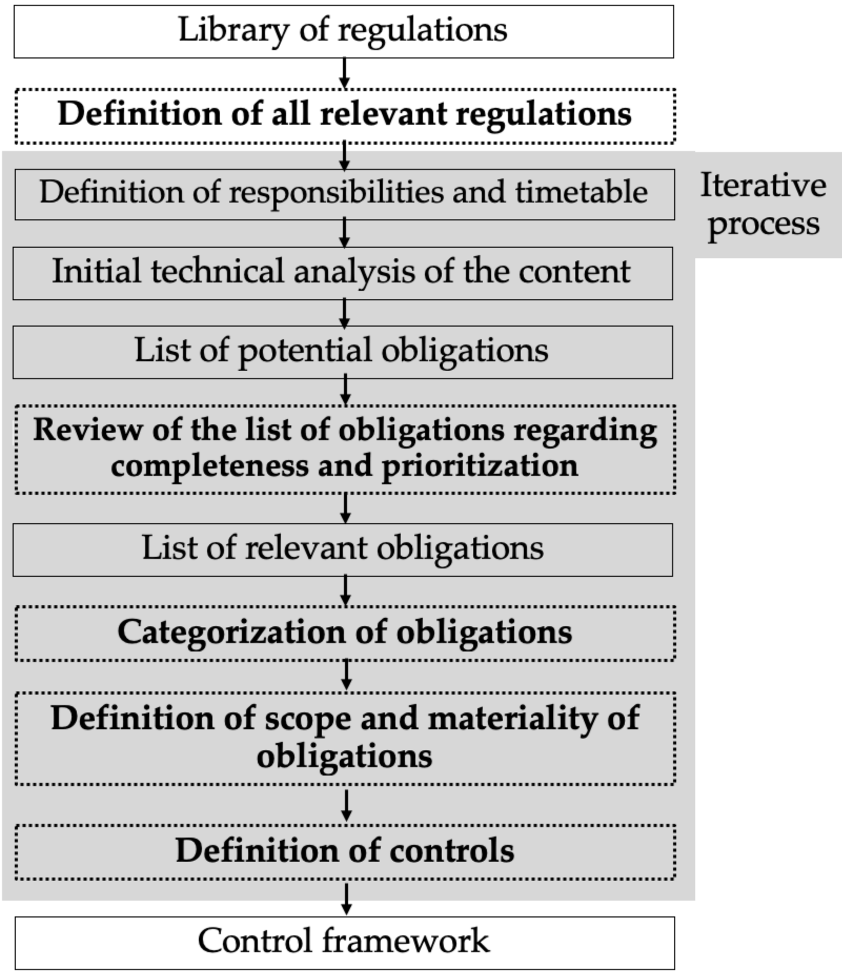


Figure 49: Implementation procedure

[source: own presentation based on (Becker and Buchkremer, 2018a)]

The newly-developed process chain to implement regulatory requirements is summarized in figure 49. It must be considered that the first step during this implementation procedure is carried out only once at the beginning of the project. The consecutive process steps are highlighted through a grey background color as they are part of the iterative cycle. This process chain has to be repeated for each legal document. The application IBM WRC analyses and evaluates each regulatory document individually based on the knowledge it has stored. In a further step, the experts of the institution review the automatically generated results and optimize them if it is required. Therefore, the application is able to learn from the feedback of the experts and to enhance its knowledge with each iteration. The manual effort is considerably reduced compared to a manual evaluation of the legal texts due to the automatic initial evaluation. The controls that result from each iteration are added to the control framework of the institution. Figure 49 shows that an iterative procedure is essential to implement a technical solution that is featured with machine learning capabilities in order to enhance the outcomes. The execution of each further iteration leads to a greater knowledge of the application and to an optimization of the automatically generated initial results. Moreover, the WRC application automates the identification of changes in regulations and initiates a workflow to review business controls (IBM, 2018d; Becker and Buchkremer, 2018a).

When the analysis and evaluation of all relevant legal documents for an institution is complete, several standardised and customized reports can be created. An example for a report is the comparison of controls required for different versions of a legal framework. The aim of this comparison is to analyse potential modifications or extensions of regulations (IBM, 2017b). The screenshot of the WRC application in figure 50 illustrates a comparison of the controls required for the MiFID directive and the MiFID 2 directive.

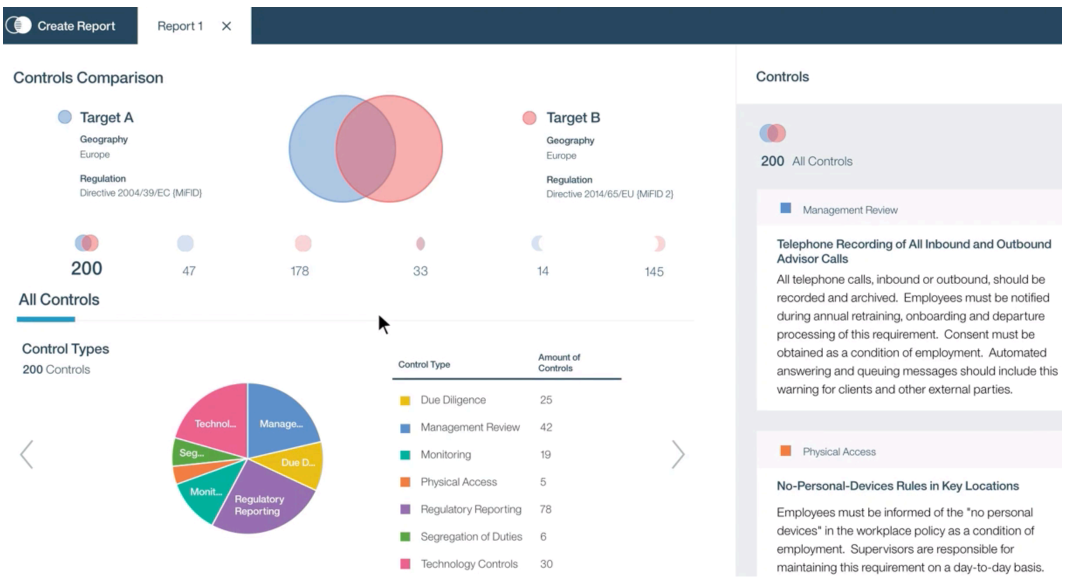


Figure 50: Comparison of regulations

[source: (IBM, 2018d; IBM, 2017b)]

The two circles at the top of figure 50 show a visual comparison of the two directives. The blue circle represents the original MiFID directive that was published in 2004 and the red circle represents the MiFID 2 directive from the year 2014. On the right side of the screen, all controls of these two legal documents are listed (IBM, 2017b; BaFin, 2018).

In order to carry out a more detailed comparison of the two directives, the user can drill in to analyse the new controls required for MiFID 2 that have not been included in the original MiFID directive (see figure 51).

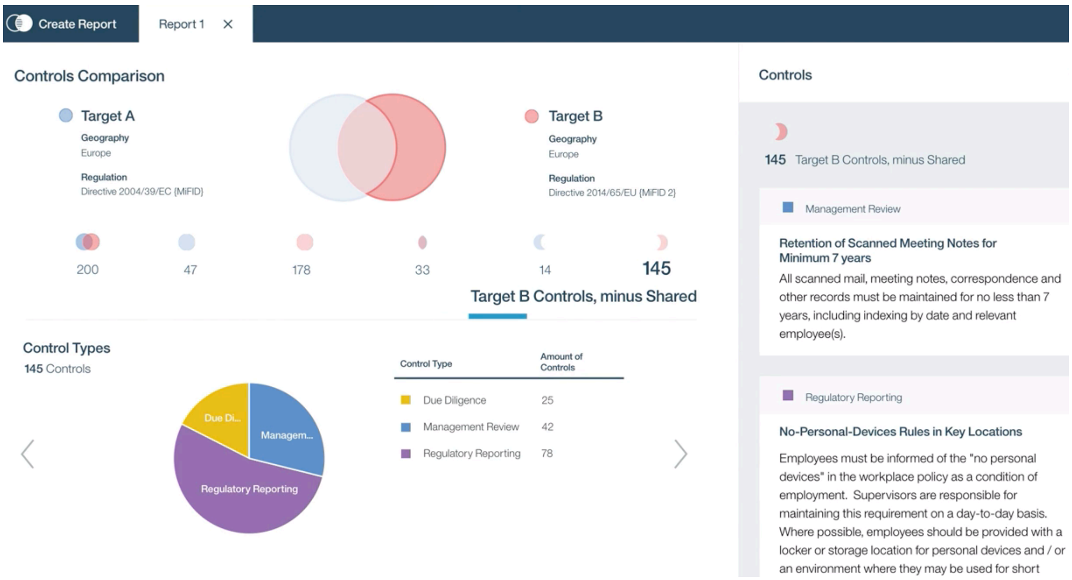


Figure 51: Discovery of new controls required for MiFID 2

[source: (IBM, 2018d; IBM, 2017b)]

On the right side of the screen, the new controls for the MiFID 2 directive are presented. Besides, the user can analyse the different types of controls. In the example in figure 51, the new controls concern "due diligence", "management review" and "regulatory reporting" (IBM, 2017b). Moreover, the expert can also analyse overlapping or different control requirements across these two directives. Therefore, the function to create automatically generated reports enables a real-time view of current compliance standing of an institution (IBM, 2018d).

For risk and compliance reporting purposes, selected data stored in IBM WRC can be transferred using XBRL (see chapter 2.3.2) or exported in different formats (e.g. PDF).

The data that is processed and created in WRC can be integrated into the IBM OpenPages GRC platform to perform further analysis and evaluations. For instance, the following insights that result from the investigation of regulations can be integrated (IBM, 2018b):

- obligations (requirements and governance)
- descriptions and interpretations of obligations
- categorization of obligations
- scope and materiality of obligations
- control framework
- responsibilities for controls

OpenPages consists of eight single applications that can either be used separately or together to enable a holistic view on the GRC management of an institution. The following tools are part of the GRC platform (IBM, 2018b):

- Watson Regulatory Compliance
- OpenPages Operational Risk Management
- OpenPages Internal Audit Management
- OpenPages Financial Controls Management
- OpenPages IT Governance
- OpenPages Model Risk Governance
- OpenPages Vendor Risk Management
- OpenPages Policy and Compliance Management

Please note that these eight applications were part of the OpenPages platform in June 2018. The platform might have a different composition at a later point in time. As an example, the obligations and the control framework that are created in WRC can be integrated in OpenPages Financial Controls Management. This application allows an automatization of the financial controls' management process. In particular, it can automate the testing, review and attestation processes of financial controls and obligations. Therefore, the aim of this tool is to increase both the effectiveness and efficiency of the controls management and to optimize the transparency in the state of financial controls (IBM, 2018a). In a further step, OpenPages Financial Controls Management can be integrated with OpenPages Internal Audit Management to enhance auditing procedures. The aim of this application is to provide internal auditors with a holistic view of compliance management procedures across the institution. Besides, internal audits can be processed automatically to ensure a standardized and objective risk assessment (IBM, 2018c). This exemplary interaction between different OpenPages applications is visualized in figure 52.

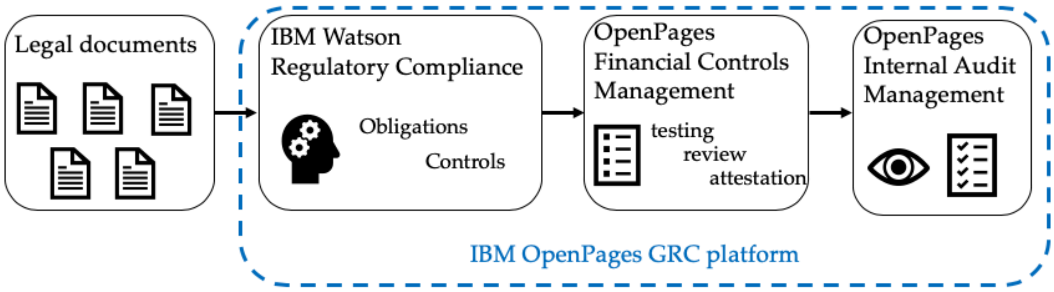


Figure 52: Interaction between IBM OpenPages GRC applications

[source: own presentation based on (IBM, 2018b; IBM, 2018d)]

The workflow in figure 52 shows that each application within the OpenPages GRC platform fulfils different tasks that can be combined to increase the insights. In this example, relevant legal documents are analysed in the WRC tool in order to determine obligations and controls that result from the legal texts. The emerging list of obligations and the control framework are integrated with the OpenPages Financial Controls Management tool. In a consecutive step, testing, review and attestation processes are implemented to address the controls and obligations. The insights of the control management can be integrated with OpenPages Internal Audit Management. Auditors are provided with a holistic view of the control framework and the management of the controls (IBM, 2018b; IBM, 2018d).

This example shows how the evaluations and insights of the WRC application can be integrated in a holistic GRC management. For this purpose, WRC can be combined with any of the seven further OpenPages applications. The overreaching goal of this approach is to implement a holistic control lifecycle management. A practical example for the implementation of the OpenPages platform to increase the efficiency of managing controls is provided by HypoVereinsbank. OpenPages enabled this FI to enhance its control assessment workflows for more than 3,000 internal controls. According to IBM (2017a), personnel requirements for the management of controls could be reduced by 33 %. Moreover, the German HypoVereinsbank could also streamline and automate its controls management processes (IBM, 2017a).

In summary, the developed iterative implementation procedure that is supported by cognitive computing technologies can help FIs to streamline the identification and analysis of potential obligations and corresponding controls required to address regulatory requirements. Furthermore, it enables FIs to manage the lifecycle of implementing constantly changing regulations more efficiently (IBM, 2018d; Becker and Buchkremer, 2018a). In the following section, this newly-developed iterative approach to implement and analyse regulatory requirements with WRC is compared to a traditional approach without the use of cognitive computing technologies and an iterative procedure (see chapter 4.1.3).

4.1.3 Comparison of traditional and cognitive implementation strategies

The major objective of the comparison of a traditional and the newly-developed procedure model is to discover potential benefits of the approaches. At first, it is required to select and introduce a traditional strategy to process regulatory requirements at banks and other FIs. For the purpose of this research, the procedure that is applied at the IBM Credit Bank in Germany is presented exemplarily. The following descriptions are based on the insights provided by Roland Bayer, Executive Risk Manager and Julia Buedenbender, Compliance Officer at the IBM Credit Bank in Germany (see chapter 3.3.3).

When a new regulation or a new version of an existing regulation is published by the supervisory authorities, the compliance officer and designated other experts need to evaluate whether the legal document is relevant for the individual institution. If the investigated legal text is relevant, the affected experts have to analyse its content in detail. For this purpose, the specialists are required to read through a legal document line by line in order to create a holistic list of obligations that result from a specific regulation.

In a further step, a document is created for each identified obligation. This document can contain, for instance, the following aspects:

- citation of the legal text
- obligation description
- obligation interpretation
- responsibilities
- obligation categorization (affected departments, business processes...)
- obligation scope and materiality

These initial tasks to process a legal document are exemplified in figure 53 using spreadsheets to create the list of obligations and text documents to describe the obligation details (Bayer and Buedenbender, personal communication, July 2018).

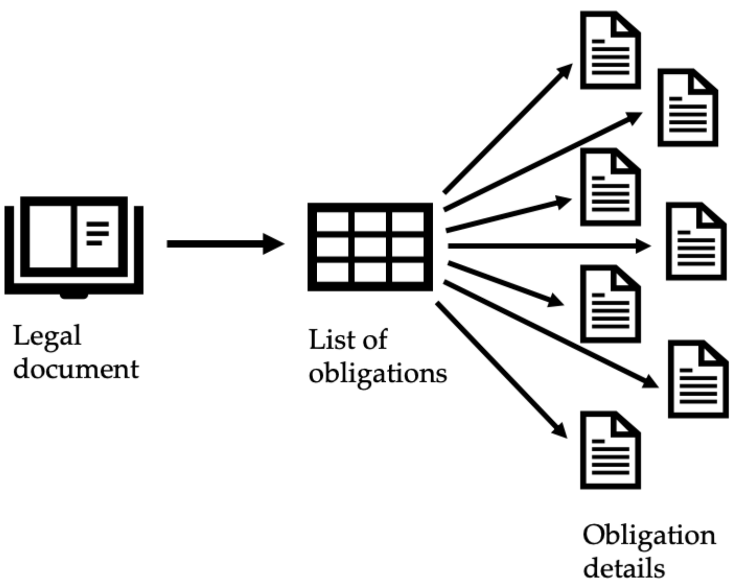


Figure 53: Spreadsheet-based list of obligations

Figure 53 shows the initial steps to process a legal document at the credit bank. When the list of obligations is complete for a specific regulation, the individual obligations need to be mapped to the existing processes and work instructions. Compliance and risk managers have to update each process or instruction together with the process owner or create new instructions to take these obligations into consideration. In addition, the control framework of the institution has to be amended to include the new requirements and to ensure that the compliance with the obligations that result from a legal text is part of the regular monitoring process. To perform this task, each obligation has to be mapped to existing controls or new controls have to be created. In a subsequent step, the individual controls are summarized in a holistic list of controls. The creation and mapping of the controls and the resulting list is visualized in figure 54 (Bayer and Buedenbender, personal communication, July 2018).

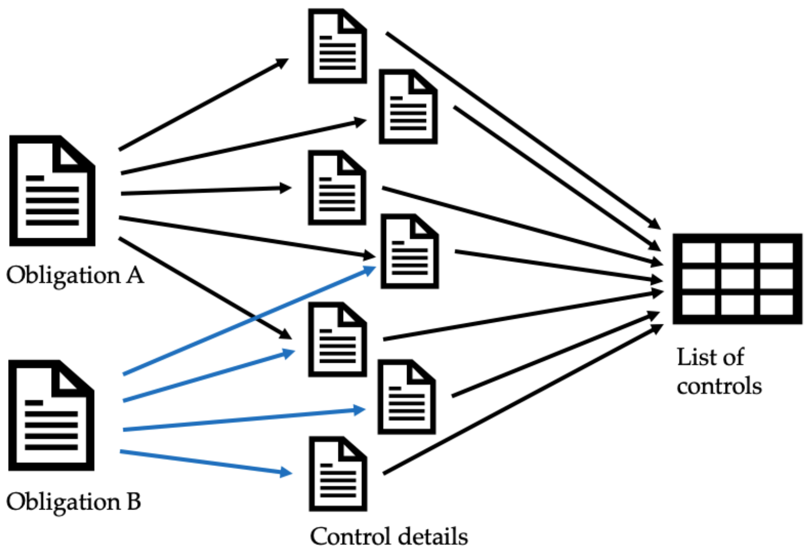


Figure 54: Spreadsheet-based list of controls

Figure 54 illustrates that more than one obligation can relate to the same control. In this example, five controls are identified for obligation A and four controls are identified for obligation B. In two cases, the obligations are mapped to the same control document. The text that is created for each control can contain, for instance, the following aspects:

- control description
- control interpretation
- related obligation(s)
- responsibilities
- control categorization (affected departments, business processes...)
- control mechanisms

An institution has to ensure that it complies with all obligations and corresponding controls that result from the framework of regulations. The full traceability of the process from a regulation to institution-specific controls is therefore a key element for an efficient risk and compliance management (Bayer and Buedenbender, personal communication, July 2018).

In summary, the different steps to create a holistic list of controls for one legal document using a traditional approach are presented in table 15.

Task #	**Task**
Task 1	Analysis of the regulation
Task 2	Creation of the list of obligations
Task 3	Definition of obligation details
Task 4	Mapping of obligations to the control framework
Task 5	Definition of new controls
Task 6	Creation/expansion of the list of controls

Table 15: Tasks to process a legal document

These six steps need to be carried out for each relevant legal document that is identified by the experts of a FI to create or expand the list of relevant controls. Please note that the update or creation of business processes or work instructions that are affected by an obligation is not included in table 15 since this task is not in the scope of the evaluation in this research. This step is out of scope as it is highly institution-specific, and the time needed to carry out this task differs significantly (Bayer and Buedenbender, personal communication, July 2018).

This traditional approach to process regulatory requirements is compared to the newly-developed procedure model that is presented in chapter 4.1.2. As a result, the comparison of these two approaches shows that the effort required to process regulations can be reduced significantly by using the newly-developed procedure model and a cognitive computing application rather than performing each step manually. When the traditional spreadsheet-based strategy is used, understanding the way a regulation impacts an institution is a fragmented set of tasks that requires many different documents. However, when the newly-developed iterative implementation procedure and a cognitive computing application are used, especially tasks 4 and 6 are more streamlined processes (IBM, 2018d).

In summary, by using the newly-developed strategy and a cognitive computing system, obligations that result from a legal document can be tracked more effectively and business controls can be rationalized. Rather than reading through many pages line by line, the regulations are fed to a cognitive computing system that uses AI, data mining and machine learning capabilities to carry out an initial analysis (IBM, 2017b). Therefore, time, effort and corresponding cost associated with regulatory compliance management can be reduced.

4.2 DEVELOPMENT OF A PROCESS MINING STRATEGY

Business processes define how individual tasks are carried out within an organization (see chapter 2.2). In general, the analysis of business processes is regarded from two different perspectives. On the one hand, the procedures that are described in the institution-specific work instructions. These documents define how business processes are to be executed in theory. On the other hand, the actual execution of business processes in the daily routine. The development of an optimization strategy for existing processes requires that these two perspectives are considered. The first step is to regard the descriptions of individual processes. Secondly, the real-life execution of these business processes is evaluated in order to discover optimization possibilities (Eggert, 2014; Becker et al., 2016). However, it needs to be considered that the analysis of business process executions requires managing large data sets. Consequently, technical solutions are essential to enable a detailed analysis. These process mining applications allow FIs to regard the real-life execution of business processes in a detailed manner (see chapter 2.2.3). Therefore, FIs are enabled to discover conspicuous activities and inefficiencies in the process executions (van der Aalst, 2016).

This research aims to develop and implement a process mining strategy in the risk management area of FIs. In a first step, selected process mining applications from different technology companies are presented and compared. The aim of this approach is to select a process mining tool for the practical strategy development (see chapter 4.2.1). Secondly, the implementation strategy of a process mining application in the risk management environment is introduced (see chapter 4.2.2). In a subsequent step, a selected business process that is carried out in the risk management departments of FIs is regarded. For this purpose, the theoretical procedures of this process and its sub-processes that are defined in the work instructions of an institution are presented (see chapter 4.2.3) and the practical implementation procedures are explained (see chapter 4.2.4). In chapter 4.2.5, the evaluation of the newly developed process mining strategy is presented.

Selected aspects of this process mining strategy have been published by the researcher in the “Journal of Financial Regulation and Compliance” (Becker and Buchkremer, 2019).

4.2.1 Analysis of selected process mining applications

This section presents a comparison of selected process mining tools from different companies. In a further step, one business-oriented application is chosen for the development of the implementation strategy. An overview of the tools that are investigated is presented in table 16. The analysis of these process mining tools was carried out in October 2018. One condition is that the selected application is made for the analysis of real-life business processes at economic companies. This requirement is necessary since some process mining applications are made predominantly for academic purposes (Becker and Buchkremer, 2019). One example for a research-oriented platform is the Process Mining framework (ProM) that was released by the Eindhoven Technical University in the Netherlands. It is an open source platform that offers users and developers several process mining algorithms (ProM, 2018). However, table 16 doses not present a complete list of business-oriented tools that fulfil this requirement. It is rather intended to be an overview of common applications (Becker and Buchkremer, 2019).

Provider	Process mining application
Celonis	Celonis Process Mining
Cognitive Technology	myInvenio Process Analyst
Fluxicon	Disco
Lana Labs	LANA Process Mining
QPR Software	QPR ProcessAnalyzer
Signavio	Signavio Process Intelligence

Table 16: Process mining applications

[source: own presentation based on (Becker and Buchkremer, 2019)]

Table 16 shows six process mining applications that are analysed in this research. These applications have in common that they have been implemented at several business organizations in different countries.

The application Celonis Process Mining (CPM) is an integral part of the Intelligent Business Cloud system of the Celonis Societas Europaea (SE). Celonis SE is a technology company that was founded in the year 2011 and is based in Munich, Germany (Celonis, 2018b). The CPM tool uses AI and machine learning capabilities to analyze existing process data from IT systems of an institution to reconstruct how business processes are executed in real-life. Celonis SE defines six major fields of application for its CPM tool:

- Operational excellence
- Internal audit
- Shared services
- ERP harmonization & migration
- Robotic process automation
- Business process outsourcing

Operational excellence is the constant monitoring and optimization of business processes in an organization in order to increase the efficiency of the executed processes. The implementation of CPM to support internal audits aims to discover processes that are not executed in compliance with the internal or external guidelines. Moreover, CPM enables auditors to monitor the execution of business processes in real time. One further field of application is shared services. In this context, CPM can help organizations to discover similar processes from different business areas and to consolidate and centralize them. Besides, CPM helps institutions to discover business processes that need to be harmonized or migrated when a new ERP system is implemented. In the context of robotic process automation, CPM enables organizations to identify processes that can be automatized and to monitor the execution of automated processes. Furthermore, CPM can help institutions to identify business processes that can be outsourced (Celonis, 2018a).

Another application that is presented in table 16 is myInvenio Process Analyst (MPA). This tool is offered by the technology company Cognitive Technology. MPA is available both as a cloud-based and as an on-premise solution. The main functionalities of MPA are to analyze past patterns of business processes, to monitor the execution of present processes and to predict future process trends. These capabilities allow users to check compliance of business processes with internal or external requirements. Furthermore, potential bottlenecks of processes can be identified using the process check-up feature of MPA. This functionality enables organizations to highlight critical activities and resources. Besides, key performance indicators (KPIs) can be customized and visualized. One further functionality of MPA is the animation of process flows. This feature enables users to follow the timeline of business process executions. Moreover, the Social Network perspective allows organizations to identify relations between several resources. Therefore, key resources of a business process can be identified (Cognitive Technology, 2018).

The process mining application Disco is offered by Fluxicon, a technology company in Eindhoven, in the Netherlands. The product name "disco" refers to the term "discover" in the context "discover your processes" (Fluxicon, 2018a). Through the use of AI and machine learning algorithms, the application creates smart flow diagrams of real-life business processes in an institution. For this purpose, the user defines the level of detail and the process visualization. Besides, the Disco tool offers the chance to compare processes to uncover potential deviations. Disco is an on-premise software that can be downloaded from the website of Fluxicon (Fluxicon, 2018b).[23]

One further application that is analysed in this research is LANA Process Mining (LPM). LPM was developed by the software company Lana Labs GmbH, based in Berlin, Germany (Lana Labs, 2018b). This web-based solution includes process discovery, process conformance and process optimization capabilities. When process discovery tasks are performed, LPM enables institutions to discover existing bottlenecks through the integrated performance view. Skipped activities, errors or avoidable duplication of effort can be identified when the process conformance capabilities are used. Therefore, the application compares the real process execution with a predefined target model. In the process optimization phase, LPM automatically creates a list of deviations in the execution of business processes. Moreover, the application prioritizes the occurring deviations based on

23 The latest version of the process mining application Disco can be downloaded from the website of Fluxicon: http://fluxicon.com/disco/

its frequencies or based on the costs associated with a process or sub-process (Lana Labs, 2018a).

The process mining tool QPR ProcessAnalyzer (QPA) is a product offered by the QPR Software Plc, based in Helsinki, Finland. QPA can be used either cloud-based or on premise (QPR, 2018a). The application offers the following key functionalities:

- Flowchart analysis
- Influence analysis
- KPI analysis
- Lead time analysis
- Conformance analysis

The flowchart analysis function offers an automatic process visualization of as-is processes. This functionality allows an organization to identify variations, repetitions, loops and delays in their business processes. Influence analysis enable institutions to discover the impact of specific attributes on process variations. These root cause analysis help organizations to discover the factors that contribute most to variations in their processes. Furthermore, QPA allows the creation of KPI dashboards to monitor whether processes meet defined KPIs in real time. The lead time analysis functionality shows the duration of processes in order to identify potential bottlenecks. The execution of conformance analysis activities enables institutions to monitor conformity of processes and to discover non-conforming cases (QPR, 2018b).

Another process mining application that is analysed in this research is Signavio Process Intelligence (SPI). This cloud-based tool is offered by the technology company Signavio GmbH, based in Berlin, Germany. SPI is an integral part of the Signavio Business Transformation Suite. The SPI application allows real time process analysis and monitoring. For this purpose, users can choose between standardized and configurable, customized dashboards. Besides, impacts of changes in the process design can be analysed using the Business Impact Calculator functionality. Moreover, SPI has an integrated conformance checking functionality that allows organizations to analyse whether their processes are compliant with internal or external regulations (Signavio, 2018a).

The next step for the strategy development is to select a specific process mining tool. Therefore, several criteria are defined that a process mining solution has to meet in the context of this dissertation (Becker and Buchkremer, 2019). These demanded functionalities are presented in table 17. The selection of an application was carried out in October 2018. Therefore, table 17 considers the features of the applications that were available at that point in time.

Criterion	CPM	MPA	Disco	LPM	QPA	SPI
Data import and export functionalities	yes	yes	yes	yes	yes	yes
Large data sets can be analysed	yes	yes	yes	yes	yes	yes
On premise installation	-	yes	yes	-	yes	-
Process analysis functionalities	yes	yes	yes	yes	yes	yes
Process discovery functionalities	yes	yes	yes	yes	yes	yes
Real-time process analysis	yes	yes	yes	yes	yes	yes

Table 17: Comparison of selected process mining applications

[source: own presentation based on (Becker and Buchkremer, 2019)]

The descending order of criteria was generated alphabetically. The term "yes" means that a criterion is provided by an application. The comparison of the presented process mining tools shows that one of these conditions could not be fulfilled by each tool. In particular, three of six applications allow that the software is installed on premise.

This requirement is defined due to data privacy and security limitations in the risk management departments of FIs. Since the purpose of the newly developed process mining strategy is to evaluate risk management process data by individual employees, the privacy policies of several banks and other FIs do not allow to upload these data in a cloud environment that is hosted by a third party. In particular, the process mining tools MPA, Disco and QPA can be installed on premise. Therefore, each of these applications is suitable for the purposes of this research (Becker and Buchkremer, 2019). In detail, the process mining tool Disco by Fluxicon is selected and used, since it delivers a free full version for researchers of selected universities as well as other academic partners (Fluxicon, 2018b). It is required to work with a full version in order to use and analyse the full range of functionalities (Becker and Buchkremer, 2019). In this case, the full version can be requested by using the E-Mail address of the researcher that is provided by the participating university or scientific institution.

4.2.2 Strategy introduction

Traditional management approaches for business processes often deal with optimizing theoretical to be-business processes, rather than focusing on the actual execution of these processes within an institution. As a consequence, traditional process optimization efforts often do not lead to the anticipated results. On the contrary, some business processes management efforts result in more complex models of processes. These processes cannot be executed efficiently in the daily business of an organization (Rother, 2016). One further problem is that several traditional business process management procedures are time consuming for an institution. In order to discover potential fields of optimization, procedures like group meetings, workshops, interviews or third-party consultancy services are used. The outcomes of these activities are often subjective snapshots of the individual situations. Besides, these tasks often take weeks or even months (Bergener et al., 2015; de Vreede, Verbraeck and Eijck, 2003). As a potential solution to these problems, process mining procedures enable institutions to make the actual execution of business processes measurable and to analyse them in real-time (van der Aalst, 2018).

However, new solutions like process mining are at a comparatively early stage of usage in the risk and compliance management departments of FIs. For this reason, an implementation strategy for a process mining tool in the risk and compliance management areas of FIs is created and evaluated in this research. This strategy has two major goals. The first objective is to discover potential for the optimization of currently applied risk management business processes. For this purpose, inefficiencies in the real-life execution of processes shall be discovered. The second aim of the strategy that is introduced in this chapter is to monitor whether processes are executed in compliance with the process requirements (Becker and Buchkremer, 2019).

At first, it is necessary to present analysis questions that are in accordance with these two goals. The usage of a process mining tool has the purpose to answer these five questions (based on van der Aalst, 2016; Becker and Buchkremer, 2019):

- How is a selected business process most frequently executed in an institution?
- Which alternative procedures exist and how often do they appear?
- What are the reasons for alternative procedures? Are they allowed or even required?
- Which potential bottlenecks do exist? Is there potential for optimization of the regarded process?
- Is the process execution in compliance with all guidelines?

It is essential to consider these questions during the development of the process mining implementation strategy. One further task is the definition of the parts of the business process management lifecycle where process mining procedures will be applied (Becker and Buchkremer, 2019). For this reason, the lifecycle that was introduced in chapter 2.2.2 is analysed. The first two questions ("How is a selected business process most frequently executed in an institution?" and "Which alternative procedures exist and how often do they appear?") deal with the modelling of the real-life execution of a business process and are therefore raised in the process discovery phase. Questions three, four and five ("What are the reasons for alternative procedures? Are they allowed or even required?" and "Which potential bottlenecks do exist? Is there potential for optimization of the regarded process?" and "Is the process execution in compliance with all guidelines?") can be answered when the process design is analysed in detail. For this reason, these questions are raised in the process analysis phase. However, it must be considered that all five questions are also investigated in the process controlling and monitoring stage in order to ensure that the currently applied business processes are efficient and comply with both internal and external requirements. With regard to the business process management lifecycle, the following major fields of implementation are identified:

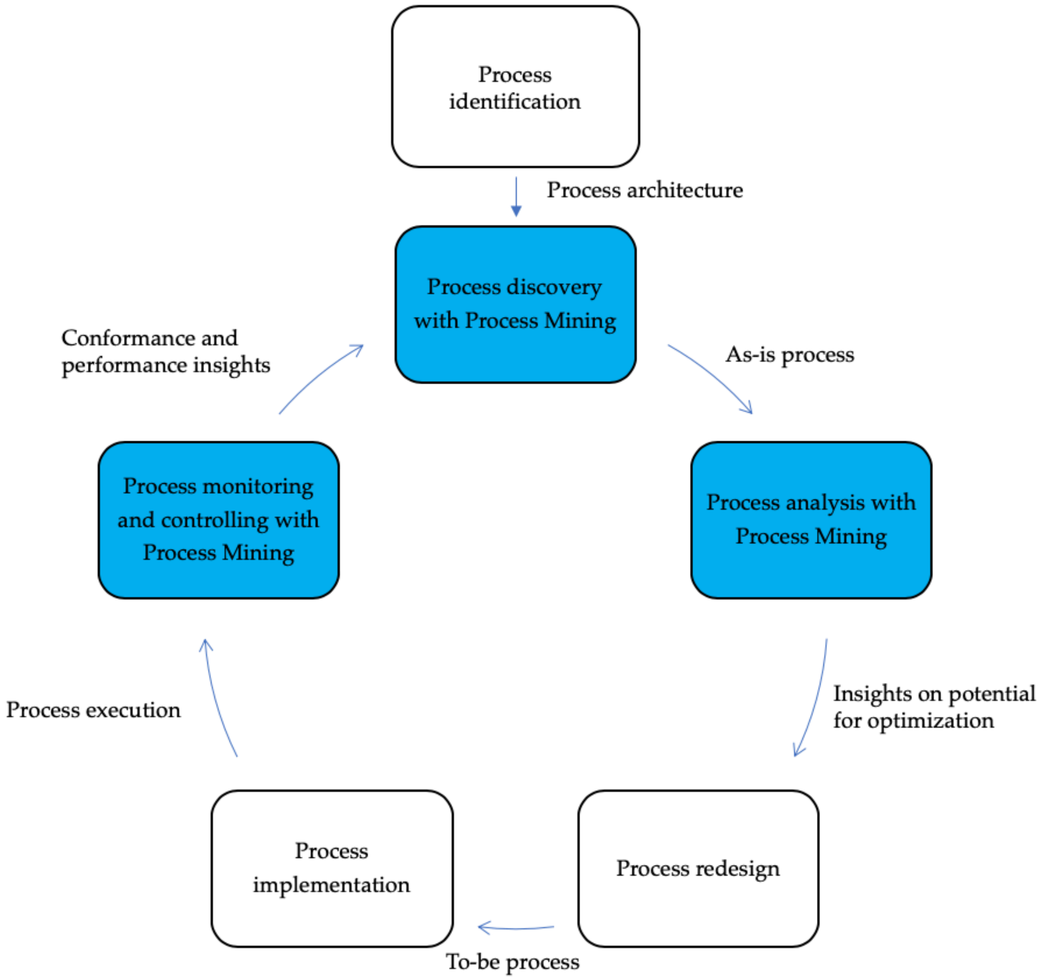


Figure 55: Integration of Process Mining in the Business Process Management Lifecycle [source: own presentation based on (Dumas et al., 2013, p. 21)]

Figure 55 shows the business process management lifecycle based on Dumas et al. (2013). The phases in which process mining can be used to address the presented analysis questions are highlighted with a blue background color.

At first, process mining can be integrated into the process discovery phase. As described in chapter 2.2.2, this phase deals with modelling and understanding of business processes. In this context, process mining approaches can help to model the real-life execution of business processes in an institution. As an output of the process discovery phase, the as-is process is presented. In a subsequent step, this as-is process is analysed in detail to identify potential weaknesses. According to Dumas et al. (2013, pp. 15-21), this phase is therefore called process analysis. In this phase, process mining can help institutions to discover potential opportunities for the optimization of an as-is process. Therefore, the output of the process analysis phase are insights on potentials for process optimization. To carry out the two following steps process redesign and process implementation, process mining procedures are not necessarily required. The output of the implementation of the redesigned process is the execution of the adjusted business process. To determine whether the redesigned process meets the intended expectations, regular monitoring and controlling activities need to be executed. Process mining applications can facilitate and partly automate these tasks. When a process is identified to be inefficient or not compliant with internal or external regulations, it needs to be discovered, analysed and redesigned again (Dumas et al., 2013, pp. 15-21). For this reason, the different business process management activities are presented as a continuous cycle (see chapter 2.2.2).

The subsequent task is to plan the implementation of the process mining tool. Before an application is implemented and used, the following six general questions need to be taken into consideration (based on van der Aalst, 2016; Becker and Buchkremer, 2019):

- Which process is observed? What are the objectives of the analysis?
- Which actions (individual steps, sub-processes) are relevant?
- Which IT systems, resources and individuals are involved?
- What kind of data is accessible in which IT systems?
- How can the necessary data be exported?
- Are data privacy standards considered?

These aspects are considered regarding a specific risk management business process and its sub-processes of a German FI (see chapters 4.2.3 and 4.2.4).

The next step is the definition of selection criteria that a process has to fulfil to be suitable for this research. In particular, a risk management process is required to meet these basic criteria (Becker and Buchkremer, 2019):

- Process chain is performed more than 100 times a year
- Process data contains more than 1,000 individual process steps
- Process data is available and accessible
- Process data is exportable
- Risk management process is critical
- Data privacy of the FI and the process participants is ensured

Risk management business processes that do not meet all criteria are not considered any further. An essential requirement for the purpose of this research is that the process chain is performed more than 100 times a year with a total of more than 1,000 individual process steps. This condition aims to ensure that the evaluated set of data has an acceptable size for the creation of meaningful insights with the implemented process mining tool (van der Aalst, 2016; Becker and Buchkremer, 2019). Besides, it is essential that the process data are accessible and exportable. A business process cannot be analysed without the availability of data that are imported into the application. Further conditions are that the risk management process is critical and that data privacy of the institution as well as the process participants is ensured. The selection of a risk management business process was executed with the support of the IBM Credit Bank in October 2018. The risk managers of the bank regarded the internal work instructions under consideration of the presented criteria. In particular, they chose a risk management business process that has a significant relevance for financial organizations and is appropriate for this research. As a result, the "Annual Account Review" (AAR) process was selected (Becker and Buchkremer, 2019). The aim of this risk management process and its procedure are presented in chapter 4.2.3 and the analysis of the AAR process with Disco is outlined in chapters 4.2.4 and 4.2.5.

4.2.3 Annual account review process

In this section, a business process and its sub-processes are presented that are part of the risk management activities of FIs in Germany. The following descriptions of the individual process steps are based on the information provided by the risk management experts of the IBM Credit Bank in Germany, the available work instructions and the legal framework “Minimum Requirements for Risk Management” (MaRisk) that was published in October 2017 (see chapter 2.3.1). The selected business process is presented at a high level of abstraction and in a slightly modified manner. The aim of this approach is to protect data privacy regulations of the investigated FI.

The “Annual Account Review” business process regulates the frequent monitoring of credit customer accounts of FIs. This process is regulated in BTO 1.2.2 MaRisk. In general, BTO 1

“...sets out the requirements that apply to the organisational and operational structure, the procedures for the early detection of risks and the procedures for the classification of risks in the lending business (...)”

(BaFin Federal Financial Supervisory Authority, 2017: MaRisk BTO 1 item 1). BTO 1.2 is entitled “Requirements for lending business processes” and defines in item 1:

“...the institution has to set up loan processing procedures (the granting and further processing of the loan), the monitoring of loan processing (...). Responsibility for the development and quality of these processes has to lie outside of the front office”

(BaFin Federal Financial Supervisory Authority, 2017: MaRisk BTO 1.2 item 1). In terms of loan processing, BTO 1.2.2 (Further processing of loans) defines:

“1. Whether or not the borrower is complying with the terms of the contract has to be monitored in the further processing of loans. In the case of special-purpose loans, the institution has to monitor whether or not the funds made available are being used as agreed (monitoring of the loan purpose).

2. Counterparty risk is to be assessed annually, whereby the intensity of ongoing assessments depends on the risk content of the exposure (...)”

(BaFin Federal Financial Supervisory Authority, 2017: MaRisk BTO 1.2.2).

The major purpose of these procedures is described in BTO 1.3 “Procedure for the early detection of risks” item 1:

“The procedure for the early detection of risks is intended primarily to identify, in a timely manner, borrowers whose loans are beginning to show signs of increased risk. With such a system in hand, the institution shall be able to initiate countermeasures at the earliest possible stage (e.g. intensified loan management)”

(BaFin Federal Financial Supervisory Authority, 2017: MaRisk BTO 1.3 item 1). Furthermore, BTO 1.1 (Segregation of functions and voting) item 1 MaRisk defines the process participants as follows:

“The basic principle that applies to the structure of processes in lending business is the clear structural separation of the front office and back office up to and including the management board level (...)”

(BaFin Federal Financial Supervisory Authority, 2017: MaRisk BTO 1.1 item 1). However, there are certain exceptions for the segregation of functions defined in the MaRisk. These exceptional cases are not regarded further in this research. Two participating groups are involved in the performance of the AAR process. In particular, it is the account managers (front office) task to review the credit customer accounts. Besides, the risk manager (back office) monitors the account managers review activities. This separation of responsibilities is required to minimize the risk of errors and mistakes (Becker and Buchkremer, 2019).

The execution of the AAR process is visualised in figure 56 using the modelling language BPMN since it is one of the most common modelling concepts in the financial industry (see chapter 2.2.1). As a modelling tool, the web-based application Signavio Process Manager is used (Signavio, 2018b). The basic elements of BPMN are explained in chapter 2.2.1.

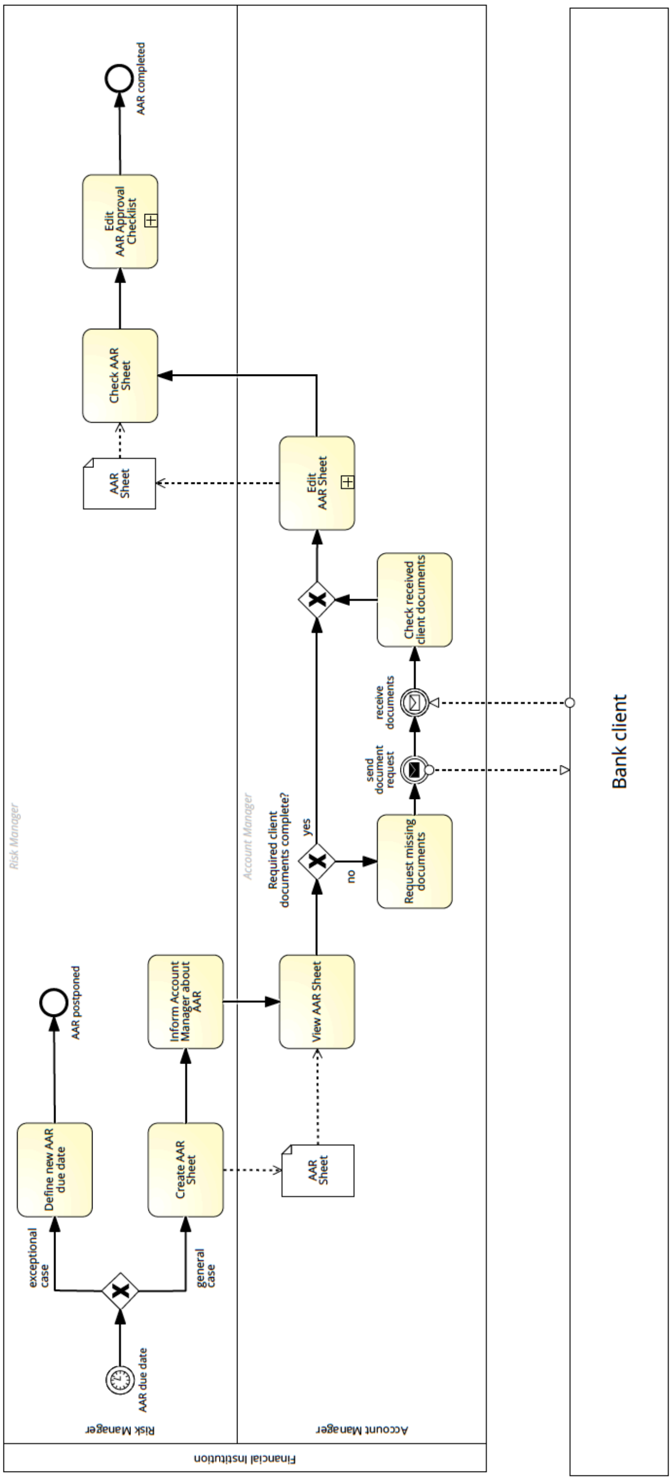


Figure 56: Annual Account Review process modelled with BPMN

In this case illustrated in figure 56, it is defined that the AAR process has to be performed within twelve months since the last AAR has been carried out for a client account. However, there are specific exception criteria defined that can lead to a temporal shift of the AAR process. When these exception criteria are fulfilled, the account is classified as an "exceptional case" by the risk manager. In contrast to that, an account that does not meet with the exception criteria is defined as a "general case". In terms of an exceptional case, the AAR is postponed, and the process is completed. When the account is classified as a general case, the risk manager creates the "AAR Sheet" for this client account. Besides, the expert informs the responsible account manager about the AAR. In a subsequent step, the account manager views the AAR Sheet and checks whether the client documents that are required to carry out the AAR are complete. If the client documents are not complete, the account manager requests the missing documents. To execute this task, a letter or an E-Mail is sent to the client requesting the missing documents. The process continues when the client sends the requested documents. In this case, the account manager has to check the received client documents for completeness. As soon as the necessary client documents are complete, the account manager fills out the AAR Sheet. This step is visualised as a sub-process since it requires further steps (see figure 57). As soon as the account manager submits the AAR Sheet, the risk manager is required to check it to ensure an appropriate data quality. For this purpose, the "AAR Approval Checklist" has to be filled out. Since this task has several possible outcomes, it is presented as a separate sub-process (see figure 58). When the risk manager has completed the AAR Approval Checklist, the AAR is complete.

In the following, the sub-process entitled "Edit AAR Sheet" is visualised in figure 57.

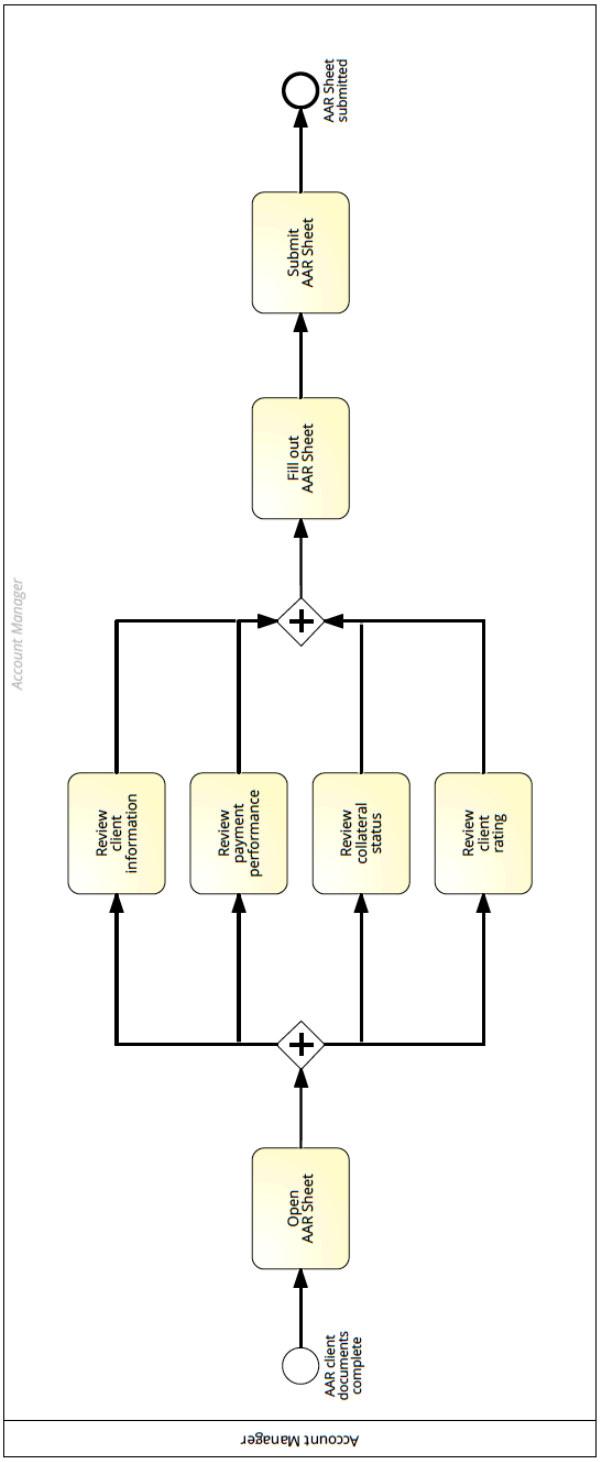


Figure 57: Edit AAR Sheet sub-process modelled with BPMN

In a first step, the account manager opens the AAR Sheet. Afterwards it is necessary to carry out four review tasks. In particular, the manager has to check whether the client information are up-to-date and complete. For instance, the account manager has to review whether all authorized persons that are stated in the contract are identified and still active. Besides, the payment performance of the client needs to be reviewed. To carry out this task, the account manager controls whether payments are overdue. In addition, the status of the collateral is checked. Furthermore, the internal and external ratings of the client are reviewed with regard to possible rating changes. Since these four tasks have to be carried out before the next step can be executed, a "+" gateway is used in BPMN. When these activities are complete, the account manager fills out the AAR Sheet and submits the completed document. The sub-process ends as soon as the AAR Sheet is submitted. Please note that these four review tasks can lead to additional activities that are not investigated in further detail in this research.

One further sub-process within the AAR is entitled "Edit AAR Checklist". This sub-process is carried out by the risk manager after the AAR Sheet is submitted. Its execution is presented in figure 58.

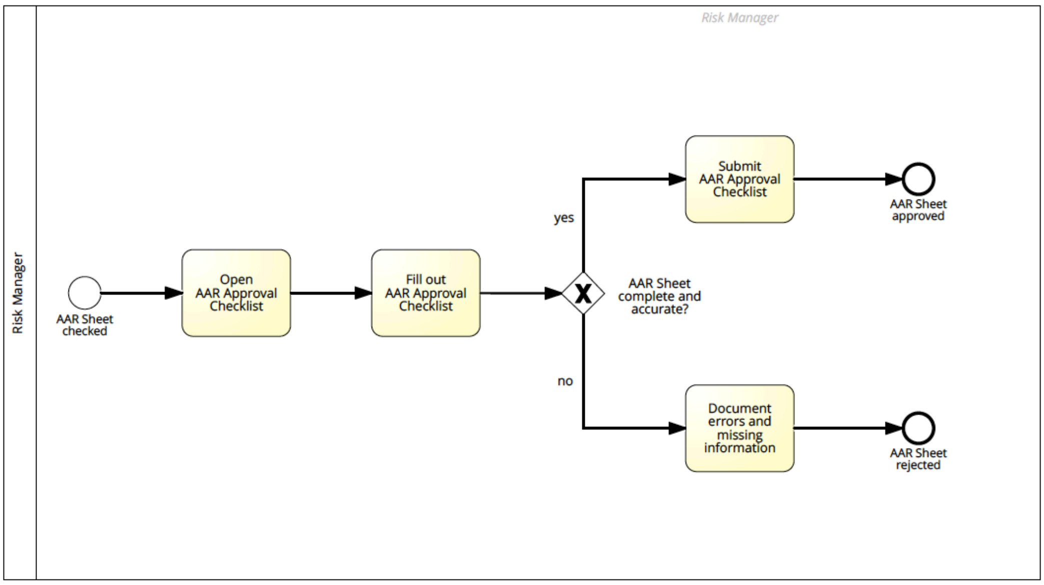


Figure 58: Edit AAR approval checklist sub-process modelled with BPMN

As soon as the AAR Sheet is checked, the risk manager opens the AAR Approval Checklist. When filling out the checklist, the expert has to control whether the information in the AAR Sheet are complete and accurate. When the AAR Sheet has not been filled out complete and correct, the risk manager documents the errors and missing information. In this case, the AAR Sheet is rejected. When the AAR Sheet is filled out correctly and complete, the risk manager submits the AAR Approval Checklist. In this scenario, the AAR Sheet is approved. It must be considered that the AAR Approval Checklist is more extensive than the AAR Sheet since the risk manager is required to check certain information in a more detailed manner than the account manager.

Please note that the descriptions of the execution of these process steps are based on the information provided by the IBM Credit Bank in Germany and on legal requirements for FIs in Germany. Other banks and FIs might have different process steps defined to carry out this task. However, since this process is legally required by the MaRisk, each German FI that carries out credit business has to define a process chain for a regular account review. In the following sections, the real-life execution of the AAR process is analysed and evaluated using the process mining application Disco (see chapters 4.2.4 and 4.2.5).

4.2.4 Implementation procedure

This part of the research presents the required activities to evaluate the AAR business process using the process mining tool Disco. The procedures and screenshots refer to Disco version 2.2.1, which was usable in October 2018.

To access and export the required data is the first and often most critical task. In a general case, the data are normally accessible in log files. In this case, log files are documents that contain information concerning the actual execution of individual process steps. These log files have to be consolidated and stored in a repository before they can be uploaded into Disco. The application is capable of generating a process model that visualizes the actual execution of the process chain based on the available data from the uploaded log files (Fluxicon, 2018a; Becker and Buchkremer, 2019). Figure 59 shows an overview of these procedures.

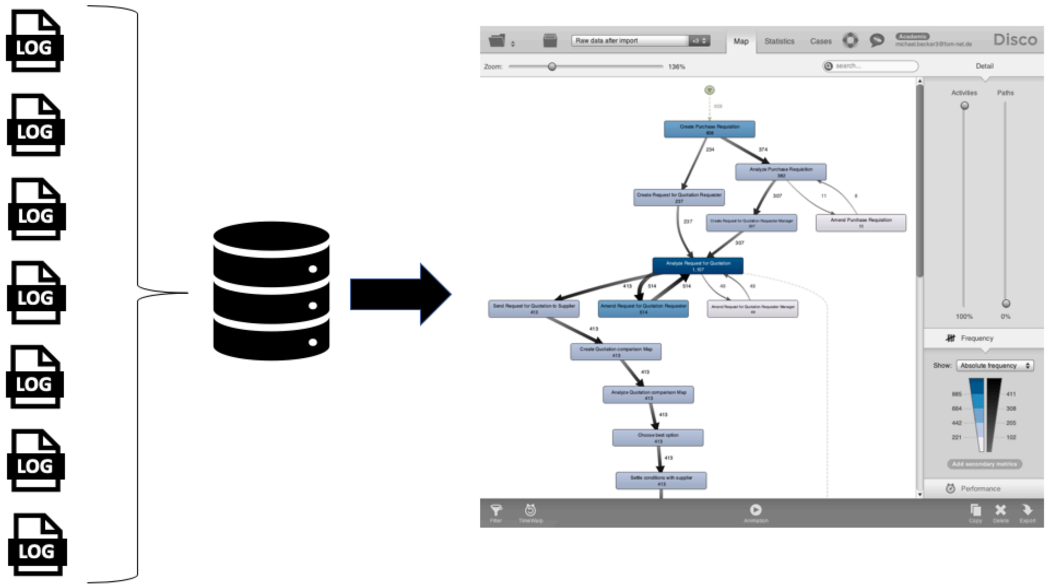


Figure 59: Data upload into the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

A requirement for an analysis with Disco is that the log files contain certain information regarding the execution of the business process. At first, a unique identifier (ID) is needed for each process execution. The individual ID can be displayed as a numeric value, one or more letters, a symbol or a combination of these elements. For the purpose of this dissertation, a consecutive number is used. Besides, information regarding the event which represents a process activity are required. An activity is to be associated to a unique ID. In addition, the employee or organizational unit that carries out an activity is linked to an ID. Each employee or responsible unit has to have a unique description. Moreover, a record of the date and time of the activity is necessary (Fluxicon, 2018a; Becker and Buchkremer, 2019). The log files are consolidated in a defined data format that can be processed by Disco in a central repository. With regard to this research project, a Comma-separated values (CSV) file is used that contains the information of the log files. However, it is essential that the restrictions regarding data privacy of the credit bank are observed. For this purpose, two main limitations had to be considered.

On the one side, it is required to anonymize the data of the individual process participants to prevent that process data could be associated to an individual employee. Therefore, the process participant data only comprises the job roles of the employees. To be able to distinguish between individuals with a similar position, the job role is followed by a unique number for each employee (e.g. Risk Manager 1, Risk Manager 2...). On the other side, the timestamps of the process step executions are slightly modified. The aim of this approach is that the exact time and duration of each process step is not visible. With reference to this research, these limitations are acceptable since the aim of this evaluation is to provide an overview how a process mining featured application can support FIs to optimize their risk and compliance management activities rather than to present detailed information of one particular bank. In consequence, the CSV file includes all necessary information about the execution of the AAR process and is in accordance with the data privacy limitations of the FI (Becker and Buchkremer, 2019).

The file that is uploaded in Disco comprises process data in the time period between November 01, 2017 and October 31, 2018. As a result, only processes that did not start before November 01, 2017 were included in this CSV file. When a process chain started before this date and ended after November 01, this process was excluded from the file. Besides, only business processes that were completed until October 31, 2018 were considered. Consequently, processes that started before this date and ended after October 31, 2018 were also excluded from the CSV file.

An extract of this CSV file is presented in table 18.

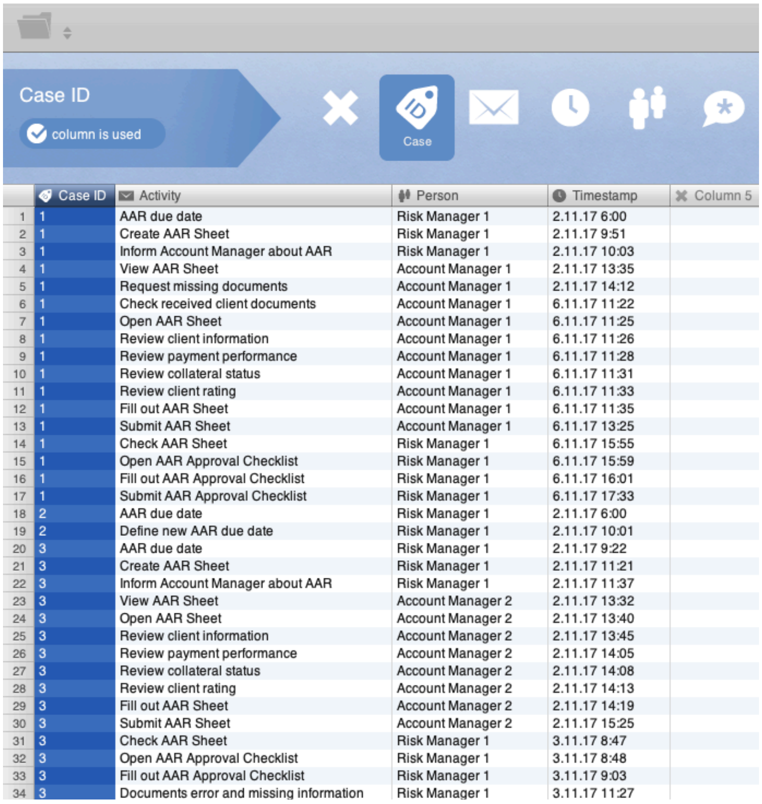
Case ID	**Activity**	**Person**	**Timestamp**
0001	AAR due date	Risk Manager 1	02.11.2017 06:00
0001	Create AAR Sheet	Risk Manager 1	02.11.2017 09:51
0001	Inform Account Manager about AAR	Risk Manager 1	02.11.2017 10:03
0001	View AAR Sheet	Account Manager 1	02.11.2017 13:35
0001	Request missing information	Account Manager 1	02.11.2017 14:12
0001	Check received client documents	Account Manager 1	06.11.2017 11:22
0001	Open AAR Sheet	Account Manager 1	06.11.2017 11:25
0001	Review client information	Account Manager 1	06.11.2017 11:26
0001	Review payment performance	Account Manager 1	06.11.2017 11:28
0001	Review collateral status	Account Manager 1	06.11.2017 11:31
0001	Review client rating	Account Manager 1	06.11.2017 11:33
0001	Fill out AAR Sheet	Account Manager 1	06.11.2017 11:35
0001	Submit AAR Sheet	Account Manager 1	06.11.2017 13:25
0001	Check AAR Sheet	Risk Manager 1	06.11.2017 15:55
0001	Open AAR Approval Checklist	Risk Manager 1	06.11.2017 15:59
0001	Fill out AAR Approval Checklist	Risk Manager 1	06.11.2017 16:01
0001	Submit AAR Approval Checklist	Risk Manager 1	06.11.2017 17:33

Table 18: Extract of the log file

Table 18 shows that each process execution has a unique four-digit case ID. This information is essential to be capable of analyzing the process chain of an individual process execution in detail. Besides, the individual activities that are carried out in this process are presented in the second column and are linked to a case ID. Furthermore, the extract in table 18 contains an information of the process participants that carry out the individual activities of each process. In addition, the timestamp of each activity is recorded in a unified format.

The next step is to upload the CSV file into the process mining application. To perform this task, it is required to allocate the information in the file to the types of information needed by Disco (Fluxicon, 2018a; Becker and Buchkremer, 2019).

The screenshot in figure 60 shows how this task is fulfilled.



	Case ID	Activity	Person	Timestamp	Column 5
1	1	AAR due date	Risk Manager 1	2.11.17 6:00	
2	1	Create AAR Sheet	Risk Manager 1	2.11.17 9:51	
3	1	Inform Account Manager about AAR	Risk Manager 1	2.11.17 10:03	
4	1	View AAR Sheet	Account Manager 1	2.11.17 13:35	
5	1	Request missing documents	Account Manager 1	2.11.17 14:12	
6	1	Check received client documents	Account Manager 1	6.11.17 11:22	
7	1	Open AAR Sheet	Account Manager 1	6.11.17 11:25	
8	1	Review client information	Account Manager 1	6.11.17 11:26	
9	1	Review payment performance	Account Manager 1	6.11.17 11:28	
10	1	Review collateral status	Account Manager 1	6.11.17 11:31	
11	1	Review client rating	Account Manager 1	6.11.17 11:33	
12	1	Fill out AAR Sheet	Account Manager 1	6.11.17 11:35	
13	1	Submit AAR Sheet	Account Manager 1	6.11.17 13:25	
14	1	Check AAR Sheet	Risk Manager 1	6.11.17 15:55	
15	1	Open AAR Approval Checklist	Risk Manager 1	6.11.17 15:59	
16	1	Fill out AAR Approval Checklist	Risk Manager 1	6.11.17 16:01	
17	1	Submit AAR Approval Checklist	Risk Manager 1	6.11.17 17:33	
18	2	AAR due date	Risk Manager 1	2.11.17 6:00	
19	2	Define new AAR due date	Risk Manager 1	2.11.17 10:01	
20	3	AAR due date	Risk Manager 1	2.11.17 9:22	
21	3	Create AAR Sheet	Risk Manager 1	2.11.17 11:21	
22	3	Inform Account Manager about AAR	Risk Manager 1	2.11.17 11:37	
23	3	View AAR Sheet	Account Manager 2	2.11.17 13:32	
24	3	Open AAR Sheet	Account Manager 2	2.11.17 13:40	
25	3	Review client information	Account Manager 2	2.11.17 13:45	
26	3	Review payment performance	Account Manager 2	2.11.17 14:05	
27	3	Review collateral status	Account Manager 2	2.11.17 14:08	
28	3	Review client rating	Account Manager 2	2.11.17 14:13	
29	3	Fill out AAR Sheet	Account Manager 2	2.11.17 14:19	
30	3	Submit AAR Sheet	Account Manager 2	2.11.17 15:25	
31	3	Check AAR Sheet	Risk Manager 1	3.11.17 8:47	
32	3	Open AAR Approval Checklist	Risk Manager 1	3.11.17 8:48	
33	3	Fill out AAR Approval Checklist	Risk Manager 1	3.11.17 9:03	
34	3	Documents error and missing information	Risk Manager 1	3.11.17 11:27	

Figure 60: Data allocation in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

At the top of the figure, different images visualize the information that are required by the tool. The individual case ID for each process chain is represented by the ID badge symbol. The process activities are visualized through the mail symbol and the timestamp is presented through the clock next to the mail symbol. In addition, the process participants are visualized through the symbol of two human beings and possible additional information are represented through the speech bubble symbol. This last field is optional and not filled in this research project (Fluxicon, 2018a; Becker and Buchkremer, 2019).

When the content of the CSV file is allocated to the types of information required by Disco, the format of the timestamp has to be reviewed (see figure 61).

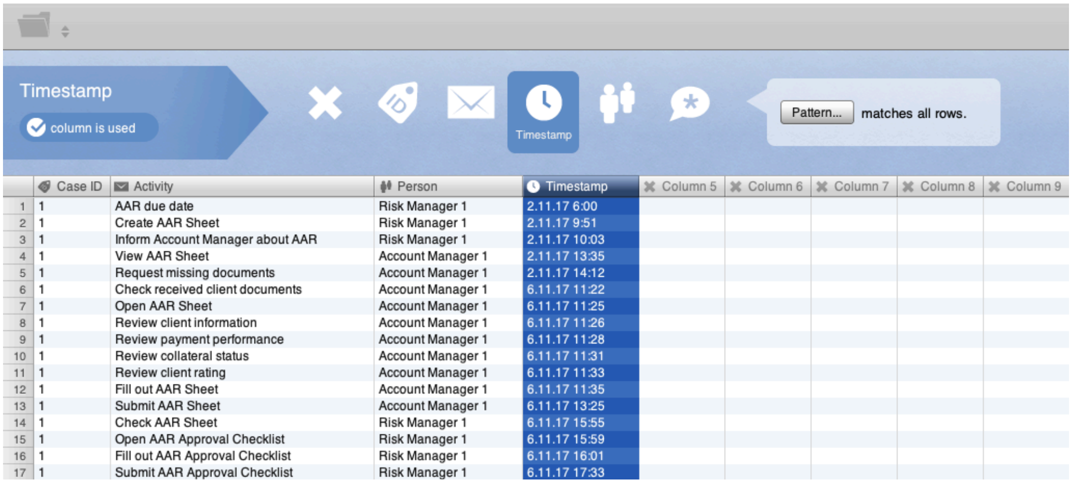


Figure 61: Timestamp review in the Disco application

[source: own presentation based on (Fluxicon, 2018a)]

The screenshot in figure 61 shows that the timestamp format is checked automatically by the application. When all timestamps have a similar and consistent format, the note “matches all rows” appears. The user is also given the opportunity to customize the format of the date and time information by clicking on the “pattern” button on the top-right corner of the screen (Fluxicon, 2018a). This step is illustrated in figure 62.

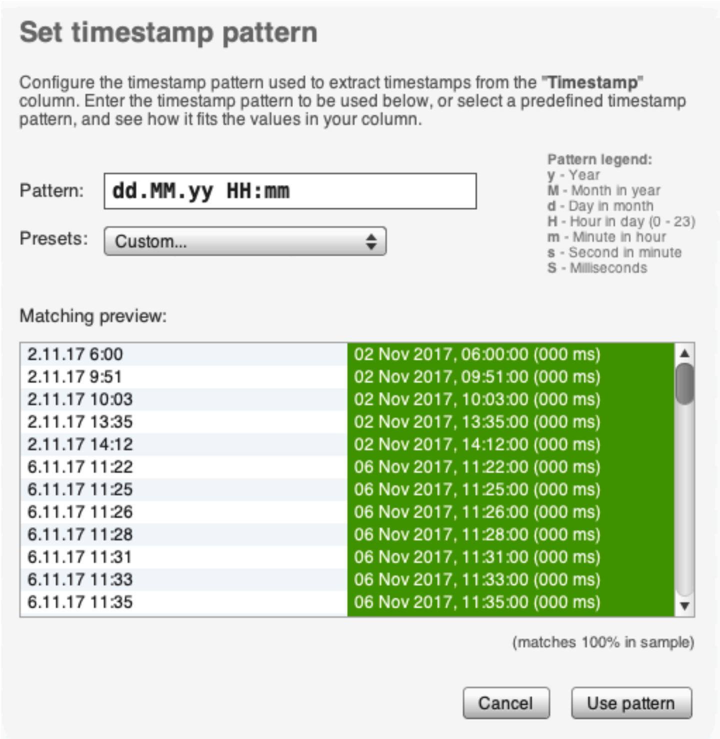


Figure 62: Set timestamp pattern in the Disco application

[source: own presentation based on (Fluxicon, 2018a)]

Therefore, the user is enabled to define a uniform pattern for the date and time information of the uploaded data by typing a format in the text box next to the term "pattern". As an alternative, the user can also select a predefined timestamp format by selecting the dropdown menu under the text box. When the format is defined, the user has to click on the "use pattern" button to apply the settings (Fluxicon, 2018a).

The data import is executed by clicking on the button entitled "start import". Based on the uploaded data, the process mining application is capable of creating a business process model (Fluxicon, 2018a; Becker and Buchkremer, 2019). This process model is evaluated in the subsequent section of this dissertation (see chapter 4.2.5).

4.2.5 Strategy evaluation

Process mining tools present several models and statistical data. The user is given the chance to choose the evaluations that are most convenient with regard to the purpose of the research (Fluxicon, 2018a; Becker and Buchkremer, 2019). The overreaching goals of this research project are to monitor the compliance of a selected business process and to determine enhancement possibilities. As an initial analysis, the process mining application Disco provides a high-level overview regarding the actual execution of the investigated process (see figure 63).

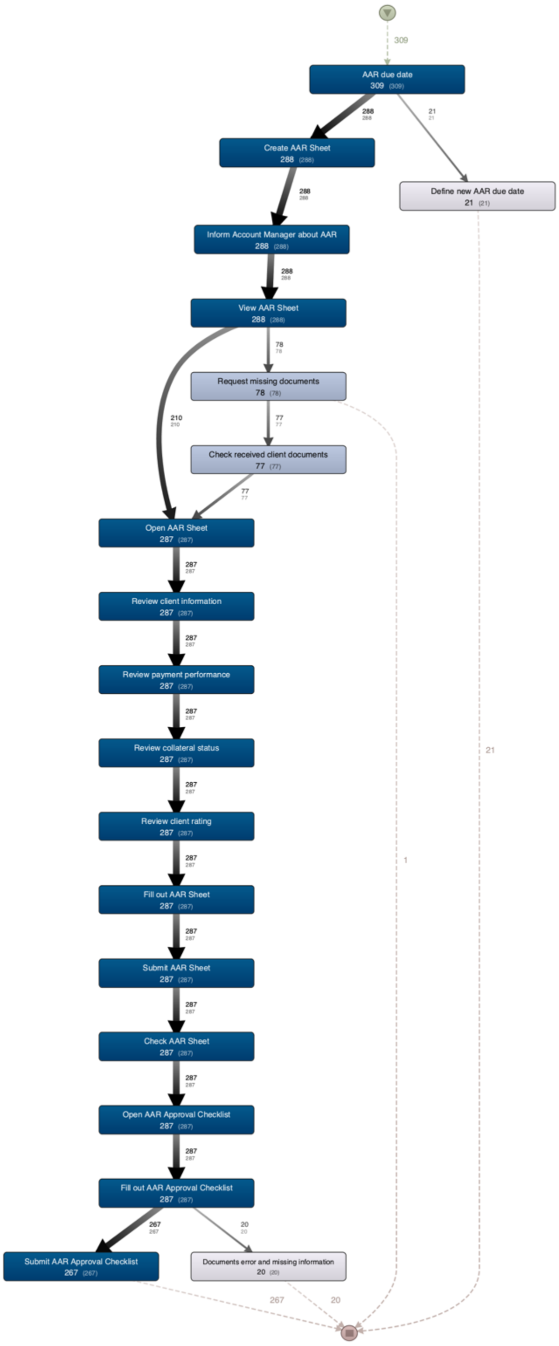


Figure 63: Process overview in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

Figure 63 visualizes each process path that appeared. Besides, the frequency of individual executions of a process step is presented by using different colors for the activity boxes. The brighter the color of a specific box, the less often this process step is carried out. Furthermore, arrows represent the sequence of the individual process steps (Fluxicon, 2018a; Becker and Buchkremer, 2019). In a further step, this actual model of process executions is compared to the descriptions of the process in the work instructions of the FI. The aim of this approach is to discover conspicuous activities. In this research, one particular process chain is not in compliance with the work instructions of the institution. In more detail, the process chain that ends after the step "Request missing documents" is non-compliant. This event is regarded more precisely in the next step (Becker and Buchkremer, 2019). The further process executions presented in figure 63 are compliant with the guidelines.

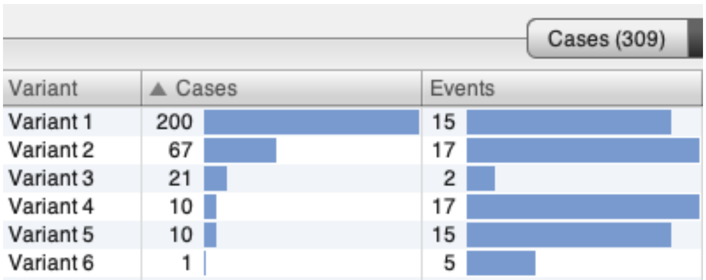


Figure 64: Process variants in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

Figure 64 shows how often the different variants occurred during the regarded time frame (Becker and Buchkremer, 2019). The expert can select the non-compliant process chain (variant 6) to have a more precise look on its execution (see figure 65).

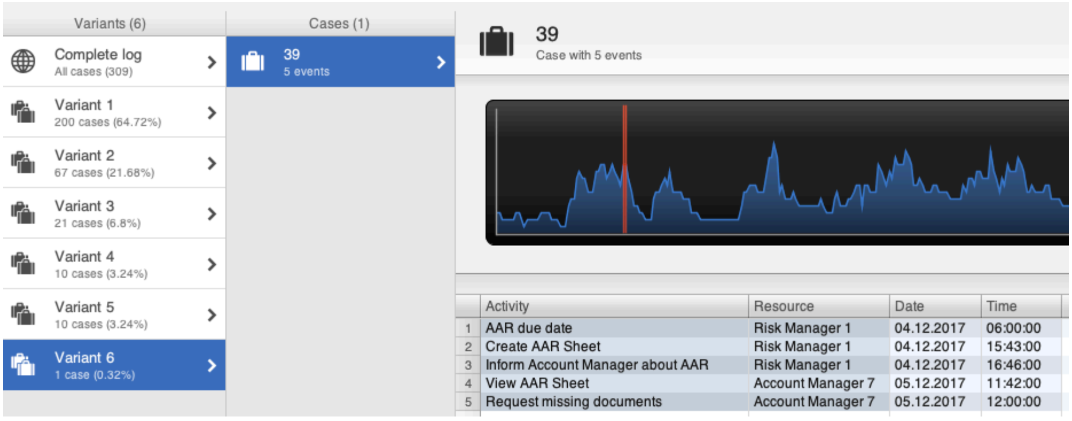
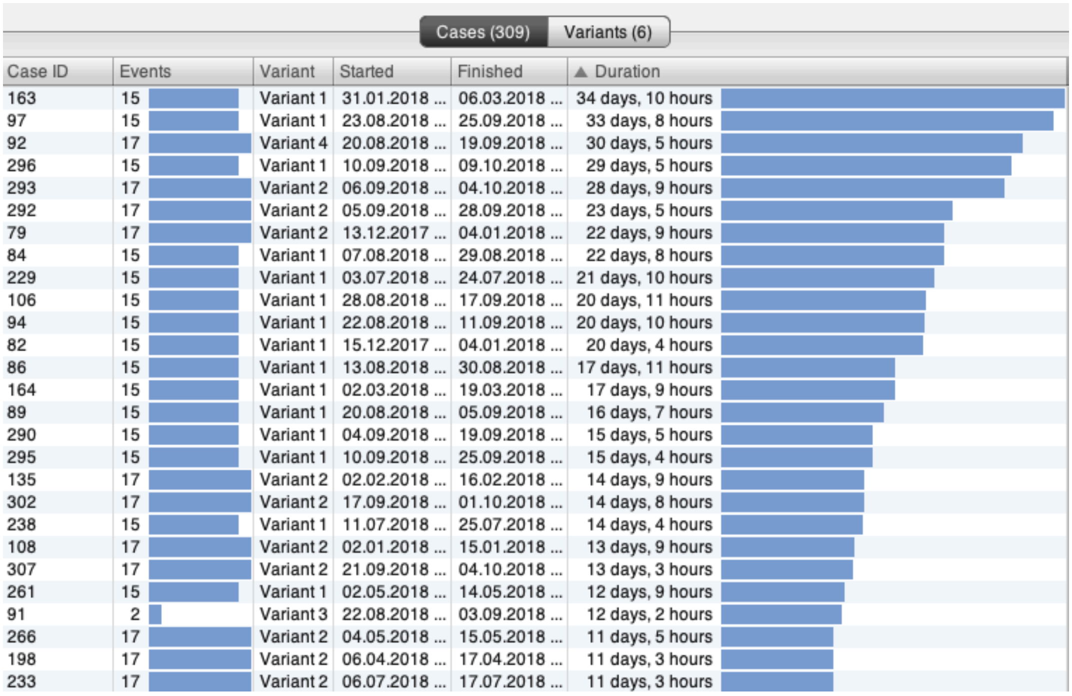


Figure 65: Case analysis in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

The assessment of case 39 makes visible that the process starts on December 04, 2017. The initial tasks are carried out by risk manager 1. The next day, account manager 7 executes the task to request missing client documents. In this case, the process execution ends at this point. The reason for this situation is that the client has not submitted the documents that were requested. In a further step, the responsible compliance manager or auditor has the opportunity to ask account manager 7 for the reason that the process execution did not end in a compliant manner. In this scenario, the client has cancelled both the credit contract as well as the bank account a few days after December 05, 2017. As a result, the client has not submitted the documents. In this particular case, this nonconformity is acceptable for the compliance manager since the AAR business process is not applicable for accounts that have been cancelled. Since the other process chains have been executed in accordance with the instructions, it is confirmed and ensured that the actual execution of this process is compliant in the time frame that was investigated. In summary, the compliance manager or auditor can carry out this analysis in several minutes with the process mining tool Disco. Besides, conspicuous activities can be analysed that might not have been made visible if the evaluation would have been carried out manually (Becker and Buchkremer, 2019).

A further task is to review the process durations and to analyse whether they are in accordance with the regulations of the FI (see figure 66).



Case ID	Events	Variant	Started	Finished	▲ Duration
163	15	Variant 1	31.01.2018 ...	06.03.2018 ...	34 days, 10 hours
97	15	Variant 1	23.08.2018 ...	25.09.2018 ...	33 days, 8 hours
92	17	Variant 4	20.08.2018 ...	19.09.2018 ...	30 days, 5 hours
296	15	Variant 1	10.09.2018 ...	09.10.2018 ...	29 days, 5 hours
293	17	Variant 2	06.09.2018 ...	04.10.2018 ...	28 days, 9 hours
292	17	Variant 2	05.09.2018 ...	28.09.2018 ...	23 days, 5 hours
79	17	Variant 2	13.12.2017 ...	04.01.2018 ...	22 days, 9 hours
84	15	Variant 1	07.08.2018 ...	29.08.2018 ...	22 days, 8 hours
229	15	Variant 1	03.07.2018 ...	24.07.2018 ...	21 days, 10 hours
106	15	Variant 1	28.08.2018 ...	17.09.2018 ...	20 days, 11 hours
94	15	Variant 1	22.08.2018 ...	11.09.2018 ...	20 days, 10 hours
82	15	Variant 1	15.12.2017 ...	04.01.2018 ...	20 days, 4 hours
86	15	Variant 1	13.08.2018 ...	30.08.2018 ...	17 days, 11 hours
164	15	Variant 1	02.03.2018 ...	19.03.2018 ...	17 days, 9 hours
89	15	Variant 1	20.08.2018 ...	05.09.2018 ...	16 days, 7 hours
290	15	Variant 1	04.09.2018 ...	19.09.2018 ...	15 days, 5 hours
295	15	Variant 1	10.09.2018 ...	25.09.2018 ...	15 days, 4 hours
135	17	Variant 2	02.02.2018 ...	16.02.2018 ...	14 days, 9 hours
302	17	Variant 2	17.09.2018 ...	01.10.2018 ...	14 days, 8 hours
238	15	Variant 1	11.07.2018 ...	25.07.2018 ...	14 days, 4 hours
108	17	Variant 2	02.01.2018 ...	15.01.2018 ...	13 days, 9 hours
307	17	Variant 2	21.09.2018 ...	04.10.2018 ...	13 days, 3 hours
261	15	Variant 1	02.05.2018 ...	14.05.2018 ...	12 days, 9 hours
91	2	Variant 3	22.08.2018 ...	03.09.2018 ...	12 days, 2 hours
266	17	Variant 2	04.05.2018 ...	15.05.2018 ...	11 days, 5 hours
198	17	Variant 2	06.04.2018 ...	17.04.2018 ...	11 days, 3 hours
233	17	Variant 2	06.07.2018 ...	17.07.2018 ...	11 days, 3 hours

Figure 66: Case duration analysis in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

The process duration of each process chain is shown in descending order in the last column of figure 66. It must be considered that case ID 163 has the longest process execution time with a total of 34 days and 10 hours. Unfortunately, it is defined in the work instructions of the FI that the AAR business process has to be executed in a maximum time of 30 days after the AAR due date. With regard to this research, this requirement is not fulfilled for case IDs 163, 97 and 92. The process mining tool offers the chance to analyse these three cases in more detail in order to discover the reasons for the comparatively long durations (Becker and Buchkremer, 2019).

Figure 67 exemplifies a detailed view on case ID 163.

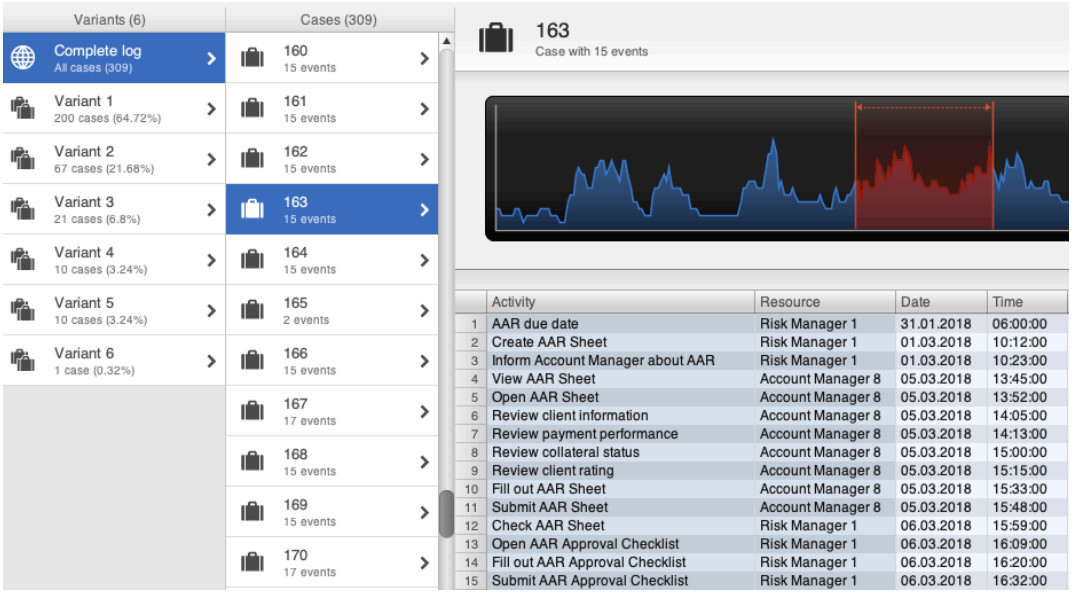


Figure 67: Case ID 163 analysis in the Disco application

[source: own presentation based on (Fluxicon, 2018a)]

The case analysis shows that the "AAR due date" was on January 31, 2018. However, the consecutive process step "Create AAR Sheet" is carried out more than one month later on March 01, 2018. This long time period between the first and the second process step is the main reason for the non-compliant execution time. Therefore, the compliance manager or auditor can contact risk manager 1 to discover the reason for this non-compliant event. Due to data privacy restrictions, these nonconformities are not investigated further in this dissertation.

In consequence, the compliance manager can analyse within several minutes whether the process duration is in accordance with the regulations and discover potential reasons in case of deviations (Becker and Buchkremer, 2019). Moreover, potential bottlenecks can be discovered when the durations of the process steps are analysed (see figure 68).

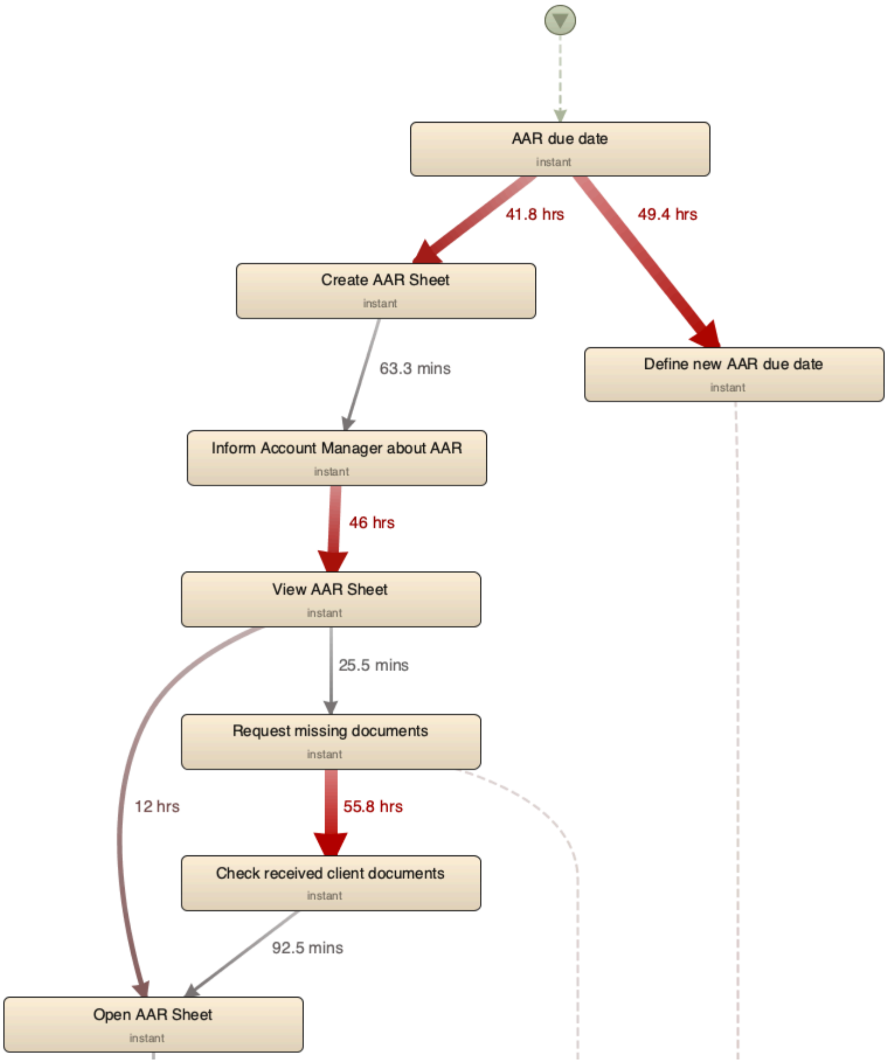


Figure 68: Average activity duration in the Disco application

[source: own presentation based on (Fluxicon, 2018a; Becker and Buchkremer, 2019)]

Figure 68 shows that it takes an average time of 55.8 hours until the account manager checks the requested missing documents. One major reason for this comparatively long time is that it took the clients some time to respond to the account managers requests. In this case, an average duration of 55.8 hours is tolerable for the institution. In summary, the durations of the process steps are acceptable for the FI (Becker and Buchkremer, 2019).

Besides, Disco offers the opportunity to analyse the individual resources that participate in the process execution (Fluxicon, 2018a). In this case, the numbers of cases that are carried out by each process participant are regarded. This evaluation report is visualized in figure 69.

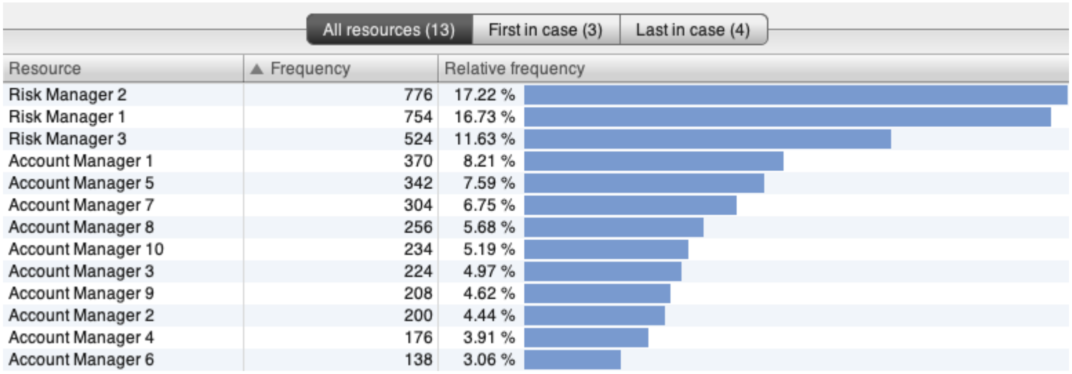


Figure 69: Resource analysis in the Disco application

[source: own presentation based on (Fluxicon, 2018a)]

This resource report shows that risk manager 2 carried out most tasks in the analysed time frame (776 events, 17.22 %). Closely behind, risk manager 1 executed 754 tasks, which equals a portion of 16.73 %. The third risk manager carried out significantly less tasks than the other two risk managers (524 events, 11.63 %). Moreover, the executed events of the seven account managers also differ significantly. In a subsequent step, the potential reasons for these deviations can be analysed. To protect data privacy of the individual process participants, the reasons for these deviations are not regarded any further in this research.

In summary, the evaluation of the process data shows that a compliance manager, auditor or other responsible person that uses a process mining application can monitor quickly and in an easy manner if a specific business process is carried out efficiently and compliant. When inconsistencies are noticed by the expert, the user can contact the responsible persons or departments. The compliance officer or auditor is enabled to regard non-compliant or inefficient executions in real-time and immediately take countermeasures. Besides, the evaluations in this research display that the durations of process steps can be regarded at different levels of detail (Becker and Buchkremer, 2019).

To conclude this section, it must be considered that compliance management activities of FIs can be facilitated through the use of a process mining tool. Further research could focus on the main advantages of process mining featured applications in comparison to traditional business process compliance management approaches (Becker and Buchkremer, 2019).

5 DISCUSSION

In this chapter, the research procedures, evaluations and results are discussed. For this purpose, the insights presented in this thesis are compared to selected other scientific studies that deal with similar thematic fields. The first section discusses the implementation strategy for regulatory requirements that was presented in chapter 4.1. In particular, it needs to be evaluated to what extent cognitive computing technologies like AI and machine learning can enhance the processing of regulations that affect banks and other FIs (see chapter 5.1). In the second part of this chapter, the insights of the process mining strategy that was developed and evaluated in chapter 4.2 of this thesis are discussed. Therefore, the conclusions that were derived from the research results are compared to the insights presented by other research projects that also deal with the implementation of process mining applications at financial organizations (see chapter 5.2). In chapter 5.3, potential limitations of the insights of this research are presented. These restrictions are mainly derived from the scope and focus of this thesis. Besides, the applicability of the two presented strategies in the risk and compliance management environment of FIs is analysed in this section. In the last part of this chapter, suggestions and recommendations for further research on the subject matter are specified (see chapter 5.4).

5.1 PROCESSING REGULATIONS WITH COGNITIVE TECHNOLOGIES

The implementation strategy presented in chapter 4.1 showed that cognitive computing technologies like AI and machine learning can be used to automate several tasks in the processing of new or extended existing regulations at FIs. In this research, the initial analysis of regulations was carried out through the application IBM WRC. This system was not only able to read and process regulatory requirements through text mining and AI technologies, but also to derive potential obligations that result from a legal document. Therefore, the application generated a probability-weighted list of obligations. In a further step, the experts of the institution or external parties were required to review the initial technical analysis of a regulation and decide how obligations are processed within the individual institution. Through the usage of machine learning capabilities, the WRC application is able to learn from the decisions of the experts and enhance its initial technical analysis when further legal documents are processed.

As a result, the iterative procedure model for the implementation of regulatory requirements showed that applications that use cognitive computing technologies can facilitate the processing of new or extended existing regulations at FIs. Due to the system-based initial evaluation of a legal document, the manual effort of the experts can be reduced compared to an entirely manual evaluation of the legal text. However, this research also pointed out that the usage of a cognitive computing featured application to process regulations does not replace the expertise of human beings. It is rather a tool that can assist regulatory experts in dealing with the increasing amount and complexity of regulations in the financial sector. Moreover, the strategy that was presented in this research can assist FIs in managing the implementation lifecycle of constantly changing legal requirements in a more efficient manner.

It needs to be considered that this research focused on the business perspective rather than on the technical details of the application that was used. Therefore, chapter 4.1 presented an implementation strategy that can be taken as a foundation for the practical implementation of a similar technological solution at a bank or other FI. Detailed technical descriptions and analysis how the application IBM WRC uses AI and machine learning capabilities to process legal documents are not in the scope of this research. These IT-driven aspects are described, for instance, by Ashley (2017). In particular, Ashley deals with the technical details of the usage of cognitive computing technologies to process regulations. For this purpose, this research analyses how new technologies like machine learning can help to extract relevant information from legal documents. Ashley also concludes that new technological solutions can enhance the processing of legal documents significantly (Ashley, 2017).

With regard to further topic-related scientific literature, Moreno and Redondo (2016) provide an overview of selected text analytics concepts and techniques. In a further step, they present use cases and examples for the practical use of text analytics applications. One of these examples is the extraction of information from legal texts. In accordance with this research, Moreno and Redondo point out that new technological solutions that use big data and AI technologies can enhance processing of legal documents and regulatory requirements. One major difference of this research and the study by Moreno and Redondo is that their research analyses the usage of text analytics in different industries whereas this research is limited to the financial sector. Moreno and Redondo conclude that cognitive computing applications can expand the capabilities of human beings and help them to carry out their tasks more efficiently (Moreno and Redondo, 2016).

In conclusion, this research project as well as other topic-related studies show that applications that feature cognitive computing technologies like AI, data mining and machine learning are capable of enhancing the processing of legal documents at banks and other FIs. Consequently, the time, effort and associated cost with the implementation of new or extended regulatory requirements can be reduced by new technological solutions. For these reasons, it is recommended that the risk and compliance management departments as well as other areas deal with the usage of cognitive computing applications in the near future.

5.2 PROCESS MINING IN PRACTICE

The evaluation of the process data in this research showed that a compliance manager, auditor or other responsible person that uses a process mining application like Disco can monitor quickly and in an easy manner whether the analysed business processes are carried out efficiently and in accordance with the descriptions in the work instructions of the institution. Therefore, the use of process mining applications can increase the insights gathered from the real-life execution of business processes. However, this research also showed that data privacy and data security restrictions need to be considered when a process mining tool is implemented and used within an organization. The example presented in this research made clear that the user can possibly analyse each process execution in a detailed manner. This means that the person who carried out a process step and the precise date and time of execution can be tracked. This aspect can be useful and necessary when non-compliant activities are detected and investigated. However, it could also be used as an employee tracking tool that presents the performance and working speed of individual people. Therefore, it is essential to clearly define the purpose of the usage of the process mining tool in order to decide which data is imported at what level of detail.

One further aspect that needs to be considered is that process mining is still at an early stage of development and implementation. As a result, at that point in time, there were only few long-term studies and experiences with the use of this technology available. There might be negative aspects of the usage of process mining within an organization that have not been regarded yet. On the other side, an early implementation and usage of this technology might give institutions a competitive advantage against their competitors since they might be able to analyse and enhance their business processes in a more efficient manner than companies that do not use process mining or comparable technologies. According to van der Aalst (2018), the number of available process mining applications and the application domains have been growing in recent years. In the year 2018, there have been more than 20 process mining tools available that are mainly used for commercial purposes (van der Aalst, 2018). The increasing number of business-oriented applications shows the growing interest in process mining applications in several industries.

An analysis of the topic-related scientific literature also shows a wide range of fields of application for process mining procedures. For instance, Martinez-Milana et al. (2019) analyse the use of a process mining console in the operating rooms of a hospital in order to enhance the management of clinical interventions. An example from the commercial sector is provided by Dogan et al. (2019). Their research presents an analysis of customer paths in a shopping mall. The aim of their study is to investigate gender-specific customer behavior in malls. The research results show that the behaviors of male and female shopping mall visitors differ significantly. In terms of risk and compliance management, Werner (2017) describes how process mining applications can be used to support auditors to analyse process data. In his research, three extensive real-world data sets are used to evaluate the main advantages of using process mining to support financial audits. The results show that the generated process models are comparatively easy to evaluate and provide accurate information for auditing purposes (Werner, 2017).

With regard to the financial sector, Jans, Alles and Vasarhelyi (2014) demonstrate the usage of process mining procedures as an analytical auditing procedure at a large international bank. Their research shows that the usage of process mining enables auditors to identify financial transactions that are considered to be relevant for auditing. As practical examples for audit-relevant information, they name payments that were made without required approvals, various types of violations against segregation of duties regulations, and different types of violations of institution-specific internal guidelines. Moreover, Jans, Alles and Vasarhelyi compare the insights gathered from using process mining procedures with conventional auditing methods. This comparison shows that several audit-relevant anomalies that were detected by using a process mining tool were not discovered by the auditors of the bank by using conventional procedures. As a result, their research recommends the usage of process mining to complement existing internal auditing methods in order to increase the insights and the quality of the audits (Jans, Alles and Vasarhelyi, 2014). A further study that deals with the implementation of process mining at banks and other FIs is provided by Moreira et al. (2018). Their research presents the usage of process mining procedures with real-world loan applications. The purpose of their study is to create a decision model that includes the underlying processes that are relevant for the loan application service (Moreira et al., 2018).

As a result, the presented studies show that process mining applications have already been successfully implemented and used at several banks and other FIs for different purposes. One particular field of action in this research project as well as in the scientific literature is the usage of process mining procedures to enhance risk and compliance management related approaches and business processes.

5.3 LIMITATIONS

In this research, implementation strategies for cognitive computing technologies in the risk and regulatory compliance management departments of FIs were developed and evaluated. When the procedures and results of this research are regarded, some limitations must be taken into consideration.

As described in chapter 1.3, this research project is limited to the banking sector in Germany. This predefined limitation is required since regulations in the financial sector are partly country-specific. Therefore, FIs that are based in other countries than Germany are affected by other regulatory requirements. However, most descriptions of the newly-developed implementation strategies are general and can therefore also be taken as a foundation for the strategy development for FIs that operate in other countries.

Besides, this research is limited to the risk and compliance management departments of FIs. Therefore, this thesis does not provide a holistic overview of bank departments and procedures that could benefit from the implementation of cognitive computing technologies and applications. However, other departments in financial organizations might also benefit from the usage of cognitive computing technologies in the risk and compliance management environment. For instance, credit departments could benefit from more efficient credit risk management procedures and business processes. When the credit approval processes in the back office are optimized, the overall time to grant a credit could be reduced.

In chapter 4, two practical use cases for the development of an implementation strategy for cognitive computing technologies were presented. These use cases were implemented at a selected FI in Germany. Therefore, the corresponding strategy evaluations refer to this financial organization. These institution-specific research results cannot be taken as general results that are valid for all FIs in Germany. Since each FI has individual risk and compliance management procedures, an institution-specific evaluation is required. The descriptions in chapter 4 can rather be taken as an orientation for other banks and FIs how the risk and compliance management departments could benefit from the implementation of cognitive computing technologies.

Further aspects that need to be taken into consideration are data privacy and data security restrictions that might be relevant when new cognitive computing technologies are implemented and used. Each FI has institution-specific regulations regarding the processing of data. Therefore, it is an essential task to evaluate whether the data privacy and security regulations allow the processing of data in a cognitive computing featured application. With regard to this research, the application IBM WRC that is presented in chapter 4.1, is a cloud-based application. Some institutions might have restrictions regarding the usage of cloud environments in the risk and regulatory compliance management area. Furthermore, the process mining strategy that is presented in chapter 4.2 requires processing of sensitive data regarding the real-time execution of business process steps by individual employees. The data privacy restrictions of some institutions might not allow FIs to process these kinds of data in a process mining tool.

Moreover, a further condition for the usage of a process mining application is that the analysed business processes and the according data are digitalized and exportable. This aspect is especially relevant for banks and other FIs that have not digitalized their risk and compliance management business processes yet. For these institutions, the first step is to digitalize their risk and compliance management activities and the second step is to implement and use cognitive computing technologies to enhance the insights gathered from the digitalized processes.

Besides, some cognitive computing technologies like machine learning and AI are often regarded as a kind of black box for the end users of the applications. Depending on the individual tool, it might not be traceable how the algorithms of the application evaluated the analysed data. For this reason, technical experts might be required to check and validate the technical results that are created through cognitive computing technologies. Regarding the target group of this research, it might occur that the risk and compliance management departments of FIs would need to consult specialists that have both IT-driven skills and risk and compliance management skills.

In addition to the presented limitations, there might be further restrictions and barriers that need to be taken into consideration as they could be relevant for risk and compliance management experts as well as for researchers.

5.4 RECOMMENDATIONS FOR FURTHER RESEARCH

The descriptions and evaluations presented in this thesis can be taken as a foundation for further research on the subject matter or on other related topics. Based on the procedures and results of this research project, recommendations for further research are presented in this section.

Chapter 3.1 showed a systemic literature review that used AI-featured technologies to analyse a large number of scientific publications. This system-based research focused on cognitive computing technologies in the banking sector. For this purpose, more than 2,200 journal articles were evaluated through text mining and cluster analysis procedures. Further topic-related systemic literature reviews could be carried out in a larger scale to enhance the insights of the analysis. For instance, additional search commands could be used to increase the number of evaluated articles. Besides, other types of publications like conference proceedings or book chapters could be included in the corpus. In addition, different or extended research methodologies could be used to gain further insights from the evaluated literature. As presented by Gampfer et al. (2018), predictive analytics technologies could be used to predict the future development of certain topics.

In chapters 3.3 and 3.4, expert interviews and a survey regarding the future of risk and regulatory compliance management of FIs were presented. The main target group of both the interviews and the survey were executive risk and compliance management experts of financial organizations in Germany. As a result, six expert interviews were carried out and 62 survey forms were evaluated in this research project. Further related studies could focus on other target groups in order to gain further insights on the subject matter. For instance, topic-related surveys could include the expertise of risk and compliance managers from other countries. Therefore, international surveys could focus on larger geographic regions like Europe or Asia. Besides, the expert interview questions as well as the survey forms could be altered and extended to gain further insights on the subject matter. Expert interviews could, for instance, ask more specific and more detailed questions about the usage of new technological solutions in the risk and compliance management environment of FIs.

Another recommendation for further research is related to the case studies that are introduced in chapter 4. To analyse the benefits and potential disadvantages of the newly-developed strategies, they could be applied to other banks and FIs as well and the research results could be compared to the insights presented in this research. This approach could enhance the validity of the research results. Besides, further aspects that have not been discovered in this research could also be considered. Additionally, case studies for FIs that operate in other countries with other regulatory requirements could be developed and evaluated.

With reference to chapter 4.2, the implementation and usage of a process mining application in the risk and compliance management environment could be carried out in a larger scale in further research projects. Whereas this research focused on the evaluation of one specific business process, further projects could analyse more business processes with a process mining tool to discover further advantages or possible disadvantages of using new technologies. In addition, this research is limited to the process data in a time frame of one year. Other studies could evaluate larger data sets of process data. In chapter 4.2.1, the process mining application Disco was selected and used for the development and evaluation of the implementation strategy. Further research projects could use other process mining tools and compare the evaluation possibilities. Likewise, the same processes and data sets could be uploaded into different process mining applications and the insights could be compared in order to discover differences between the individual tools. Further research projects could also carry out a long-term study how the usage of process mining applications can enhance risk and compliance management procedures of FIs over a long period of time. For this purpose, changes that are made to business processes and activities due to the insights provided by process mining tools could be monitored in a specific time frame. In addition, further studies could make the daily usage of the process mining application by compliance management experts subject of discussion.

6 CONCLUSION

The aim of this research was to define, develop and evaluate strategies for the improvement of risk and regulatory compliance management activities and business processes of FIs by utilizing cognitive computing technologies like AI, machine learning and process mining. In order to reach this objective, three research questions were derived and investigated. The first question aimed to identify the major fields of action to improve the risk and regulatory compliance management of FIs (RQ 1). For this purpose, a systemic literature review, expert interviews as well as a survey were carried out. In a first step, the review of 2,279 journal articles that deal with cognitive computing in the banking and finance sector showed that risk and compliance management activities like auditing, bankruptcy prediction, credit risk measurement and fraud detection are main topics of interest. In further detail, the evaluation of six interviews and 62 survey forms displayed that a vast majority of the participating executive risk and compliance managers feels overburdened by the increasing number and complexity of regulations in the banking sector. As a result, most risk and compliance management experts were convinced that FIs would need to deal with new technologies like AI to be capable of managing regulatory requirements more efficiently in the future. These insights were taken as a foundation for the development of two implementation strategies.

The first strategy that was developed in this research aimed to answer the question how the management of regulatory requirements could be improved by cognitive computing technologies (RQ 2). The use case showed that the application IBM WRC can facilitate the management of new or extended regulations that are published by banking supervision authorities. In particular, the AI and machine learning capabilities of the application analyse the content of financial regulations and create a probability-weighted initial list of obligations that result from a legal document. Furthermore, based on the information that are stored in the system, IBM WRC identifies departments, business lines and controls that could be affected by the respective obligations. In a further step, the compliance manager analyses the initial technical results and makes adjustments. The evaluation of this use case showed that the processing of regulatory requirements can be facilitated through the use of cognitive computing technologies. The expert receives an initial list of obligations that result from a regulation without having to read a legal text line by line first. Therefore, time and cost associated with the management of regulations can be reduced significantly.

The second strategy focused on the enhancement of risk and compliance management business processes. For this purpose, the research investigated how this objective can be reached by using cognitive computing technologies (RQ 3). To answer this question, an implementation strategy for a process mining application was created and realized at a selected FI in Germany. In particular, the process mining tool Disco was used to analyse a specific business process in the risk management environment of FIs. The evaluation of this use case showed that a process mining featured application can help compliance managers to discover potential non-compliant activities in real time and to analyse the discovered deviations in a detailed manner. Therefore, this tool enabled the user to investigate how individual process steps were carried out. Besides, the exact time of execution and the responsible persons can be identified. Consequently, the compliance manager can react immediately when conspicuous activities are detected. Furthermore, inefficiencies and bottlenecks in the real-life execution of business processes can be discovered. These insights offer FIs the chance to optimize both their business processes and the associated workload of the individual process participants.

All in all, the results of the present research showed that investing in new technological solutions offers FIs the chance to enhance their risk and compliance management actions and business processes. Besides, it is recommended for FIs to deal with the implementation of cognitive computing technologies due to the increasing complexity and corresponding costs for risk and regulatory compliance management activities. Therefore, this research presented two practical use cases that can be regarded as a foundation for further research and the practical implementation of cognitive computing technologies in the risk and compliance management environment. To draw a conclusion, the last major step for FIs to improve their risk and compliance management activities and business processes was to digitalize them and the next major step is to implement intelligence through the utilization of cognitive computing technologies.

APPENDIX

Annex 1: English version of the survey form

Survey on the future of risk and regulatory compliance management at financial institutions in Germany

1. Name of your employer *(optional)*:

____

2. Which of the following categories best describes your employer?

- o Cooperative bank
- o Private bank
- o Public savings bank
- o Other financial institution *(please specify)*:
  ____

3. Which of the following job titles best describes your current occupation?

- o Compliance Officer
- o IT specialist
- o Risk Manager
- o Other *(please specify)*:
  ____

4. Which of the following best describes the management level of your above mentioned occupation?

- o Chief executive (top level management)
- o Executive (middle level management)
- o Group leader (first level management)
- o No management tasks

5. How long is your professional experience at the above mentioned occupation?

__________ years *(please round to the nearest whole number)*

6. How would you rate the current relevance of the following risk categories for the risk management of your institution?

Risk category	very low relevance	low relevance	middle relevance	high relevance	very high relevance
Credit Risk	○	○	○	○	○
Liquidity Risk	○	○	○	○	○
Market Risk	○	○	○	○	○
Operational Risk	○	○	○	○	○
Regulatory Risk	○	○	○	○	○
Reputational Risk	○	○	○	○	○

7. Please create a ranking of the current relevance of the above mentioned risk categories for the risk management of your institution on a scale from 1 to 6.
(1 represents the most relevant category and 6 represents the least relevant category)

Risk category	rank
Credit Risk	
Liquidity Risk	
Market Risk	
Operational Risk	
Regulatory Risk	
Reputational Risk	

8. In your opinion, how will the ranking of the above mentioned risk categories look like in 5 years from now? Please create a ranking of the estimated relevance of the risk categories for the risk management of your institution in 5 years from now on a scale from 1 to 6.
(1 represents the most relevant category and 6 represents the least relevant category)

Risk category	rank
Credit Risk	
Liquidity Risk	
Market Risk	
Operational Risk	
Regulatory Risk	
Reputational Risk	

9. How would you rate the current extent of regulatory requirements for your institution?

- o not extensive enough
- o appropriate
- o too extensive

10. How would you rate the degree of complexity of the current regulatory requirements for your institution?

- o too simple
- o appropriate
- o too complex

11. Since the world-wide financial an economic crisis of 2008, the number of regulatory requirements for financial institutions increases steadily. Do you think that your institution will need to implement new technological solutions in order to manage the increasing number of regulatory requirements in the next 5 years?

- o no
- o yes
- o not sure

12. How would you rate the relevance of the following new technologies for the risk and regulatory compliance management of your institution in the next 5 years?

Technology	very low relevance	low relevance	middle relevance	high relevance	very high relevance
Artificial Intelligence	○	○	○	○	○
Big Data	○	○	○	○	○
Blockchain	○	○	○	○	○
Cloud Computing	○	○	○	○	○
Cybersecurity	○	○	○	○	○
Machine Learning	○	○	○	○	○

13. Please create a ranking of the estimated relevance of the above mentioned new technologies for the risk and regulatory compliance management of your institution in the next 5 years on a scale from 1 to 6.
(1 represents the most relevant technology and 6 represents the least relevant technology)

Technology	rank
Artificial Intelligence	
Big Data	
Blockchain	
Cloud Computing	
Cybersecurity	
Machine Learning	

14. In your opinion, what is currently the main reason for investing in new technologies for financial institutions in Germany?

- o Competitive advantage
- o Compliance with regulatory requirements
- o Long term cost savings
- o Risk reduction
- o Other *(please specify)*:

____

15. When did the risk and regulatory compliance management department(s) of your institution officially start to deal with the field of Artificial Intelligence?

- o not started yet
- o 0 - 1 year(s) ago
- o 1 - 2 year(s) ago
- o 2 - 3 years ago
- o 3 - 4 years ago
- o more than 4 years ago

16. When do you think Artificial Intelligence solutions will be implemented and used to improve the risk and regulatory compliance management processes of your institution?

- o already in use
- o in the next 0 - 2 years
- o in the next 2 - 5 years
- o in the next 5 - 10 years
- o later than in the next 10 years
- o never

17. In your opinion, how will your institution mainly develop Artificial Intelligence solutions for the risk and regulatory compliance management in the future?

- o with existing internal capabilities
- o with future internal capabilities (e.g. hiring of artificial intelligence experts)
- o with external experts (e.g. technical consultants, artificial intelligence experts)
- o through partnerships with other institutions
- o Other *(please specify)*:

____

BIBLIOGRAPHY

Achim, S.A. (2015) 'Recent Trends in the Study of Mergers and Acquisitions', *E & M Ekonomie a Management*, 18(1), pp. 123-133.

Adobe Reader (2017) Adobe Acrobat Reader DC [Online]. Available at: https://get.adobe.com/de/reader/ (Accessed: 01 December 2017).

Adrian, T. (2017) 'Risk management and regulation', *Journal of Risk*, 20(1), pp. 23-57.

Afflerbach, P., Hohendorf, M. and Manderscheid, J. (2017) 'Design it like Darwin - A value-based application of evolutionary algorithms for proper and unambiguous business process redesign', *Information Systems Frontiers*, 19(5), pp. 1101-1121.

Agarwal, A., Ganesan, B., Gupta, A., Jain, N., Karanam, H.P., Kumar, A., Madaan, N., Munigala, V. and Tamilselvam, S.G. (2017) 'Cognitive Compliance for Financial Regulations', *IT Professional*, 19(4), pp. 28-35.

Aich, A., Sen, A. and Dash, S.R. (2015) 'A Survey on Cloud Environment Security Risk and Remedy', *International Conference on Computational Intelligence and Networks 2015*, Bhubaneshwar.

Aktan, B. and Ince, H. (2009) 'A comparison of data mining techniques for credit scoring in banking: A managerial perspective', *Journal of Business Economics and Management*, 10(3), pp. 233-240.

Allen, F., Goldstein, I. and Jagtiani, J. (2018) 'The Interplay among Financial Regulations, Resilience, and Growth', *Journal of Financial Services Research*, 53(2-3), pp. 141-162.

Alparslan, A. and Kannemacher, M. (2015) 'Datenmanagement und Datentransparenz' in Heithecker, D. and Dschuschke, D. (eds.) *Bearbeitungs- und Prüfungsleitfaden Management von Modellrisiken*. Heidelberg: Finanz Colloquium.

American Economic Association (2018) JEL Classification System [Online]. Available at: https://www.aeaweb.org/econlit/jelCodes.php (Accessed: 10 February 2018)

Ames, M., Schuermann, T. and Scott, H.S. (2015) 'Bank capital for operational risk: A tale of fragility and instability', *Journal of Risk Management in Financial Institutions*, 8(3), pp. 227-243.

Arner, D.W., Barberis, J.N. and Buckley, R.P. (2017) 'FinTech, RegTech and the Reconceptualization of Financial Regulation', *Northwestern Journal of International Law & Business*, 37(3), pp. 371-413.

Ashby, S., Buck, T., North-Zahn, S. and Peisl, T. (2018) 'Emerging IT Risks: Insights form German Banking', *Geneva Papers on Risk and Insurance-Issues and Practice*, 43(2), pp. 180-207.

Ashley, K.D. (2017) *Artificial Intelligence and legal analytics: new tools for law practice in the digital age.* Cambridge University Press.

Association for Computer Machinery (2017) About the ACM Organization [Online]. Available at: https://www.acm.org/about-acm/about-the-acm-organization (Accessed: 01 November 2017).

Atteslander, P. (2010) *Methoden der empirischen Sozialforschung*. 13th edn., Berlin: Erich Schmidt Verlag.

Augustine, S. (2005) *Managing agile projects*. Upper Saddle River: Prentice Hall.

Azzollini, M. and Pacelli, V. (2011) 'An artificial neural network approach for credit risk management', *Journal of Intelligent Learning Systems and Applications*, 3, pp. 103-112.

BaFin Federal Financial Supervisory Authority (2011) Minimum requirements for risk management [Online]. Available at: https://www.bundesbank.de/Redaktion/EN/Downloads/Tasks/Banking_supervision/PDF/minimum_requirements_for_risk_management_mindestanforderungen_an_das_risikomanagement_marisk.pdf?__blob=publicationFile (Accessed: 01 September 2017).

BaFin Federal Financial Supervisory Authority (2014) BaFin publishes English translation of MaRisk [Online]. Available at: https://www.bafin.de/SharedDocs/Veroeffentlichungen/EN/Meldung/2

014/meldung_140815_marisk_uebersetzung_en.html (Accessed: 03 September 2017).

BaFin Federal Financial Supervisory Authority (2017) Rundschreiben 09/2017 (BA) - Mindestanforderungen an das Risikomanagement -MaRisk [Online]. Available at: https://www.bafin.de/SharedDocs/Veroeffentlichungen/DE/Rundschreiben/2017/rs_1709_marisk_ba.html (Accessed: 23 December 2017).

BaFin Federal Financial Supervisory Authority (2018) Marktabfrage zu MiFID II, MiFIR und Art. 4 MAR [Online]. Available at: https://www.bafin.de/DE/Internationales/MiFID/mifid_mifir_node.html (Accessed: 22 August 2018).

Bahrammirzaee, A. (2010) 'A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems', *Neural Computing and Applications*, 19(8), pp. 1165-1195.

Bankenfachverband e.V. (2017) The experts in financing [Online]. Available at: https://www.bfach.de/bankenfachverband.php/cat/44/aid/1723/title/The_Experts_in_Financing (Accessed: 15 October 2017).

Bank for International Settlements (1999) Principles for the Management of Credit Risk [Online]. Available at: https://www.bis.org/publ/bcbs54.htm (Accessed: 30 October 2017).

Bank for International Settlements (2017) Basel III: international regulatory framework for banks [Online]. Available at: http://www.bis.org/bcbs/basel3.htm?m=3%7C14%7C572 (Accessed: 29 September 2017).

Barakat, A. and Hussainey, K. (2013) 'Bank governance, regulation, supervision, and reporting: Evidence from operational risk disclosures in European banks', *International Review of Financial Analysis*, 30, pp. 254-273.

Basel Committee on Banking Supervision (2001) Operational Risk [Online]. Available at: https://www.bis.org/publ/bcbsca07.pdf (Accesssed: 01 November 2017).

Basel Committee on Banking Supervision (2009) Principles for sound stress testing practices and supervision [Online]. Available at: https://www.bis.org/publ/bcbs155.pdf (Accessed: 05 November 2017).

Basel Committee on Banking Supervision (2013a) Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools [Online]. Available at: https://www.bis.org/publ/bcbs238.pdf (Accessed: 05 November 2017).

Basel Committee on Banking Supervision (2013b) Monitoring tools for intraday liquidity management [Online]. Available at: https://www.bis.org/publ/bcbs248.pdf (Accessed: 05 November 2017).

Basel Committee on Banking Supervision (2013c) Principles for effective risk data aggregation and risk reporting [Online]. Available at: http://www.bis.org/publ/bcbs239.pdf (Accessed: 09 October 2017).

Basel Committee on Banking Supervision (2014) Basel III: the net stable funding ratio [Online]. Available at: https://www.bis.org/bcbs/publ/d295.pdf (Accessed: 05 November 2017).

Baxter, L.G. (2016) 'Adaptive Financial Regulation and RegTech: A concept article on realistic protection for victims of bank failures', *Duke Law Journal*, 66(3), pp. 567-604.

Becker, J., Breuker, D., Weiss, B. and Winkelmann, A. (2010) 'Exploring the status quo of business process modelling languages in the banking sector - An empirical insight into the usage of methods in banks', *Proceedings of the Twenty-first Australasian Conference on Information Systems*, Brisbane.

Becker, J., Delfmann, P., Dietrich, H.A., Steinhorst, M. and Eggert, M. (2016) 'Business process compliance checking - applying and evaluating a generic pattern matching approach for conceptual models in the financial sector', *Information Systems Frontiers*, 18(2), pp. 359-405.

Becker, J. and Kahn, D. (2003) 'The Process in Focus' in Becker, J., Kugler, M. and Rosemann, M. (eds.), *Process Management: A guide for the design of business processes*. Berlin: Springer.

Becker, M. and Buchkremer, R. (2018a) 'Implementierung einer Regulatory Technology Lösung bei Finanzinstituten unter Berücksichtigung agiler Vorgehensmodelle' in Mikusz, M., Volland, A., Engstler, M., Fazal-Baqaie, M., Hanser, E. and Linssen, O. (eds.) *Projektmanagement und Vorgehensmodelle 2018 – Der Einfluss der Digitalisierung auf Projektmanagementmethoden und Entwicklungsprozesse.* Bonn: Gesellschaft für Informatik, pp. 125-134.

Becker, M. and Buchkremer, R. (2018b) 'Ranking of current information technologies by risk and regulatory compliance officers at financial institutions - a German perspective', *The Review of Finance and Banking*, 10(1), pp. 7-26.

Becker, M. and Buchkremer, R. (2019) 'A practical process mining approach for compliance management', *Journal of Financial Regulation and Compliance*, ahead-of-print [online]. Available at: https://doi.org/10.1108/JFRC-12-2018-0163 (Accessed: 21 July 2019).

Beiersdorfer, S. and Buchholz, J.P. (2014) 'Weiterentwicklung und Prozessqualität' in Helfer, M. and Schnüttgen, M. (eds.) *Prozessmanagement in Regionalbanken*. Heidelberg: Finanz Colloquium.

Bergener, P., Delfmann, P., Weiss, B. and Winkelmann, A. (2015) 'Detecting potential weaknesses in business processes. An exploration of semantic pattern matching in process models', *Business Process Management Journal*, 21(1), pp. 25-54.

Bergeron, B. (2004) *Essentials of XBRL: Financial reporting in the 21st century*, 30th edn. New York: John Wiley & Sons.

Bethlehem, J. (2010) 'Selection Bias in Web Surveys', *International Statistical Review*, 78(2), pp. 161-188.

Board of Governors of the Federal Reserve System (2018) Comprehensive Capital Analysis and Review 2018: Assessment Framework and Results - June 2018 [Online]. Available at: https://www.federalreserve.gov/publications/files/2018-ccar-assessment-framework-results-20180628.pdf (Accessed: 29 June 2018).

Boehm, B. and Turner, R. (2004) *Balancing agility and discipline: A guide for the perplexed.* Boston: Addison-Wesley.

Boella, G., Janssen, M., Hulstijn, J., Humphreys, L. and van der Torre, L. (2013) 'Managing legal interpretation in regulatory compliance', *Proceedings of the Fourteenth International Conference on Artificial Intelligence and Law*, June 2013, pp. 23-32.

Bongaerts, D. and Charlier, E. (2009) 'Private equity and regulatory capital', *Journal of Banking and Finance*, 33(7), pp. 1211-1220.

Bretz, J. (2015) 'Anforderungen der Aufsicht' in Andelfinger, U., Bretz, J. and Busse, A. (eds.) *IT im Fokus der Bankenaufsicht*. 2nd Edition. Heidelberg: Finanz Colloquium.

Buchkremer, R. (2016) 'Text mining im marketing- und sales Umfeld', *Business Intelligence Erfolgreich Umsetzen*, Symposion, pp. 101-119.

Cambridge University Press (2017) Business dictionary [Online]. Available at: https://dictionary.cambridge.org/dictionary/english/ (Accessed: 01 December 2017).

Cao, J. (2012) *Banking Regulation and the Financial Crisis*, New York: Routledge.

CB Insights (2017) The Global Fintech Report: Q3'17 [Online]. Available at: https://www.cbinsights.com/research/report/fintech-trends-q3-2017/ (Accessed: 12 December 2017).

CB Insights (2018) Regtech Europe: 60+ Startups Helping Financial Services Companies Navigate Regulations [Online]. Available at: https://app.cbinsights.com/research/regtech-europe-market-map/ (Accessed 28 June 2018).

Celonis SE (2018a) Process Mining Technologie [Online]. Available at: https://www.celonis.com/de/intelligent-business-cloud/process-mining-technology/ (Accessed: 21 October 2018).

Celonis SE (2018b) Über Celonis [Online]. Available at: https://www.celonis.com/de/company/ (Accessed 21 October 2018).

Chen, S.H., Olsen, D.L. and Wu, D.D., (2014) 'Business Intelligence in risk management: Some recent progresses', *Information Science*, 256, pp. 1-7.

Claaßen, M. and Matzen, H. (2015) 'Anwendungsmanagement' in Andelfinger, U., Bretz, J. and Busse, A. (eds.) *IT im Fokus der Bankenaufsicht*. 2nd Edition. Heidelberg: Finanz Colloquium.

Clarivate (2017) Web of Science [Online]. Available at: https://clarivate.com/products/web-of-science/ (Accessed: 11 November 2017).

Cognitive Technology (2018) MyInvenio Process Analyst [Online]. Available at: https://www.my-invenio.com/myinvenio-process-analyst/ (Accessed: 21 October 2018).

Cohn, M. (2005) *Agile estimating and planning*. New York: Prentice Hall.

Cohn, J. (2016) 'Risks of regulation', *Journal of Risk Management in Financial Institutions*, 9(2), pp. 108-114.

Cornett, M.M., McNutt, J.J., Strahan, P.E. and Tehranian, H. (2011) 'Liquidity risk management and credit supply in the financial crisis', *Journal of Financial Economics*, 101(2), pp. 297-312.

Cuny, D. (2018) 'Deutsche Bank échoue aux stress tests de la Fed', *La Tribune* [Online]. Available at: https://www.latribune.fr/entreprises-finance/banques-finance/deutsche-bank-echoue-aux-stress-tests-de-la-fed-783505.html (Accessed: 29 June 2018).

Davenport, T.H. (1993) *Process innovation: Reengineering Work through Information Technology*. Boston: Harvard Business Press.

Davenport, T.H. (2006) 'Competing on Analytics', *Harvard Business Review*, 84(1), pp. 98-107.

Davies, D.L. and Bouldin, D.W. (1979) 'A cluster separation measure', *IEEE Trans. Pattern Anal. Mach. Intell. PAMI-1*, pp. 224-227.

Deloitte (2017) AI and you: Perceptions of Artificial Intelligence from the EMEA financial services industry [Online]. Available at: https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/technology/deloitte-cn-tech-ai-and-you-en-170801.pdf (Accessed: 15 December 2017).

Demyanyk, Y. and Hasan, I. (2010) 'Financial crisis and bank failures: A review of prediction methods', *Omega*, 38(5), pp. 315-324.

Deutsche Bank (2017) Geschäftsstellenbericht 2016 [Online]. Available at: https://geschaeftsbericht.deutsche-bank.de/2016/gb/abschluss/konzernbilanz.html (Accessed: 10 January 2018).

Deutsche Bank (2018) Deutschlands größte Bank für Privat- und Firmenkunden startet [Online]. Available at: https://www.db.com/newsroom_news/18_05_25_MI_Bank_fuer_Privat_und_Firmenkunden.pdf (Accessed: 11 June 2019).

Deutsche Bundesbank (2017a) Banking Supervision [Online]. Available at: https://www.bundesbank.de/en/tasks/banking-supervision/banking-supervision-622544 (Accessed: 02 September 2017).

Deutsche Bundesbank (2017b) Banking Supervision form centre [Online]. Available at: https://www.bundesbank.de/Navigation/EN/Service/Reporting_systems/Banking_supervision_form_centre/banking_supervision_form_centre.html (Accessed: 04 September 2017).

Deutsche Bundesbank (2017c) Bankstellenbericht 2016: Entwicklung des Bankstellennetzes im Jahr 2016 [Online]. Available at: https://www.bundesbank.de/Redaktion/DE/Downloads/Aufgaben/Bankenaufsicht/Bankstellenstatistik/bankstellenbericht_2016.html (Accessed: 28 October 2017).

Deutsche Bundesbank (2017d) Basel III [Online]. Available at: https://www.bundesbank.de/Navigation/EN/Tasks/Banking_supervision/Rechtsgrundlagen/Basel/basel.html (Accessed: 29 September 2017).

Deutsche Bundesbank (2018) Das Banken- und Finanzsystem [Online]. Available at: https://www.bundesbank.de/Redaktion/DE/Dossier/Service/schule_und_bildung_kapitel_4.html?notFirst=true&docId=147552#doc147552bodyText1 (Accessed: 10 January 2018).

de Vreede, G.J., Verbraeck, A. and van Eijck, D.T.T. (2003) 'Integrating the conceptualization and simulation of business processes: A modeling method and arena template', *Simulation-Transactions of the Society for Modeling and Simulation International*, 79(1), pp. 43-55.

Dogan, O., Bayo-Monton, J.L., Fernandez-Llates, C. and Oztaysi, B. (2019) 'Analyzing of Gender Behaviors from Paths Using Process Mining: A Shopping Mall Application', *Sensors*, 19(3), 557.

Dolpp, A. (2017) 'Grundlagen des Prozessmanagements und Bedeutung für die Interne Revision' in Becker, A. (ed.) *Systemprüfungen in Kreditinstituten: Neue Prüfungsansätze für die Bankpraxis*. Berlin: Erich Schmidt Verlag.

Dreyfus, H.L. (1965) Alchemy and Artificial Intelligence [Online]. Available at: http://courses.csail.mit.edu/6.803/pdf/dreyfus.pdf (Accessed: 09 January 2017).

Dumas, M., La Rosa, M., Mendling, J. and Reijers, H.A. (2013) *Fundamentals of Business Process Management*. Heidelberg: Springer.

Duncan, J. (2010) 'The multi-demand (MD) system of the primate brain: mental programs in intelligent behaviour', *Trends in Cognitive Sciences*, 14(4), pp. 172-179.

Egan, M. (2018) 'Deutsche bank flunks Fed stress test; 3 other banks get flagged', *CNN Money* [Online]. Available at: http://money.cnn.com/2018/06/28/investing/deutsche-bank-fed-stress-test/index.html (Accessed: 29 June 2018).

Eggert, M. (2014) *Compliance Management in Financial Industries – A Model-based Business Process and Reporting Perspective*. Heidelberg: Springer.

Eisenhardt, K. and Tabrizi, B.N. (1995) 'Accelerating adaptive processes: Product innovation in the global computer industry', *Administrative Science Quarterly*, 40(1), pp. 84-110.

el Ata, N.A. and Schmandt, R. (2016) *The Tyranny of Uncertainty – A New Framework to Predict, Remediate and Monitor Risk*. Berlin: Springer.

Elsevier (2017) ScienceDirect [Online]. Available at: https://www.elsevier.com/solutions/sciencedirect (Accessed: 01 November 2017).

Emerald Publishing (2018) About Emerald [Online]. Available at: http://www.emeraldgrouppublishing.com/about/index.htm (Accessed: 15 February 2018).

enuvo GmbH (2017) About us [Online]. Available at: https://www.enuvo.ch (Accessed: 14 October 2017).

Erskine, J.R., Peterson, B.E., Mullins, B.E. and Grimaila, M.R. (2010) 'Developing cyberspace data understanding', *Proc. Sixth. Annu. Work. Cyber Secur. Inf. Intell. Res. – CSIIRW'10*, ACM Press, New York, USA.

Ernst & Young (2016) European Banking Barometer - 2016: Seeking stability in an uncertain world [Online]. Available at: http://www.ey.com/Publication/vwLUAssets/ey-european-banking-barometer-2016/$FILE/ey-european-banking-barometer-2016.pdf (Accessed 02 October 2017).

Ernst & Young (2017) Restore, rationalize and reinvent: A fundamental shift in the way banks manage risk [Online]. Available at: http://www.ey.com/Publication/vwLUAssets/ey-eighth-annual-global-eyiif-bank-risk-management-survey/$FILE/ey-eighth-annual-global-eyiif-bank-risk-management-survey.pdf (Accessed: 15 October 2017).

Ertel, W. (2011) *Introduction to Artificial Intelligence*. London: Springer.

European Banking Authority (2017) Market risk [Online]. Available at: https://www.eba.europa.eu/regulation-and-policy/market-risk (Accessed: 30 October 2017).

European Banking Authority (2018) Guidelines on stress testing and supervisory stress testing [Online]. Available at: https://www.eba.europa.eu/regulation-and-policy/supervisory-review-and-evaluation-srep-and-pillar-2/guidelines-on-stress-testing2 (Accessed: 29 June 2018).

European Central Bank (2018) List of supervised banks [Online]. Available at: https://www.bankingsupervision.europa.eu/banking/list/who/html/index.en.html (Accessed: 10 January 2018).

Fayyad, U.M. (1996) 'Data Mining and Knowledge Discovery: Making Sense Out of Data', *IEEE Expert: Intelligent Systems and Their Applications*, 11(5), pp. 20-25.

Fethi, M.D. and Pasiouras, F. (2010) 'Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey', *European Journal of Operational Research*, 204(2), pp. 189-198.

Finlay, S. (2017) *Artificial Intelligence and Machine Learning for Business: A no-nonsense guide to data driven technologies*. Great Britain: Relativistic.

Fluxicon (2018a) Disco [Online]. Available at: http://fluxicon.com/disco/ (Accessed: 21 October 2018).

Fluxicon (2018b) Technology [Online]. Available at: http://fluxicon.com/technology/ (Accessed: 21 October 2018).

French, R.M. (2000) 'The Turing test: the first 50 years', *Trends in Cognitive Sciences*, 4(3), pp. 115-122.

Future of Life Institute (2017) An Open Letter: Research priorities for robust and beneficial artificial intelligence [Online]. Available at: https://futureoflife.org/ai-open-letter (Accessed: 28 September 2017).

Gabor, D. and Brooks, S.H. (2017) 'The digital revolution in financial inclusion: international development in the fintech era', *New Political Economy*, 22(4), pp. 423-436.

Gampfer, F., Jürgens, A., Müller, M. and Buchkremer, R. (2018) 'Past, current and future trends in enterprise architecture – A view beyond the horizon', *Computers in Industry*, 100, pp. 70-84.

Gartner (2017) Top trends in the Gartner Hype Cycle for Emerging Technologies 2017 [Online]. Available at: https://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/ (Accessed: 14 June 2018).

Gerber, F. (2015) 'Strategie, Governance und Berichtswesen' in Andelfinger, U., Bretz, J. and Busse, A. (eds.) *IT im Fokus der Bankenaufsicht*. 2nd Edition. Heidelberg: Finanz Colloquium.

Gersten, W., Wirth, R. and Arndt, D. (2000) 'Predictive modeling in automotive direct marketing', *Proc. Sixth ACM SIGKDD Int Conf. Knowl. Discov. Data Min. – KDD'00*, ACM Press, New York, USA.

Ginsberg, M. (1993) *Essentials of Artificial Intelligence*. San Francisco: Morgan Kaufmann Publishers.

Giroux, G. (2008) 'What Went Wrong? Accounting Fraud and Lessons from the Recent Scandals', *Social Research*, 75(4), pp. 1205-1238.

Global Regulation (2018) Alerts dashboard [Online]. Available at: https://www.global-regulation.com/alerts.php (Accessed: 30 June 2018).

Goltz, N. and Mayo, M. (2017) 'Enhancing Regulatory Compliance by Using Artificial Intelligence Text Mining to Identify Penalty Clauses in Legislation', *MIREL 2017 - Workshop on 'Mining and Reasoning with Legal texts'*, June 2017, London.

Göpfert, J. and Lindenbach, H. (2013) *Geschäftsprozessmodellierung mit BPMN 2.0: Business Process Model and Notation*. Munich: Oldenburg Verlag.

Greve, R. (2009) 'The German Cooperative Banking Group as a Strategic Network', *Canadian Journal of Development Studies*, 29(1-2), pp. 65-100.

Griffiths, M. (2006) Planning is too important for the beginning of a project [Online]. Available at: http://leadinganswers.typepad.com/leading_answers/2006/09/planning_is_too.html (Accessed: 30 June 2018).

Grossmann, W. and Rinderle-Ma, S. (2015*) Fundamentals of Business Intelligence*. Heidelberg: Springer.

Groth, S.S. and Muntermann, J. (2011) 'An intraday market risk management approach based on textual analysis', *Decision Support System*, 50(4), pp. 680-691.

Hallerberg, M. and Markgraf, J. (2018) 'The Corporate Governance of Public Banks before and after the Global Financial Crisis', *Global Polic*y, 9, pp. 43-53.

Hallevy, G. (2015) *Liability for Crimes Involving Artificial Intelligence Systems*. New York: Springer.

Han, J., Kamber, M. and Pei, J. (2012) *Data Mining: Concepts and Techniques*. Waltham MA: Morgan Kaufmann Publishers.

Hansen, H.R. and Neumann, G. (2005) *Wirtschaftsinformatik 1 - Grundlagen und Anwendungen*. 9th Edition. Stuttgart: UTB.

Hanson, S.G., Kashyap, A.K. and Stein, J.C. (2011) 'A Macroprudential Approach for Financial Regulations', *Journal of Economic Perspe*ctives, 25(1), pp. 3-28.

Hassel, T. and Leyer, M. (2012) 'Transparente Kreditprozesse im Backoffice', *Bankinformation*, 2, pp. 58-59.

Haun, M. (2014) *Cognitive Computing: Steigerung des systemischen Intelligenzprofils*. Berlin: Springer.

Hauschka, C.E. (ed.) (2007) *Corporate Compliance: Handbuch der Haftungsvermeidung im Unternehmen*. Munich: Beck.

Hawley, D.D., Johnson, J.D. and Raina, D. (1990) 'Artificial Neural Systems: A New Tool for Financial Decision-Making', *Financial Analysts Journal*, 46(6), pp. 63-72.

Hern, A. (2016) 'Stephen Hawking: AI will be 'either best or worst thing' for humanity', *The Guardian* [Online]. Available at: https://www.theguardian.com/science/2016/oct/19/stephen-hawking-ai-best-or-worst-thing-for-humanity-cambridge (Accessed: 14 September 2017).

Herring, R.J. (2018) 'The Evolving Complexity of Capital Regulation', *Journal of Financial Services Research*, 53(2-3), pp. 183-205.

Highsmith, J. (2004) *Agile project management: Creating innovative products*. Boston: Addison-Wesley.

Hodge, F.D., Kennedy, J.J. and Maines, L.A. (2004) 'Does search-facilitating technology improve the transparency of financial reporting?', *Accounting Review*, 79(3), pp. 687-703.

Hull, J. (2010) *Risk Management and Financial Institutions*. 2nd Edition. New Jersey: John Wiley & Sons.

Hull, J. (2015) *Risk Management and Financial Instit*utions. 4th Edition. New Jersey: John Wiley & Sons.

Human Brain Project (2018) Human Brain Project [Online]. Available at: https://www.humanbrainproject.eu/en/ (Accessed: 09 February 2018).

Hurwitz, J.S., Kaufman, M. and Bowles, A. (2015) *Cognitive Computing and Big Data Analytics*. Indianapolis: John Wiley & Sons.

IBM (2016) IBM Watson Regulatory Compliance [Online]. Available at: https://www.ibm.com/marketplace/cloud/regulatory-compliance-management/us/en-us (Accessed: 03 November 2016).

IBM (2017a) HypoVereinsbank, Member of UniCredit [Online]. Available at: https://www.ibm.com/case-studies/hypovereinsbank (Accessed: 22 August 2018).

IBM (2017b) *Transform Regulatory Compliance with Watson* [Online video]. 08 September 2017. Available at: https://www.youtube.com/watch?v=qyipbXNj3jw (Accessed: 30 June 2018).

IBM (2017c) What Is Blockchain [Online]. Available at: https://www.ibm.com/blockchain/what-is-blockchain.html (Accessed: 30 October 2017).

IBM (2018a) IBM OpenPages Financial Controls Management [Online]. Available at: https://www.ibm.com/us-en/marketplace/openpages-financial-controls-mgmt (Accessed: 22 August 2018).

IBM (2018b) IBM OpenPages GRC Platform [Online]. Available at: https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?htmlfid=YTD03107USEN& (Accessed: 30 June 2018).

IBM (2018c) IBM OpenPages Internal Audit Management [Online]. Available at: https://www.ibm.com/us-en/marketplace/openpages-internal-audit-management (Accessed: 23 August 2018).

IBM (2018d) IBM Watson Regulatory Compliance [Online]. Available at: https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?htmlfid=ASS12364USEN& (Accessed: 30 June 2018).

IBM Institute for Business Value analysis (2016) *The CFO mission to uncover the unknown – Applying analytics and cognitive computing for efficiency and insight*, New York: IBM.

Institute of Electrical and Electronics Engineers (2017) About IEEE Xplore [Online]. Available at: http://ieeexplore.ieee.org/Xplorehelp/#/overview-of-ieee-xplore/about-ieee-xplore (Accessed: 15 February 2018)

Institute of International Finance (2015) Regtech: Exploring Solutions for Regulatory Challenges [Online]. Available at: https://www.iif.com/topics/regtech/regtech-exploring-solutions-regulatory-challenges (Accessed: 09 October 2017).

Institute of International Finance (2016a) Digitizing Intelligence: AI, robots and the future of finance [Online]. Available at: https://www.iif.com/publication/research-note/digitizing-intelligence-ai-robots-and-future-finance (Accessed: 05 October 2017).

Institute of International Finance (2016b) IIF/EY Release Seventh Annual Global Bank Risk Management Survey [Online]. Available at: https://www.iif.com/press/iifey-release-seventh-annual-global-bank-risk-management-survey (Accessed: 13 November 2016).

Institute of International Finance (2016c) Regtech in Financial Services: Technology solutions for Compliance and Reporting [Online]. Available at: https://www.iif.com/publication/research-note/regtech-financial-services-solutions-compliance-and-reporting (Accessed: 09 October 2017).

Institute of International Finance (2017) About the IIF [Online]. Available at: https://www.iif.com/about (Accessed: 06 October 2017).

Jain, A.K., Murty, M.N. and Flynn, P.J. (1999) Data clustering: a review, *ACM Comput. Surv. 31*, pp. 264-323.

Jans, M., Alles, M.G. and Vasarhelyi, M.A. (2014) 'A Field Study on the Use of Process Mining of Event Logs as an Analytical Procedure in Auditing', *Accounting Review*, 89(5), pp. 1751-1773.

Jobst, A.A. (2007) 'The treatment of operational risk under the New Basel framework: Critical issues', *Journal of Banking Regulation*, 8(4), pp. 316-352.

Johnson, K.N. (2015) 'Cyber Risks: Emerging Risk Management Concerns for Financial Institutions', *Georgia Law Review*, 50(1).

Kaastra, I. and Boyd, M. (1996) 'Designing a neural network for forecasting financial and economic time series', *Neurocomputing*, 10(3), pp. 215-236.

Kavassalis, P., Stieber, H., Breymann, W., Saxton, K. and Gross, F.J. (2017) 'An innovative RegTech approach to financial risk monitoring and supervisory reporting', *The Journal of Risk Finance*, 19(1), pp. 39-55.

Khandani, A.E., Kim, A.J. and Lo, A.W. (2010) 'Consumer credit-risk models via machine-learning algorithms', *Journal of Banking and Finance*, 34, pp. 2767-2787.

Krug, S., Lengnick, M. and Wohltmann, H.W. (2015) 'The impact of Basel III on financial (in)stability: an agent-based credit network approach', *Quantitative Finance*, 15(12), pp. 1917-1932.

Kulkarni, G., Chavan, N., Chandorkar, R., Waghmare, R. and Palwe, R. (2012) 'Cloud security challenges', *7th International Conference on Telecommunication Systems, Services and Applications 2012*, Bali.

Kurzweil, R. (1990) *The Age of Intelligent Machines*. Cambridge, Massachusetts.

Kuster, J., Huber, E., Lippmann, R., Schmid, A., Schneider, E., Witschi, U. and Wüst, R. (2011) *Handbuch Projektmanagement*. 3rd edn. Heidelberg: Springer Verlag.

Lackhoff, K. (2017) *Single Supervisory Mechanism.* Munich: Beck.

Lall, R. (2012) 'From failure to failure: The politics of international banking regulation', *Review of International Political Economy*, 19(4), pp. 609-638.

Lana Labs GmbH (2018a) Lana Process Mining [Online]. Available at: https://lana-labs.com/lana-process-mining/ (Accessed: 21 October 2018).

Lana Labs GmbH (2018b) Unternehmen [Online]. Available at: https://lana-labs.com/unternehmen/ (Accessed: 21 October 2018).

Langenohl, A. (2008) 'How to change other people's institutions: discursive entrepreneurship and the boundary objective of competition/competitiveness in the German banking sector', *Economy and Society*, 37(1), pp. 68-93.

Lastra, R.M. and Wood, G. (2010) 'The Crisis of 2007-09: Nature, Causes, and Reactions', *Journal of International Economic Law*, 13(3), pp. 531-550.

Laursen, G. and Thorlund, J. (2017) *Business analytics for managers: taking business intelligence beyond reporting*. New York: John Wiley & Sons.

LeBaron, B., Arthur, W.B. and Palmer, R. (1999) 'Time Series properties of an artificial stock market', *Journal of Economic Dynamics & Control*, 23, pp. 1487-1516.

Lemieux, V. (2012) *Financial Analysis and Risk Management – Date Governance, Analytics and Life Cycle Management*. New York: Springer.

Li, D. and Du, Y. (2007) *Artificial Intelligence with uncertainty*. New York: CRC press.

Lin, S.J. and Hsu, M.F. (2014) 'Enhanced risk management by an emerging multi-agent architecture', *Connection Science*, 26(3), pp. 245-259.

Ly, L.T., Maggi, F.M., Montali, M., Rinderle-Ma, S. and van der Aalst, W.M.P. (2015) 'Compliance monitoring in business processes: Functionalities, application, and tool-support', *Information Systems*, 54, pp. 209-234.

Markoff, J. (2011) 'Computer Wins on 'Jeopardy!': Trivial, It's Not', *The New York Times* [Online]. Available at: http://www.nytimes.com/2011/02/17/science/17jeopardy-watson.html?pagewanted=all (Accessed: 06 November 2016).

Marr, B. (2016) 'What Is The Difference Between Artificial Intelligence And Machine Learning', *Forbes* [Online]. Available at: https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial-intelligence-and-machine-learning/3/#1b2a4c3d2bfc (Accessed: 15 November 2017).

Martinez-Milana, A., Lizondo, A., Gatta, R., Vera, S., Salcedo, V.T. and Fernandez-Llatas, C. (2019) 'Process Mining Dashboard in Operating Rooms: Analysis of Staff Expectations with Analytic Hierarch Process', *International Journal of Environmental Research and Public Health*, 16(2), 199.

Matejasak, M., Teply, P. and Cernohorsky, J. (2009) 'The impact of regulation of banks in the US and the EU-15 countries', *E & M Ekonomie A Management*, 12(3), pp. 58-68.

Maynatz, R.K., Holm, K. and Hübner, R. (1999) *Einführung in die Methoden der empirischen Soziologie*. 5th Edition. Opladen.

McCarthy, J., Minsky, M., Rochester, N. and Shannon, C. (1956) A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence [Online]. Available at: http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html (Accessed: 10 November 2017).

McKinsey & Company (2017) The future of risk management in the digital era [Online]. Available at: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Risk/Our%20Insights/The%20future%20of%20risk%20management%20in%20the%20digital%20era/Future-of-risk-management-in-the-digital-era-IIF-and-McKinsey.ashx (Accessed: 15 December 2017).

MetricStream (2018) Regulatory Compliance Management [Online]. Available at: https://www.metricstream.com/solutions/regulatory_compliance.htm (Accessed 29 June 2018).

Miao, Y., Keselj, V. and Milios, E. (2005) 'Document clustering using character N-grams', *Proc. 14 th ACM Int. Conf. Inf. Knowl. Manag. – CIKM'05*, ACM Press, New York, USA.

Minsky, M. (1966) *Artificial Intelligence*, San Francisco: Freeman.

Mishkin, F.S. and Eakins, S.G. (2016) *Financial Markets and Institutions.* 18th edn. Boston: Pearson.

Moormann, J. (2014) 'Prozessmanagement in Regionalbanken - Herausforderungen aus wissenschaftlicher Sicht' in Helfer, M. and Schnüttgen, M. (eds.) *Prozessmanagement in Regionalbanken*. Heidelberg: Finanz Colloquium.

Moreira, C., Haven, E., Sozzo, S. and Wichert, A. (2018) 'Process mining with real world financial loan applications: Improving inference on incomplete event logs' *PLoS ONE*, 13(12), pp. 1-31.

Moreno, A. and Redondo, T. (2016) 'Text Analytics: the convergence of Big Data and Artificial Intelligence', *International Journal of Interactive Multimedia & Artificial Intelligence*, 3(6), pp. 57-64.

Moro, S., Cortez, P. and Rita, P. (2015) 'Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation', *Expert Systems with Applications*, 42(3), pp. 1314-1324.

Mustapha, A.M., Arogundade, O.T., Vincent, O.R. and Adeniran, O.J. (2018) 'Towards a compliance requirement management for SMSEs: a model and architecture', *Information Systems and E-Business Management*, 16(1), pp. 155-185.

Ngai, E.W.T., Hu, Y., Wong, Y.H. and Sun, X. (2011) 'The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature', *Decision Support Systems*, 50(3), pp. 559-569.

Nikolaou, K. (2009) 'Liquidity (Risk) concepts: Definitions and interactions', *European Central Bank Working Paper Series*, no. 1008, February 2009.

Nilsson, N. (2010) *The Quest for Artificial Intelligence: A History of Ideas and Achievements*. Cambridge: Cambridge University Press.

Nylund, A.L. (1999) 'Tracing the BI Family Tree', *Knowledge Management*, 60, pp. 70-71.

Oracle (2018) Oracle Financial Services Crime and Compliance Management Analytics [Online]. Available at: http://www.oracle.com/us/industries/financial-services/fs-crime-compliance-management-ds-3630515.pdf (Accessed: 29 June 2018).

Partnership on AI (2017) Industry leaders establish partnership on AI best practices [Online]. Available at: https://www.partnershiponai.org/industry-leaders-establish-partnership-on-ai-best-practices/ (Accessed: 28 September 2017).

Pizzolla, A. (2018) 'The Role of the European Central Bank in the Single Supervisory Mechanism: A New Paradigm for EU Governance', *European Law Review*, 43(1), pp. 3-23.

Power, M. (2005) 'The invention of operational risk', *Review of International Political Economy*, 12(4), pp. 577-599.

Project Management Institute (2017) *A Guide to the Project Management Body of Knowledge - BMBOK Guide*. 6th Edition. Project Management Institute.

ProM (2018) ProM Tools [Online]. Available at: http://www.promtools.org/doku.php (Accessed: 21 October 2018).

QPR (2018a) Process Mining [Online]. Available at: https://www.qpr.com/solutions/process-mining (Accessed: 21 October 2018).

QPR (2018b) QPR ProcessAnalyzer [Online]. Available at: https://www.qpr.com/products/qpr-processanalyzer (Accessed: 21 October 2018).

Racz, N., Weippl, E. and Seufert, A. (2010) 'A Frame of Reference for Research of Integrated Governance, Risk & Compliance (GRC)', *Communications and Multimedia Security - Lecture Notes in Computer Science*, 6109, pp. 106-117.

Raghavan, V.V., Gudivada, V.N., Govindaraju, V. and Rao, C.R (eds.) (2016) *Cognitive Computing: Theory and Applications Handbook of Statistics*. 35th Edition. New York: Elsevier.

Rath, M. and Sponholz, R. (2014) *IT-Compliance: Erfolgreiches Management regulatorischer Anforderungen*. 2nd Edition. Berlin: Erich Schmidt Verlag.

Rausch, P., Sheta, A.F. and Ayesh, A. (eds.) (2013) *Business Intelligence and performance management: theory, systems and industrial applications*. Berlin: Springer.

Regierungskommission Deutscher Corporate Governance Index (2017) Deutscher Corporate Governance Index [Online]. Available at: http://www.dcgk.de//files/dcgk/usercontent/de/download/kodex/170424_Kodex.pdf (Accessed: 22 December 2017).

Rich, E. (1988) *KI - Einführung und Anwendungen*. Hamburg: McGraw-Hil.

Riediger, H. (2015) 'Grundlegende Anforderungen und Vorgehensweise zum Management von Modellrisiken' in Heithecker, D. and Dschuschke, D. (eds.) *Bearbeitungs- und Prüfungsleitfaden Management von Modellrisiken*. Heidelberg: Finanz Colloquium.

Rosen, A. (2017) 'IBM strikes AI deal with MIT', *The Boston Globe* [Online]. Available at: https://www.bostonglobe.com/business/2017/09/07/ibm-strikes-deal-with-mit/ioBOrlikda2r1HetRtjlEK/story.html (Accessed: 27 September 2017).

Rother, T. (2016) 'So vermeiden Sie die häufigsten Fehler - Process Mining richtig einsetzen', *Computerwoche* [Online]. Available at: https://www.computerwoche.de/a/process-mining-richtig-einsetzen,3325694,2 (Accessed: 30 October 2018).

RSA (2018) RSA Archer Regulatory & Corporate Compliance Management [Online]. Available at: https://www.rsa.com/content/dam/rsa/PDF/2016/05/h14989-rsa-archer-reg-corp-compliance-mgmt-sb.pdf (Accessed: 30 June 2018).

Ruozi, R. and Ferrari, P. (2013) *Liquidity Risk Management in Banks: Economic and Regulatory Issues*. Heidelberg: Springer.

Sage Publishing (2018) Company Information [Online]. Available at: https://uk.sagepub.com/en-gb/eur/company-information (Accessed: 15 February 2018).

Saha, P., Bose, I. and Mahanti, A. (2016) 'A knowledge based scheme for risk assessment in loan processing by banks', *Decision Support Systems*, 84, pp. 78-88.

Sallos, M.P., Yoruk, E. and Garcia-Perez, A. (2017) 'A business process improvement framework for knowledge-intensive entrepreneurial ventures', *Journal of Technology Transfer*, 42(2), pp. 354-373.

SAP (2018) SAP Process Control [Online]. Available at: https://www.sap.com/germany/products/internal-control.html (Accessed: 29 June 2018).

Schmelzer, H.J. and Sesselmann, W. (2013) *Geschäftsprozessmanagement in der Praxis: Kunden zufrieden stellen - Produktivität steigern - Wert erhöhen*. 8th Edition. Munich: Hanser.

Schuemi, M.J., Weeber, M., Schijvenaars, B.J.A., van Mulligen, E.M., van der Eijk, C.C., Jelier, R., Mons, B. and Kors, J.A. (2004) 'Distribution of information in biomedical abstracts and full text-publications', *Bioinformatics*, 20, pp. 2597-2604.

Schwaber, K. and Beedle, M. (2001) *Agile software development with Scrum*. Upper Sandle River: Prentice Hall.

Schwaber, K. (2004) *Agile software development with Scrum*. Redmond: Microsoft Press.

Sebastiani, F. (2002) 'Machine learning in automated text categorization', *ACM Computing Surveys*, 34(1), pp. 1-47.

Seiter, M. (2017) *Business Analytics: Effektive Nutzung fortschrittlicher Algorithmen in der Unternehmenssteuerung*. Munich: Verlag Franz Vahlen.

Shim, J.P., Warkentin, M., Coutney, J.F., Power, D.J., Sharda, R. and Carlsson, C. (2002) 'Past, present, and future of decision support technology', *Decision Support Systems*, 33(2), pp. 111-126.

Shin, K.S. and Lee, Y.J. (2002) 'A genetic algorithm application in bankruptcy prediction modeling', *Expert Systems with Applications*, 23(3), pp. 321-328.

Shleifer, A. and Vishny, R.W. (1997) ‘A survey of corporate governance’, *Journal of Finance*, 52(2), pp. 737-783.

Shmueli, G. (2010) ‘To Explain or to Predict?’, *Statistical Science*, 25(3), pp. 289-310.

Signavio GmbH (2018a) Signavio Process Intelligence [Online]. Available at: https://www.signavio.com/de/products/process-intelligence/ (Accessed: 21 October 2018).

Signavio GmbH (2018b) Signavio Process Manager [Online]. Available at: https://www.signavio.com/de/products/process-manager/ (Accessed: 21 October 2018).

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S. Kamer, E., Kraus, S., Leyton-Brown, K., Parkes, D., Press, W., Saxenian, A., Shah, J., Tambe, M. and Teller, A. (2016) ‘Artificial Intelligence and Life in 2030’, *One Hundred Year Study on Artificial Intelligence: Report of the 2015-2016 Study Panel*, Stanford University, Stanford [Online]. Available at: http://ai100.stanford.edu/2016-report (Accessed: 10 November 2017).

Stracca, L. (2013) ‘The Global Effects of the Euro Debt Crisis’, *ECB Working Papers no. 1573* [Online]. Available at: https://ssrn.com/abstract=2302515 (Accessed: 10 November 2017).

Tech and Finance Magazine (2016) Financial Regulations Will Surpass 300 Million Pages by 2020 Says JWG [Online]. Available at: https://techandfinance.com/2016/04/20/financial-regulations-will-surpass-300-million-pages-by-2020-says-jwg/ (Accessed: 01 September 2017).

Teichmann, T. (2018) ‘Deutsche Bank fällt im Fed-Stresstest durch’, *Tagesschau* [Online]. Available at: https://www.tagesschau.de/wirtschaft/stresstest-deutsche-bank-101.html (Accessed: 29 June 2018).

Titcomb, J. (2016) ‘Stephen Hawking says artificial intelligence could be humanity's greatest disaster’, *The Telegraph* [Online]. Available at: http://www.telegraph.co.uk/technology/2016/10/19/stephen-hawking-says-artificial-intelligence-could-be-humanitys/ (Accessed: 14 September 2017).

Turing, A.M. (1950) 'Computing Machinery and Intelligence', *Mind*, 49, pp. 433-460.

van de Gevel, Ad J.W., Noussair, C.N. (2013) *The Nexus Between Artificial Intelligence and Economics*. New York: Springer.

van der Aalst, W.M.P (2016) *Process Mining: Data Science in Action*. 2nd ed. New York: Springer.

van der Aalst, W.M.P. (2018) 'Spreadsheets for business process management Using process mining to deal with "events" rather than "number"?', *Business Process Management Journal*, 24(1), pp. 105-127.

van Liebergen, B. (2017) 'Machine Learning: A revolution in risk management and compliance?', *Journal of Financial Transformation*, 45, pp. 60-67.

Varetto, F. (1998) 'Genetic algorithms applications in the analysis of insolvency risk', *Journal of Banking & Finance*, 22(10-11), pp. 1421-1439.

Vijayasarathy, L. and Turk, D. (2012) 'Drivers of agile software development use: Dialectic interplay between benefits and hindrances', *Information and Software Technology*, 02, pp. 137-148.

Weber, R.H. (2017) 'Regtech as a new legal challenge', *Journal of Financial Transformation*, 46, pp. 10-17.

Wehmeier, S., McIntosh, C., Turnbull, J. and Ashby, M. (eds.) (2005) *Oxford Advanced Learner's Dictionary of Current English*. 7th Edition. Oxford: Oxford University Press.

Werner, M. and Gehrke, N. (2015) 'Multilevel Process Mining for Financial Audits', *IEEE Transactions on Services Computing*, 8(6), pp. 820-832.

Werner, M. (2017) 'Financial process mining – Accounting data structure dependent control flow inference', *International Journal of Accounting Information Systems*, 25, pp. 57-80.

Weske, M. (2012) *Business Process Management: Concepts, Languages, Architectures*. 2nd ed. Heidelberg: Springer.

Wiley (2018) Wiley Online Library: About Us [Online]. Available at: http://olabout.wiley.com/WileyCDA/Section/id-390001.html (Accessed: 15 February 2018).

Winston, P.H. (1987) *Künstliche Intelligenz*. Bonn: Addison-Wesley.

Witten, I.H., Frank, E., Hall, M.A. and Pal, C.J. (2017) *Data Mining: Practical Machine Learning Tools and Techniques*. 4th Edition. Heidelberg: Morgan Kaufmann.

Xing (2017) Xing [Online]. Available at: https://www.xing.com (Accessed: 01 November 2017).

Young, K. (2013) 'Financial industry groups' adaption to the post-crisis regulatory environment: Changing approaches to the policy cycle', *Regulation & Governance*, 7(4), pp. 460-480.

Zahedi, F. (1991) 'An introduction to neural networks and a comparison with artificial-intelligence and expert systems', *Interfaces*, 21(2), pp. 25-38.

Zhang, G.Q., Hu, M.Y., Patuwo, B.E. and Indro, D.C. (1999) 'Artificial neural networks in bankruptcy prediction; General framework and cross-validation analysis', *European Journal of Operational Research*, 116(1), pp. 16-32.