Artificial Intelligence in Credit Scoring: Digitalization in the Banking Landscape in Germany

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Dissertation submitted in partial fulfilment of requirements for the MSc in Strategy, Entrepreneurship & Impact, at the Universidade Católica Portuguesa, 05.04.2023

Abstract

AI is rapidly transforming markets and challenging old business models. This dissertation examines the AI-readiness of German banks, specifically in credit scoring. For this purpose, three different data types were collected. A literature review shed light on the current credit system in Germany and, as a comparison, in China. Furthermore, expert interviews disclosed the potential chances and risks of AI-driven credit assessments. A quantitative survey complemented the expert opinions with those of potential users. The results indicated that the overall readiness of AI in the German credit sector is relatively low. Experts suggested that drivers to use this technology are risk optimization and cost reduction. The identified main barrier complicating the implementation stems from regulatory requirements. While advancements are low, the collected customer data showed that most survey participants would agree to an AI-driven creditworthiness assessment. A scenario analysis combined all collected insights and demonstrated potential future developments. From a management perspective, German banks need to be faster in their technological transformation, in order to not loose competitiveness in the future.

Keywords: Artificial Intelligence, Banking, Technology Acceptance, Innovation

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Sumário

A IA está a transformar rapidamente os mercados e a desafiar velhos modelos de negócio. Esta dissertação examina a prontidão da AI dos bancos alemães, especificamente na pontuação de crédito. Para este fim, foram recolhidos três tipos de dados diferentes. Uma análise bibliográfica lança luz sobre o actual sistema de crédito na Alemanha e, como comparação, na China. Além disso, entrevistas de peritos revelaram as potenciais hipóteses e riscos das avaliações de crédito orientadas para a gripe aviária. Um inquérito quantitativo complementou as opiniões dos peritos com as dos potenciais utilizadores. Os resultados indicaram que a prontidão geral da AI no sector de crédito alemão é relativamente baixa. Os peritos sugeriram que os factores que impulsionam a utilização desta tecnologia são a optimização do risco e a redução de custos. A principal barreira identificada que complica a implementação deriva de requisitos regulamentares. Embora os avanços sejam baixos, os dados recolhidos dos clientes mostraram que a maioria dos participantes no inquérito concordariam com uma avaliação de solvabilidade orientada para a gripe aviária. Uma análise de cenários combinou todas as percepções recolhidas e demonstrou potenciais desenvolvimentos futuros. De uma perspectiva de gestão, os bancos alemães precisam de ser mais rápidos na sua transformação tecnológica, a fim de não perderem competitividade no futuro.

Palavras-chave: Inteligência Artificial, Banca, Aceitação de Tecnologia, Inovação

Título: Inteligência Artificial na Pontuação do Crédito: Digitalização na Paisagem Bancária na Alemanha

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Acknowledgments

My first thank goes to Prof. Peter Rajsingh. He supported me throughout the whole process of conceptualizing and writing this thesis. Thank you for giving me new food for thought and motivating me to investigate and research outside the obvious.

Moreover, writing this thesis would not have been possible without the input from all interviewed experts. Thanks to everyone for taking the time and sharing their knowledge with me.

I would also like to express my gratitude to all my close friends who have supported me while writing this thesis and throughout my journey at Católica. Elena, for bringing lots of laughs and fun evenings in Lisbon in my life. Moritz, for many hours of phone calls and library meetings discussing our ideas. Ana, for brightening each day and making the experience of studying abroad so unique. And Luisa, who I would not want to miss on any journey in my life.

Lastly, I want to thank my family for their endless support and love. Thanks for being by my side and for all the values you taught me.

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List of Abbreviations

AI	Artificial Intelligence
DF	Driving Force
DC	Dynamic Capabilities
OA	Organizational Ambidexterity
TA	Technological Acceptance
UA	User Acceptance
PST	Potential Surprise Theory

1. Introduction

In October 2022, US-American rapper Kanye West, also known as Ye, made headlines with anti-semitic statements on his social media. Moreover, he became known for publicly criticizing partnerships. For instance, he denounced the management style of Investment Bank JP Morgan, where he reportedly held $140 million. On October 12th the bank published a letter ending all relationships with Ye (Snapes, 2022). This case is interesting for various reasons. Banks are less afraid to take a position on social issues. Moreover, banks no longer solely look at traditional data of their clients. Statements on social media or online shopping behavior could have financial consequences for ordinary citizens in the future, too. What sounds drastic for the Western world is already the order of the day in China. Not paying bills on time, receiving a speed fine, or publishing government in-conform information on the internet can all lead to a lower credit score for the Chinese citizen. This score is calculated using a large number of data points, from which an index is then formed using AI-controlled learning procedures. The inclusion of this amount of data aims, among other things, to keep payment defaults low. In the course of risk minimization, it is also worthwhile for European financial institutions to explore alternative credit scoring methods. History has proven this importance: Easy access to credit and lax evaluation criteria in the early 2000s led to incorrect credit allocations in the real estate markets. Later, in 2008, investment bank Lehman Brothers had to file for bankruptcy as many of their securitized mortgage-backed instruments collapsed in value because of default risk (Authers, 2018). A great recession followed, costing millions of people their jobs, savings, and homes. The crisis displays the vast socioeconomic effects imprecise credit scorings can have. Thus, this topic is highly relevant. Incumbents exploring these alternative tools could benefit from lower operating risks. Nevertheless, could China be a role model in this, at least partly? Moreover, how can banks walk the tightrope between efficient data use and avoiding a big-brother-like scenario?

For the reasons described, it is essential to look towards the future of credit scoring systems. With Artificial Intelligence on the rise, European credit institutions will also have to deal with this topic to remain competitive in digitalization. This paper examines how credit scoring systems differ in China and the EU. It then considers measures established for European institutions to incorporate Artificial Intelligence into credit scoring. In addition, the consumer perspective will also be surveyed to determine the willingness to allow types of data to be released for credit assessment.

2. Literature Review

This literature review describes the German credit system and compares it to the Chinese Social Scoring System. This frames how Artificial Intelligence (AI) is being used in an emerging market and the potential benefits and pitfalls of this technology. The literature review also provides an overview of AI research and the ways it can be used in credit and lending. Moreover, incumbent adaption to innovative technologies will be explained.

2.1. Credit and Lending Industry: China vs. Germany

The following chapter examines the landscape of credit and lending in two different nations, Europe and China.

China

The concept of Social Credit first came to fore in the early 2000s. On one hand, there was increasing need for governmental reforms. Information silos created large internal transaction costs. Understaffed regulatory agencies, as well as high information acquisition costs were considered reasons for reforming the system. On the other hand, authoritarian politicians recognized the Social Credit System (SCS) as a way to enforce their political ideals on a broad scale (Dai, 2020). Based on the game-theoretical view that humans are rational and self-interested, it is also a way to regulate China's 1.4 billion inhabitants. A concrete plan of action was first released in 2014 by the Central Committee of the Chinese Communist Party, named the "Planning Outline for the Construction of a Social Credit System". Under this plan, each citizen starts with a credit score of 1000 points. The score increases or decreases according to personal behavior. Scores rise if, say, a person donates blood, has a good financial credit history, takes care of the elderly or praises the government on social media. Scores decrease if one spreads rumors on the internet, participates in cults or commits traffic offenses. Large amounts of data are processed by algorithms to compute scores (Bertelsmann, 2020). Sources include traditional data, like financial or criminal history from the government, but then spill over into digital data that people leave on the internet using smartphones and laptops, as well as information gathered through video surveillance. People who fall below a score of 600 are named on a blacklist that is publicly available (Bertelsmann, 2020). For instance, over a mere six-month time span in 2018, two and a half million flights and train trips were canceled for people appearing on the government's blacklist (Chan, 2018). In contrast, the higher one's score, the more benefits a citizen can accrue (see *Table 1*). The primary goal of the SCS is to incentivize trust, punish breaking of trust, and to foster a "harmonious society" (Chinese: *hexie shehui*) (Lam, 2021, p. 79). Apart from the government, companies also use social scoring methods. Tencent and Alibaba are among eight companies that have access to data Chinese citizens left on the internet. The data are provided by the central bank. Website histories, mobile phone orders, and activities on social media all count towards the score. Moreover, having the right circle of friends and credible social connections can help raise scores too. A higher score leads to loan approvals, faster airport security, help with adopting a pet, or provides access to premium products from companies. However, most of the eight companies do not publicly disclose all the information they count towards credit ratings. This is also due to the fact that there is no clear regulation in China (Clover, 2016).

Table 1: Punish and Reward System (Bertelsmann, 2020)

Reward	Punishment
Superiority for school admission and employment	Banned from booking flights or night-speed train tickets
Simplified access to cash loans and consumer credit	Difficult access to licenses, permits and some social services
Discounted bicycle and care rental Free gym facilities	Restrticted access to credit and to public services
Discount on public transportation Advantages in the health care system	Exclusion from government jobs Denial of access to private schools

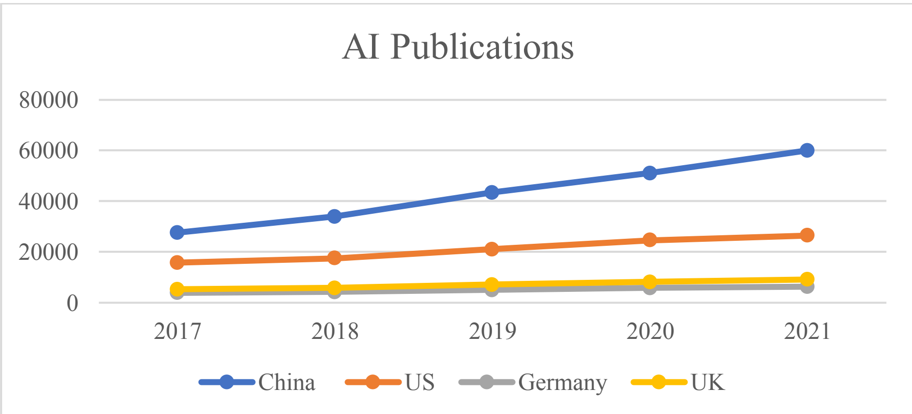
Germany

Overall, Germany relies heavily on more traditional data than China. For instance, Germany uses the SCHUFA score to compute credit scores. SCHUFA scores account for personal data like birth date, whether credit card bills or loan installments are paid on time and information about abusive or fraudulent behavior. Contrary to China, SCHUFA does not consider buying behavior or other personal data (Schufa Credit Score Report in Germany, 2020). Furthermore, creditworthiness is distinguished between personal and economic creditworthiness. Personal factors include punctuality of payments, while economic factors account for the financial situation of a person[1] (Aust, 2021). While this method seems less onerous than China's, there are pitfalls, too. In China, activities like caring for the elderly can boost credit scores, while Germans simply need financial history. The average approval rate for loans in a German bank is five to ten working days (Aust, 2021).

The Global AI-race

The different credit scoring approaches demonstrate two fundamentally distinct mentalities towards new technologies, especially Artificial Intelligence. In China, research and piloting in new technologies are strongly incentivized by the government. For instance, the Chinese government released policies like “Made in China 2025” or the “Next Generation Artificial Intelligence Development Plan” to promote innovation in this area (Li et al., 2021). These policies include encouraged data collection to generate large-data sets required to train Artificial Intelligence. While the US is still dominating, China is catching up rapidly. One-third of the published AI journal papers worldwide originate from Chinese research. For instance, in 2021 China released more than twice as many publications as the US (Figure 1). Moreover, one-fifth of the international private investment funding in 2021 went to Chinese companies (Stanford Institute for Human-Centered Artificial Intelligence, 2021). Nevertheless, unpredictable political developments influence the global AI-race. For instance, the U.S.-China trade war[2] or deglobalization [3] impact future AI domination (Li et al., 2021).

Figure 1 Number of AI publications from 2017 to 2021 (Stanford Institute for Human-Centered Artificial Intelligence, 2021)



[1] Asset situation, income and expenses

[2] Dispute between China and US imposing tariffs on goods from China/US (BBC, 2020)

[3] “movement towards a less connected world, characterised by powerful nation states, local solutions, and border controls, rather than global institutions, treaties, and free movement” (European Parliamentary Research Service, 2022, p.1)

A report by the Center for Data Innovation compared the development and usage of AI relative to each other in China, the US, and Europe. It suggests that Europe needs to accelerate deploying AI in crucial industries. Looking at talent, research, development, and hardware in AI, researchers adopted a 100-point system to measure capabilities in these four areas. While China reached a total score of 32.3 and the US 44.2, the EU scored 23.5 points (McLaughlin & Castro, 2021). For instance, the EU received less than half as much funding for AI start-ups as China did (Castro & McLaughlin, 2021). Looking specifically at the DACH region, a study by PwC showed only 2% of respondents think their government supports use of AI in business. Moreover, the study evaluates banks in the DACH region with a readiness score of 2.58 out of 5 for Artificial Intelligence solutions (PwC, 2020). Moreover, people's suspicions are a barrier to AI-backed solutions within the Financial Services Industry (PwC, 2020). While the PwC study focuses on Financial Services in general, this paper closes a research gap by explicitly looking at Germany`s AI-readiness in credit scoring. The focus relies on understanding data privacy concerns.

This Research Question is as follows:

RQ1: How are German banks using non-traditional data for credit scoring purposes?

2.2. Artificial Intelligence

The following chapter provides an overview of Artificial Intelligence, its definition and how it is used in the credit sector.

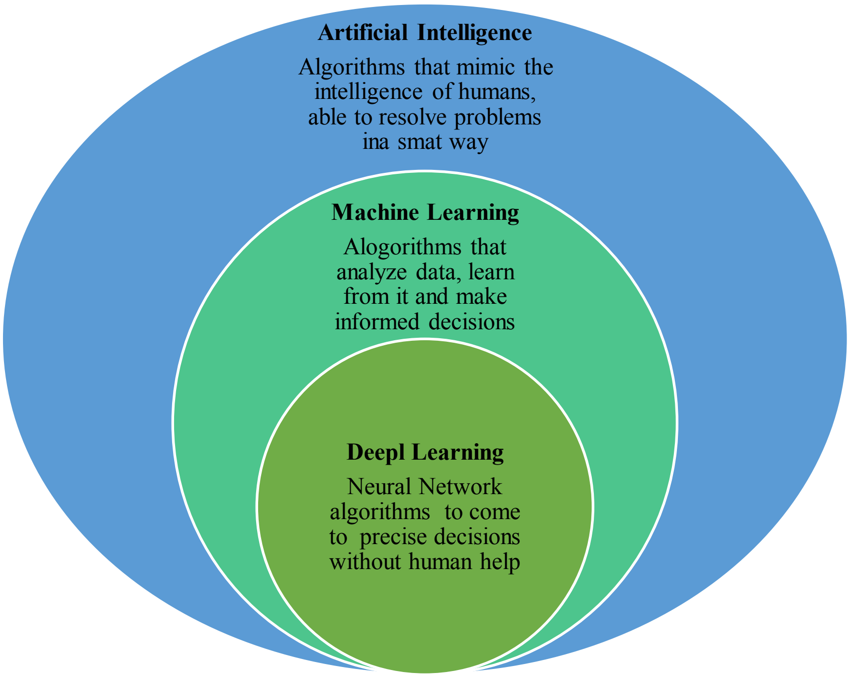
2.2.1. Definition of AI

In the previous chapter, different credit scoring systems were presented. The following chapter explains basic concepts of AI and examines how companies can implement AI in credit systems.

A summer research project at Dartmouth University with many experts gathering to discuss their work established AI as a discipline (Dick, 2019). However, the basis of AI research goes back much further. Philosophers in Greek and Roman history proposed the idea that the mind is like a machine with knowledge encoded in an internal language. Over the years, researchers deployed different approaches to AI. Human-centric methods explore AI in the context of human behavior. AI was conceived as automation of actions associated with human decision-making, problem-solving, and learning. AI research is interdisciplinary, involving psychologists, neuroscientists, economists, mathematicians, philosophers, and engineers.

Today AI is often used in the context of a term coined by Klaus Schwab – the fourth industrial revolution. This notion is related with blurring of the boundaries between the digital and physical world. It combines the power of advanced technologies like AI, 3D printing, genetic engineering, and others. With computing power accelerating, this will affect production and all industries worldwide (Schwab, 2016). Companies will have to understand these changes and use them to their advantage. AI in a business context implicates big data, cloud computing, and the internet of things (Chan et al., 2022). There are different subsets of AI which the following graphic illustrates.

Figure 2: Overview of AI subsets (Ceron, 2019)



Apart from different subsets, there are various forms of learning in AI. First, agents can learn in an inductive way, which means learning a rule from specific input-output pairs. Then there is unsupervised learning, meaning that the agent does not need any feedback to learn patterns. Agents learn from a series of punishments or rewards, called reinforcement learning. Supervised learning lets the agent learn patterns that link a specific input to an output (Russell & Norvig, 2010).

2.2.2. AI in Credit

AI is becoming more common in the credit and mortgage space. AI-backed technologies already being used include chatbots, machine learning in credit scoring, predictive analytics, and cybersecurity. Chatbots handles general tasks like balance inquiries or providing answers to frequently asked questions. Machine learning in credit scoring analyzes vast amounts of data to determine creditworthiness, and predictive analytics find patterns in these data to identify possible lending or sales chances. Cybersecurity systems identify risks to hinder cyberattacks and indicate affirmative avoidance actions (Chan et al., 2022). The following is an overview of influences of these technologies.

Credit decisioning

Customers of traditional banks might wait for over a week for credit approval whereas lenders using AI provide credit faster by analyzing data from conventional sources (bank transaction history, credit reports, and tax returns) and new sources like social media data, telecom usage, or location data. Machine learning models quickly analyze these data sets to provide personalized loan, credit for new customers without extensive credit histories, and reduce fraud risks. An example of the latter is Ping An. The Chinese company uses image analytics to identify unconscious micro-expressions. This method might help banks to detect fraudulent intentions. Moreover, banks deploying AI can offer more competitive interest rates from more precisely analyzing default risks of customers (McKinsey, 2021).

Monitoring

AI can be helpful beyond the early lending stage. Once a loan is offered and accepted, AI monitors clients to detect payment issues. This provides more security for banks (McKinsey, 2021)

Deepening relationship & optimize customer servicing and engagement

Data analysis also improves customer communication by selecting proper channels and communication styles. One example of optimizing customer service is voice and speech recognition to match agents with customers by behavioral and psychological mapping. This allows banks to better understand customer needs and generate special offers, like loans for homes, appliances or travel (McKinsey, 2021).

2.2.3. AI-related risks

Despite these positive effects, there are concerns. One is commonly referred to as the “black box problem”. As AI or ML models, specifically Deep Neural Networks, become more advanced, it is difficult to understand the decision-making process behind it. Data scientist have trouble to reconstruct why an algorithm arrived at a certain conclusion. However, being able to explain a result is crucial to foster trust and comply with legal requirements (Barredo Arrieta et al., 2020). Credit institutions are legally bound to exclude race, ethnicity, gender, religion and other similar factors in credit decision making. However, AI can express hidden biases perpetuating discrimination. First, coding of algorithms can contain prejudicial notions when categorizing groups. Moreover, grouping people can also lead to biases. Once an individual is associated with a certain category, conclusions are generated E.g., someone in a rich neighborhood is assumed to be financially responsible. Prejudicial judgments could also lead to social divisions as people might avoid interacting with certain groups (Raso et al., 2018). As China shows, AI further restricts individual freedom as a result of constant surveillance. To gain access to credit, individuals cannot hold political opinions or engage in certain social activities which will detrimentally affect finances. Lastly, AI provides power to the controlling entity that issues punishments or rewards. This, in turn, can be used to persecute specific individuals and render many of the credit process advantages offered by AI less palatable (Raso et al., 2018).

2.2.4. Regulatory frameworks

As part of the European Union, Germany has to follow regulatory frameworks concerning AI. In April 2022, the EU-commission released the EU AI Act, a law regulating the usage of AI-systems. These rules aim at securing human rights and make AI secure. The law differentiates between three categories (Future of Life Institute, 2022). The first category includes applications bearing an unacceptable risk, for instance social scoring by governments or games with voice assistance that encourages dangerous actions. High-risk applications contain CV-scanning tools, AI application in robot-assisted surgery or credit scoring “denying citizens opportunity to obtain a loan” (European Commission, 2021). For high-risk applications, the Act demands accountability. Hence, any output by an ML or AI system must be understandable for humans. In the case of credit scoring this refers to bank employees being able to explain their customers why a machine-made decision lead to a certain outcome, for instance being rejected. Therefore, by securing explainable and transparent decisions, companies can be held accountable (Doran et al., 2017). Moreover, the Act defines limited risk systems, including chatbots. Minimal or no risk systems encompass spam filters and other applications that are currently used in the EU. Moreover, since 2018 banks have to follow the GDPR, a law containing data protection rules. Organizations have to delete personal data, if individuals do not want their data to be stored (Wolford, 2019). On a national level, banks are subject to the German Federal Data Protection Act (German Parliament, 2008).

2.3. Management Theories

To provide a theoretical basis to this work, the following chapter presents different management theories. Theories are based on two perspectives. The first perspective refers to how incumbents approach new technologies. Additionally, this chapter sheds light on the consumer perspective, explaining frameworks to measure acceptance of new technologies.

2.3.1. The Innovator´s Dilemma

Incumbent firms struggle with adopting new disruptive technologies which causes them to lose ground to startups. Christensen's notion of the Innovator's Dilemma (2001) explains the paradox where successful established companies focusing on their existing customer base skews firms away from disruptive innovation.

The author developed his framework with three central claims. Firstly, he differentiates between two types of technologies that lead change: sustaining and disruptive technology. The latter occurs seldomly, but it can disrupt whole industries initially taking root in a relatively small niche customer segment. At first, disruptive innovation tends to underperform established products. In contrast, mainstream customers value sustaining innovation that make existing products better (Christensen, 1997).

An example of a successful company that avoided the innovator's dilemma is Apple. "Customers don't know what they want until you show it to them" (Isaacson, 2012, p. 97) is a quote by former Apple CEO Steve Jobs. According to Jobs, research is not forward-looking and is a poor indicator of future trends (Isaacson, 2012). Incumbent companies also tend also to be overly oriented towards steadily growing earnings for their shareholders, which prevents them from focusing on opportunities that have a long developmental tail before affecting the bottom line (Christensen, 1997).

AI is an innovative phenomenon where Chinese incumbents are already using AI in credit scoring. As the previous introduced studies suggest, Europe is on the verge of falling behind in terms of AI advancement. This raises the question if it the gap is the same for the banking sector, specifically the credit sector.

2.3.2. Dynamic Capabilities and Organizational Ambidexterity

The term "dynamic capabilities" was first coined by Teece et al., (1997), who defined it as competencies to process and respond to changing market environments. Since then, research on dynamic capability has steadily developed. While some researchers define dynamic capabilities as abilities, others see them as processes and routines (Barreto, 2010). Dynamic capabilities have also been linked with organizational ambidexterity (O'Reilly & Tushman, 2008).

Ambidexterity describes the balancing act of a company utilizing existing resources and simultaneously exploring new resources. To know when to perform more explorative tactics, senior managers have to sense changes in business environments and customer preferences. However, gauging this can be complex for senior leaders who often focus on identifying threats and managing for those threats. This mindset forecloses being open to new business opportunities (O'Reilly & Tushman, 2008). After sensing, seizing is vital for senior managers. Seizing means developing a clear vision and strategy on how to tackle challenges the business is facing. These can be in both exploitation or exploration and require allocating the right resources at the right time. The last step is to reconfigure and shift resources toward emerging growth opportunities. Consequently, leaders must constantly realign a business in the market (O'Reilly & Tushman, 2008).

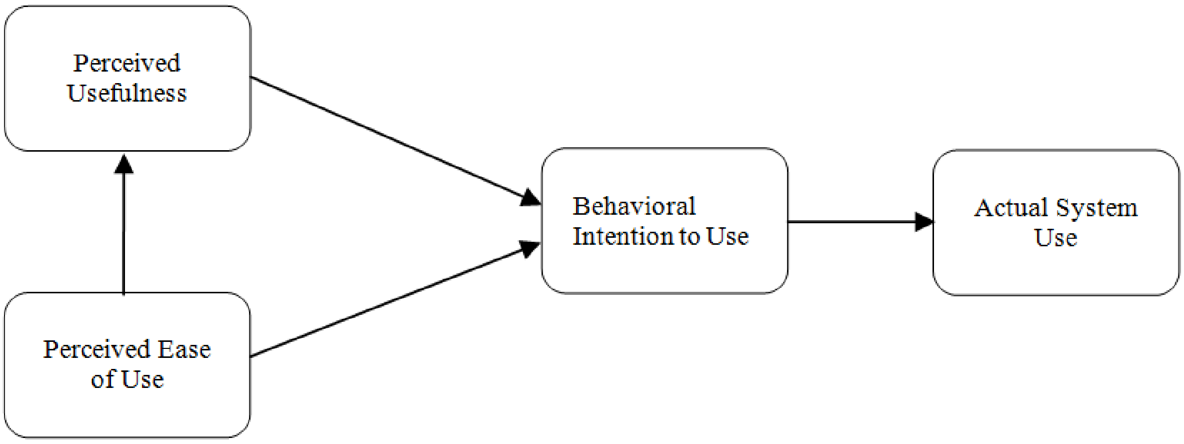
With AI being a disruptive technology, the question arises if incumbent banks in Germany are facing the Innovator's Dilemma. The majority of the customer base of traditional German banks might be satisfied with traditional credit approaches. However, niche customers, young clients, and those needing fast credit approval might be more open to AI solutions. Senior managers in banks and other lending institutions may begin exploring new opportunities using ambidextrous strategies. Therefore, both the firm and the user perspective on the adoption of AI need to be understood.

2.3.3. Technology Acceptance Model

While it is essential to understand what drives banks to adopt AI, it is equally as important to investigate the acceptance of the end-user.

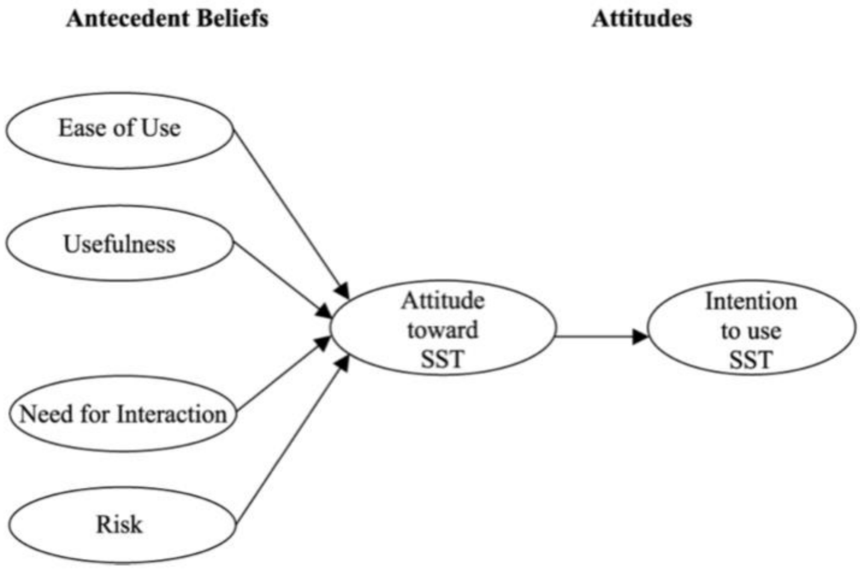
One model frequently used in acceptance research is the TAM framework, introduced by Davis in 1989. It explains user behavior across a variety of end-user computing technologies. The framework is founded on two main ideas. First, perceived usefulness, meaning the ability to complete a task more efficiently, defines the acceptance of a technology. The second dimension defined in the framework is perceived ease-of-use, referring to how easy a computer system is to use (Davis, 1989).

Figure 3: TAM framework (Davis, 1989)



In the field of financial services, TAM has been used frequently, too. According to a literature review examining 90 papers, it is one of the most dominant theories (Hentzen et al., 2022). For instance, TAM was often deployed in testing user acceptance in mobile banking. To refine the model for mobile banking, Curran & Meuter extended the model with need for interaction and risk (2005).

Figure 4: Extended TAM framework (Curran & Meuter, 2005)



However, exploration of AI requires further granularizing. For instance, researchers suggest an extension of TAM, adding AI-specific dimensions like privacy concerns, trust and perceived creepiness (Ostrom et al., 2019). However, these dimensions differ according to the type of AI[4].

Research in acceptance of AI is still in an early stage. Initial studies focus on more consumer facing solutions like chatbots. Therefore, the present work aims to close a gap in this research.

3. Methodology

The research follows a mixed-method approach. The chosen design follows triangulation to replicate multiple perspectives on AI in credit scoring in Germany. First, Interviews with Experts in the field give insights into the German banking landscape. Second, the consumer perspective sheds light on the acceptance of this technology. Last, the insights from the literature review provide theoretical knowledge. As each method has limitations and weaknesses, triangulation helps to regulate these effects and combines different points of view (Jack & Raturi, 2006).

[4] supported, augmented and performed services

3.1. Qualitative Data

Qualitative data collection was based on semi-structured interviews with different professionals in the field of AI. The interviewees come from two main fields: Management Consulting and Banking. This difference in backgrounds provides internal (Banks) and external (Consulting) perspectives on the topic and gives richness to the data. In total, 10 Interviews were conducted. Generally, using qualitative data helps with "understanding of opinions, attitudes, experiences, processes, behaviors, or predictions" (Rowley, 2012, p. 261). As AI in credit scoring is a complex topic with multiple dimensions to explore, qualitative data collection captures valuable additional information which a questionnaire would not capture. Semi-structured interviews provide greater flexibility and make it possible to readjust to different answers (Rowley, 2012). Two main interview blocks examined the banking landscape and its adoption of AI in credit scoring. First **(1)**, the interviews explore the **AI's current advancement in German banks' credit department**. The second block **(2)** includes questions to understand **future developments**.

Both blocks were designed based on previously introduced literature. Interview guidelines contained a mix of open and closed questions. Closed questions in the first block additionally quantified the overall readiness. In general, this block focused on the present. The second block relies on the introduced comparison between China and Germany in the literature review. It touches on general concerns related to using AI following Raso et al. (2018) and is future-oriented. The Appendix contains the complete interview guide and assigned literature. Questions were slightly adapted according to the expertise and position of an interviewee.

To analyze the Interviews, a blended approach was chosen. First, the data generated from closed questions are reported visually. Simple graphs and tables were built. Second, open questions were analyzed in highlight trends and arguments (Wholey et al., 2010). The following table provides an overview of interviewed experts.

Table 2: Interview guide

Section	Questions
Current state of adoption in Germany	**Q1** How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced) **Q2** What are the most important motives for implementing AI in credit scoring? **Q3** Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service **Q4** What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers? **Q5** Are you using any AI solutions in credit scoring in your organization? If no, are you discussing the topic/piloting? If yes, which non-traditional data are you assessing? *(only for interviewees from bank)*
Future developments	**Q6** US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit? **Q7** China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well? **Q8** Which non-traditional data are customers most likely to share with their bank? **Q9** Will there be built in stop parameters (E.g., Health Care data excluded) **Q10** Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

Table 3: Overview of interviewed experts

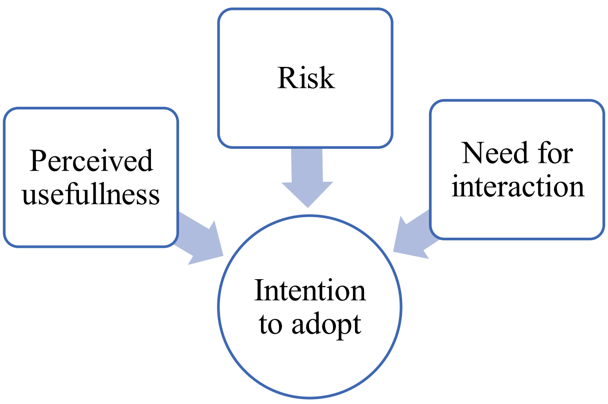
Interview	Position	Expertise	Field
Interview 1	Innovation Manager	Project lead Data Analytics, projects focused on implementing AI	Bank
Interview 2	Director Financial Services Technology	Specialized in AI, FinTech and Digital Transformation, previously worked in Asia	Consulting
Interview 3	Senior Consultant	Consulting firm specialized in digitalization solutions	Consulting
Interview 4	Senior Consultant	Consulting firm specialized in Financial Services	Consulting
Interview 5	PO Big Data & AI	Responsible for AI solutions at a public German Bank	Bank
Interview 6	Managing Director Credit Risk	Specialized in corporate and retail risk at a large German bank	Bank
Interview 7	Speaker of the Board	Knowledgeable in strategic initiatives of a German credit institution	Bank
Interview 8	Digital Value Creation Manager	Data Scientist with expertise in Private Equity and Consulting practices	Consulting
Interview 9	Senior Economist	Knowledgeable in credit analysis, DLT and AI	Bank
Interview 10	Director Analytics Practice	Specialized in risk management	Consulting

3.2. Quantitative Data

The second part of the triangulation approach consisted of quantitative data collection. A survey scrutinized users' perspectives and opinions on banks using AI in credit scoring. The underlying goal was to oppose adoption of banks with the adoption of users. The main focus was on the perspective of experts, and quantitative data was collected to gain a more comprehensive picture. Therefore, 500 people were queried within a period of two days, starting 9th of December 2022. The survey was distributed via a market research institute.

The survey consisted of three parts. First, questions retrieved demographic data like age, occupation, and household income. Subsequently, participants were asked to indicate whether they are customers of a traditional or digital bank. The second part explores which factors influence the adoption of AI-driven credit scoring. The extended TAM framework from Meuter & Curran (2005) served as the basis for developing the questions. Perceived usefulness, risk, and need for interaction were deployed, while perceived ease of use was not considered (Graphic 3). As AI in credit scoring is, contrary to internet banking, not actively used by the customer himself, this factor was ignored. To measure adoption, participants were presented a scenario. In this scenario they were in need for a loan to buy a car for commuting. The scenario described the difference between a scoring based on traditional data and on non-traditional data. On a Likert-scale from one to five, participants were then asked to state the likelihood to agree to an assessment by their bank based and non-traditional data. Welch t-tests measured differences in means for potential users and non-users of an alternative credit assessment. For this purpose, all participants assigned to the middle were excluded from the analysis to form two groups. However, descriptive statistics on the proportion of individuals assigned to the middle provide valuable information on whether people generally have strong or more neutral opinions towards this topic. Using a middle-point is advantageous in topics people potentially have insufficient knowledge (Johns, 2005). A t-test examined differences in means of customers at a traditional or a digital bank on the intention to adopt AI in credit scoring. Furthermore, the quantitative analysis examined whether age, education, or social media usage play a role in the intention to adopt.

Figure 5: Proposed framework for quantitative analysis



The last part delved into which non-traditional data customers are most likely to share with their bank. Therefore, different types of data were presented. On five-point likert scales participants classified the likelihood to share. This assessment was based on a similar study exploring willingness to share personal information online (Leon et al., 2013). Descriptive statistics and graphics support all three sections of the survey.

4. Results

Results are divided into different sections. First, the interview results are presented, followed by the quantitative results. Lastly a scenario analysis was built based on the data collected as well as the literature.

4.1. Current state of adoption in Germany

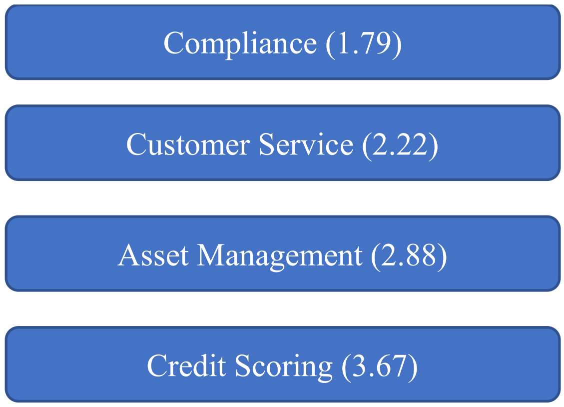
Adoption in German Banks

To assess progress of AI-driven credit scoring solutions in Germany, experts were asked to classify the level of adoption on a scale from one to five. The arithmetic mean of all answers rated the advancement level in Germany relatively low at 2.35. One Interviewee described the state of development the following: *"I would say it's still pretty low. […] Most AI projects in German banks are still on the research and development phase." (Interview 9)*

Moreover, all interviewees with banking backgrounds were asked if they used the technology at their banks. Of the five banks interviewed, only one confirmed using this technology. However, the four banks that declined using AI in credit scoring indicated that the topic is being discussed. Three of these confirmed pilot projects.

In a next step, interviewees were asked to rank four different banking areas according to what extent they are using AI. As Figure 6 shows, the ranking supports the relatively low adoption score. On average, credit scoring ranked last. Compliance was ranked highest, followed by Customer Service and Asset Management. One of the interviewees refrained from answering, as he rated his own inter-departmental knowledge as insufficient.

Figure 6: Bank divisions ranked according to AI-readiness



Motives to implement non-traditional data models

Table 4: Overview of adoption motives

Motives	Number of mentions
Risk optimization	18
Cost reduction	14
Innovation pressure	8
More personalized products	7
Shift of responsibilities	3
	$\sum = 50$

The interviews revealed five main drivers for firms to implement new models with alternative data (Table 4). The main motivation was risk optimization. This was associated with credit institutions making better decisions by more accurately predicting default risk. But default was not the only factor as missed revenue opportunities was also mentioned. *"In credit, we are always talking about the Alpha and Beta mistake. The former refers to granting bad loans, the latter to good loans not being realized" (Interview 7).*

The second strongest motive was cost reduction. This includes saving time and personnel. Reducing costs is specifically important for German banks. While in other countries like Spain or France banks have large oligopolies or monopolies, German banks operate in a *"low margin environment [...] with very intense competition*" *(Interview 9).* The description of the environment also leads to the motive of innovation pressure. This pressure stems from the competition on the one hand, as in China, Singapore or in the US there is in general more experimenting with AI *(Interview 2)*. On the other hand, Expert 10 stressed that pressure arises from banking supervision, even though these institutions are often skeptical, too. *"Regulatory authorities have expectations. They are asking banks all sorts of questions, like: have you done any trials? Can you prove that there is no better way than what you are doing at the moment?"*.

Another motive (with seven mentions) was to offer customers more personalized products and services. This aspect is strongly linked to risk optimization. By assessing risk more accurately, banks are able to grant better loan conditions. These personalized offers can translate to being a differentiating factor from competitors. Lastly, shift of responsibilities is one motive, although less frequently mentioned. The motive derives from the *"high workload of employees and information floods of regulatory requirements difficult to keeping track of" (Interview 1)*. This argument depends largely on how machine-made decisions will interact with employees' decisions.

Barriers hindering implementation

Table 5: Overview of adoption barriers

Barriers	Number of mentions
Regulatory	27
Lack of talent	11
Accountability[5]	8
Data availability	8
Customer Skepticism	7
Biased Algorithms	7
Old IT Infrastructure	6
Data Quality	4
	$\sum = 82$

While the motives provide evidence of potential benefits of incorporating new scoring approaches, the question remains why the current state of development remains relatively low. Therefore, interviewees were asked about barriers in the German market as well as potential measures to overcome them. Nine different barriers were identified. Regulatory requirements were named as the strongest barrier. Regulations refer to the GDPR, as well as the EU AI Act on a transnational level. To diminish these impediments, one interviewee suggested fostering

[5] Coding includes accountability mechanisms, for instance AI systems being explainable and transparent (Wachter et al., 2017)

stronger cooperation between legislative bodies and banks. While committees take a legal or political perspective, the banking perspective is lacking. With regulations also comes the demand for accountability. Decisions made by an AI have to be understandable and transparent. This requirement remains difficult, as regulators are content with *"using Machine Learning in some embodiments, but do not support neuronal networks or anything related to factors that are incomprehensible. The blackbox-problem is omnipresent when it comes to evaluation." (Interview 2).* Apart from the required accountability, AI-driven credit scorings have to be non-discriminatory *(*with seven mentions*)*. These biased decisions hinder the implementation of non-traditional data models, as no groups are allowed to be discriminated against by algorithms.

Secondly, lack of talent remains a strong barrier. Banks might pilot projects or consult external parties, but then lack personnel to take over these models. *"Banks typically don't have the people internally, to own such models and to operate and control them." (Interview 4).* When it comes to young professionals, Expert 2 described this gap as starting to close. German universities are tackling the problem and as a result, more professionals with AI skills are on the job market. However, when it comes to experienced hires, banks have to be prepared to *"accept English-speaking applicants or have to actively recruit experienced hires from other countries."*

Another major barrier refers to the lack of available data. On one hand, this may be the case because data is simply not available or on the other hand it is of poor quality. The former is closely connected to regulatory enforcement. Thus, although data is often theoretically retrievable, it may not be used. Poor data quality, referred to by 30% of the experts, is attributed to "*A lot of files from state institutions are still paper based and there is a lot of handwriting on it. That makes it hard to analyze. Therefore, it is not enough to only think of available data in banks but also their ecosystems" (Interview 3).* Related to data quality and availability is old IT infrastructure. Some years ago, *"banks have cut on their IT spending" (Interview 3)* and now suffer from *"technical debt"* (Interview 5).

Moreover, constraints arise from the customer perspective. This skepticism was described as people being generally willing to share data, but not with their banks. *"There is a paradox situation where people are hesitant to share data with regulated institutions. Everything can be a big scandal. But in the end, there are almost no limits when it comes to sharing their data online" (Interview 10).*

4.2. Future developments

Social Scoring – implications for Germany

Eighty percent of experts considered German adoption of a system similar to the Chinese social credit scoring as unlikely. The main reason experts concluded this pertained to the regulatory frameworks around data protection within the EU. The EU AI Act explicitly prohibits Social Scoring and enforces strong regulations for AI within credit scoring. In the EU *"ethical questions are in the focus and it is also good that these ethical questions are leading the discussion" (Interview 10).* Moreover, 30% cited the different cultural sensibility within the German population as a reason why Germany is unlikely to adapt China-like scoring structures. *"People go on the streets when it comes to Covid vaccinations or the Covid app that tracks infections. So, I think people would definitely protest"* (Interview 3). Another expert claimed that *"even simple things like highway cameras to detect stolen cars are not possible in Germany" (Interview 5).* It would need a *"political overthrow"* (Interview 8) to change these attitudes. The difference in awareness also stems from historical experience including Germany's history of state authority and power abuse.

One expert further mentioned the course of China's politics that changed the image of China within the Western nations. *"China went too far with certain things. […] they have manipulated statistics and have often fooled their people into believing that they have some economic growth. Four years ago, I could have imagined that Germany would copy a few things from China. However, China's reputation has suffered greatly in recent years, so that something like this can no longer be politically introduced in our country" (Interview 2).*

Reasons stated were regulatory requirements specifically the AI Act and different levels of state power, with the latter granting higher autonomy to the population. With higher autonomy, legal compliance was mentioned also. The Chinese system works based on issuing rewards or punishments, which is *"not necessary in our system" (Interview 8).* Therefore, most experts did not see the German System developing along the lines of the Chinese.

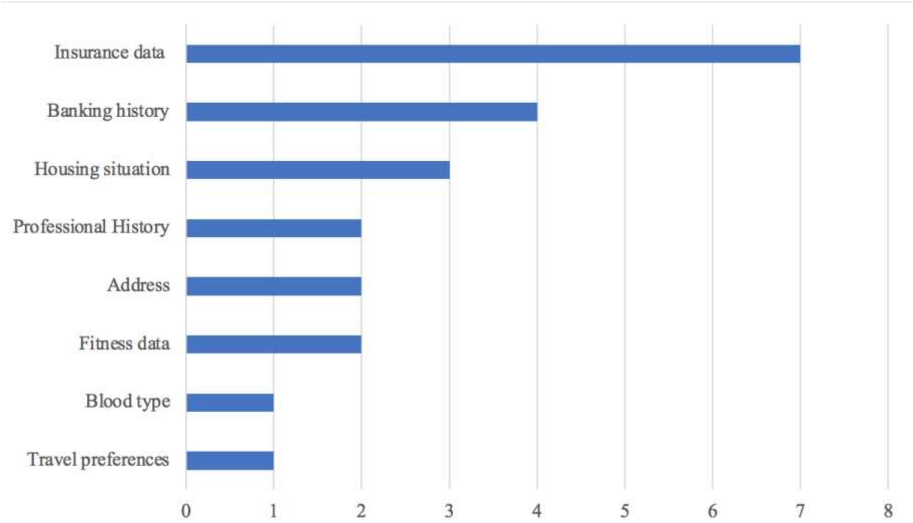
Two experts stated they can imagine a future where Germany follows a system similar to China's Social Scoring System. However, this is in the very distant future. *"If every day I move a picture for one millimeter, at one point it will hang at a different wall" (Interview 7).* When it comes to sharing personal data, two experts saw a trend to share more. *"Customers provide* *more and more insight into private data"*. They do not read data clauses thoroughly, and customer cards are adopted carelessly without thinking of consequences.

In addition, experts were asked to rate the usefulness of collecting behavioral parameters, like making your bed in the morning, for credit scoring. Here, experts stated that this question has to be seen from a purely logical and an ethical perspective. Coming from a logical point of view, as soon as correlations and causal relationships have been proven in large-scale studies, behavioral parameter can be useful. *"Thinking of my conversations in Asia [...] using social media data one can ask 'why are they using this factor?' But they could prove it with a large test audience, in sample out of sample" (Interview 2).* From an ethical point of view, this data is *"none of a bank's business" (Interview 9).*

<u>Willingness to share non-traditional data: expert perspective</u>

Experts were asked which non-traditional data customers are most likely to share with their banks. The word "insurance" received the most mentions. This refers to data that is already being assessed by insurers. However, experts did not link this to copying this data, but rather to learning from individual sub-areas and procedures from insurers. *"Banks could look into the insurance sector to learn from them, as there is more piloting happening" (Interview 4).* Another example from the insurance area is measuring driving behavior for risk assessment (Interview 4 & 5). Financial data was named four times, specifically previous banking history. Experts argued that barriers concerning sharing financial data are low when previously shared with a different bank. Moreover, three experts mentioned housing, referring to information about renting vs. owning and paying rent on time. In addition, two experts stated that address and fitness data are likely to be a shared. The latter was justified by the fact, that people already like to share fitness data on social media. For instance, there was *"a trend to post your running statistics with your network" (Interview 3).* Two experts mentioned professional history as data points customers would be willing to share with their banks. Individual mentions were blood type and travel preferences, both stated in Interview 7.

Figure 7: Overview of non-traditional data



Experts were also asked if they expect stop-parameters. All experts stated they believe stop-parameters will be vital for using AI. Three experts invoked the German AGG (Eng. anti-discriminatory law). This law names age, ethnical origin, religion, disability or sexual orientation as protected data, as it can lead to *"generalizing groups of people" (Interview 1).* Another interviewee referred to health data, claiming a distinction between fitness data and data related to illnesses. *"Having a bank know that I am getting sick before me knowing is a hard stop. Imagine being declined for a loan because your bank predicts your probability of having a heart attack" (Interview 3).* Another point addressed is that German laws grant high autonomy to customers regarding their own data. For instance, people can determine whether data should be deleted after use.

Human interaction: expert perspective

The last interview question related to human interaction in future scenarios. Ninety percent of the experts stated that they do not believe employees within credit departments will become redundant. It is more probable that a hybrid scenario will prevail. Small-volume credit decisions are automated, while large-volume loans still require the final decision of a human. Different threshold values were indicated. For instance, Expert 8 stated 10,000€, while Expert 9 thought that 80,000€ was the threshold value. As Expert 8 specified, in retail banking the role of the employee is crucial due to high risks. In the end, for both retail and commercial banking *"you need employees to drive AI based credit scores, because you have biases and discriminatory issues in every AI model".* Expert 6 described this interaction as following: *"a computer can give a green or red score, but in the end the decision is made by a human. The employee can approve a red score or decline a green score".*

<u>Additional insights</u>

Thirty percent of experts compared data usage of big tech firms and banks. *"For retail banking, if you compare it to the use of data by the big tech firms of the US, we cannot use our data. As these firms we know more about our customers than Amazon does. Amazon knows only the transactional data of you as a person, we know everything." (Interview 9).* Closely connected to that matter, they addressed people's *"inconsistency" (Interview 10*) when it comes to sharing data. While some individuals are willing to share personal information with big tech firms or other companies, they hesitate to share it with financial institutions. Subsequently, experts gave insights into how banks treat data they collect. Even if more data is used in the future, "*one must keep in mind that banks are basically a system to protect data. And they have done this for the last 300 years in perfect manner. It's extremely rare that a bank is hacked or does not use their data very carefully […] (Interview 9).* It is precisely because of this security that customers value traditional banks. Expert 9 further described what appears to be a recurring trend. While FinTechs with more advanced technologies initially appear more attractive, when it comes to large credit needs customers go back to their savings bank. *"A bank is like a nuclear power station. Nothing is allowed to happen. Therefore, it is regulated. History doesn't repeat, but it rhymes. FTX is the perfect case where [a firm] with bad incentives and no experience totally blows things up. At the end, regulations will always catch up with you".* This description emphasizes the strong position of banks and, above all, underlines the advantage they have over new competitors.

When it comes to assessing future developments, time horizon plays a crucial role with 80% of experts deeming a scenario similar to the current situation in China as unlikely. Looking further into the future, some of interviewees said that they could also imagine a different scenario. For instance, one expert stated that *"in the distant future"* this scenario is not completely out of the question.

Two experts mentioned that assessing alternative data can also benefits other areas. For instance, it could combat criminal behavior. These criminal actions can relate to banking but also day-to-day life. For the latter, it is imaginable *"using drones for crime prevention […] in subareas or in cities with where there is a lot of crime in the area" (Interview 2).* Related to banking, it could mean identifying *"gambling behavior of a person or any money withdrawals of a person at a time, where usually the society is sleeping" (Interview 10).*

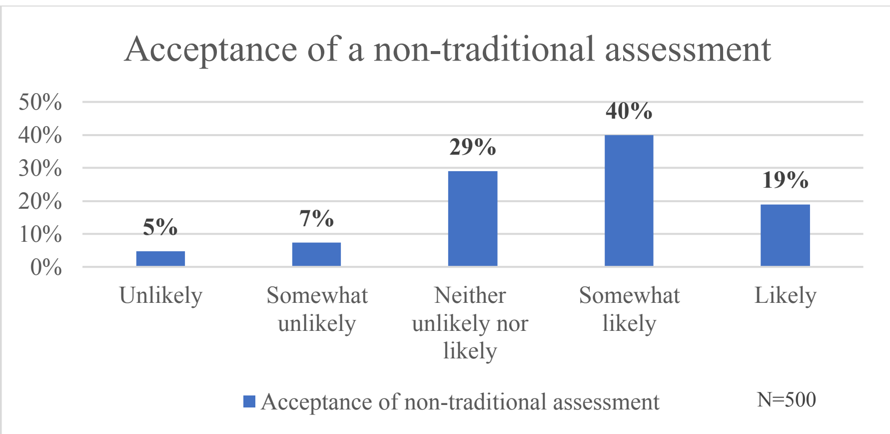
Lastly, 50% stated that using AI in credit scoring relates to the type of loan. For commercial banking, using AI-driven models can be difficult as there are not enough data for training. Looking at retail banking, financing volumes for consumer credits are lower, but the number of transactions is high. This creates a more reliable data basis. For commercial clients, *"weak AI could support in filtering external information, to see what is relevant for the object and what are cash flow relevant information" (Interview 1).*

4.3. Consumer perspective

To understand whether the perspective of industry experts overlaps with attitudes of customers, the survey measured factors influencing adoption of AI-driven credit scoring and willingness to share different types of personal information.

According to the adapted TAM Model, the dimensions perceived usefulness, risk and need for interaction were assessed (Curran & Meuter, 2005). To measure willingness to accept a non-traditional assessment, a five-point Likert scale was used. Figure 8 shows the answer distribution. The largest proportion assigned themselves to being "somewhat likely" to use the assessment (40%). Nearly one-third of respondents were in the "neither unlikely nor likely" group and the third largest group was likely to use the non-traditional assessment. Accordingly, there was a tendency for respondents to be rather positive about non-traditional assessments. The strong placement in the middle demonstrates that a large portion holds no strong opinion towards this topic.

Figure 8: Response distribution (acceptance of AI-scoring)



To further assess adoption, a dummy variable was formed to ensure a clear separation between potential users and non-users. For this purpose, the data set was corrected for the middle value, reducing the sample to n=354. Subsequently, a t-test was conducted between both groups. Table 6 provides an overview of the t-test results. As proposed by Curran & Meuter (2005), perceived usefulness and risk both showed statistically significant p-values on the 1% level. This leads eto rejecting the null hypothesis “the true difference in means in equal to zero” for both dimensions. The alternative hypothesis, proposing that the true difference is not equal to zero, can be accepted. Consequently, users who accepted non-traditional assessments were significantly more likely to perceive it as useful. Congruent with Curran & Meuter, risk was assessed regarding how secure a person felt while using a service (2005). Thus, users who accept a non-traditional assessment are significantly more likely to feel secure (and vice versa). To measure effect strength, Cohen’sD was assessed. Perceived usefulness had a strong effect with 1.5667, whereas risk had a middle-strong effect (0.475).

Need for interaction was also predicted as impacting customer adoption. Therefore, the null hypothesis was: The true difference in means is equal to zero. Looking at the p-value of a conducted Welch t-test, the difference in means for human interaction did not statistically significantly differ, as the p-value exceeded the 5% confidence interval. Consequently, having a lower need for human interaction in banking experiences does not lead to a higher chance of accepting non-traditional scorings. Thus, the null hypothesis has to be rejected and the alternative hypothesis accepted.

Table 6: Results T-tests by groups

	Mean (Credit Yes)	Mean (Credit No)	p-value	Cohen’sD
Risk	3.925	3.552	0.009***	0.475
Perceived Usefulness	3.792	2.667	3.3873e-13***	1.566
Need for Interaction	3.745	3.514	0.139	-

***1% significance level

Furthermore, a t-test explored a difference in mean values for men and women (Table 7). The test is significant on a 1% level. Therefore, the null hypothesis can be rejected and the alternative hypothesis, that there is a true difference in means, can be accepted. Statistically, men accepted an alternative credit assessment at a significantly higher level whereas women were more hesitant. Overall means were relatively high, showing, on average, a somewhat comfortable mindset towards an alternative assessment. The strength of this difference is rather weak, as a Cohen’sD value of 0.268 indicated.

Table 7: Results T-tests by gender

	Mean (Women)	Mean (Men)	p-value	CohensD
Scoring acceptance	3.56	3.90	0.001***	0.268

***1% significance level

Table 8: T-test results difference in age

	Mean (Credit Yes)	Mean (Credit No)	p-value	CohensD
Age	40.09	43.65	0.07	-

In addition, a t-test examined whether age plays a role in assessment adoption. Participants who reject non-traditional credit assessments were, on average, 3.56 years older. However, this difference showed no statistical significance. The null hypothesis, suggesting the true difference in means is zero, cannot be rejected. Accordingly, age does not play a determinative role.

<u>Additional insights</u>

To further understand factors influencing the decision to accept or decline an assessment based on non-traditional data, three Chi^2 Tests were conducted. In two cases (education and type of bank) there is no statistical dependence detectable. Consequently, the null hypothesis (implying statistical independence) cannot be rejected. A higher level of education does not influence the credit decision. Nor are customers of digital banks more positive about the assessment than those of traditional banks.

Only the frequency of social media shows statistically significant dependency. The p-value of the Chi^2 indicates a significance on the 5% level. As one cell frequency was below 5, a Fisher-test was added to reduce bias. The p-value increases slightly but is still significant on the 5% level. This leads to the conclusion that social media use and credit decision are interdependent. The strength of this effect is in the weak range (0.2149).

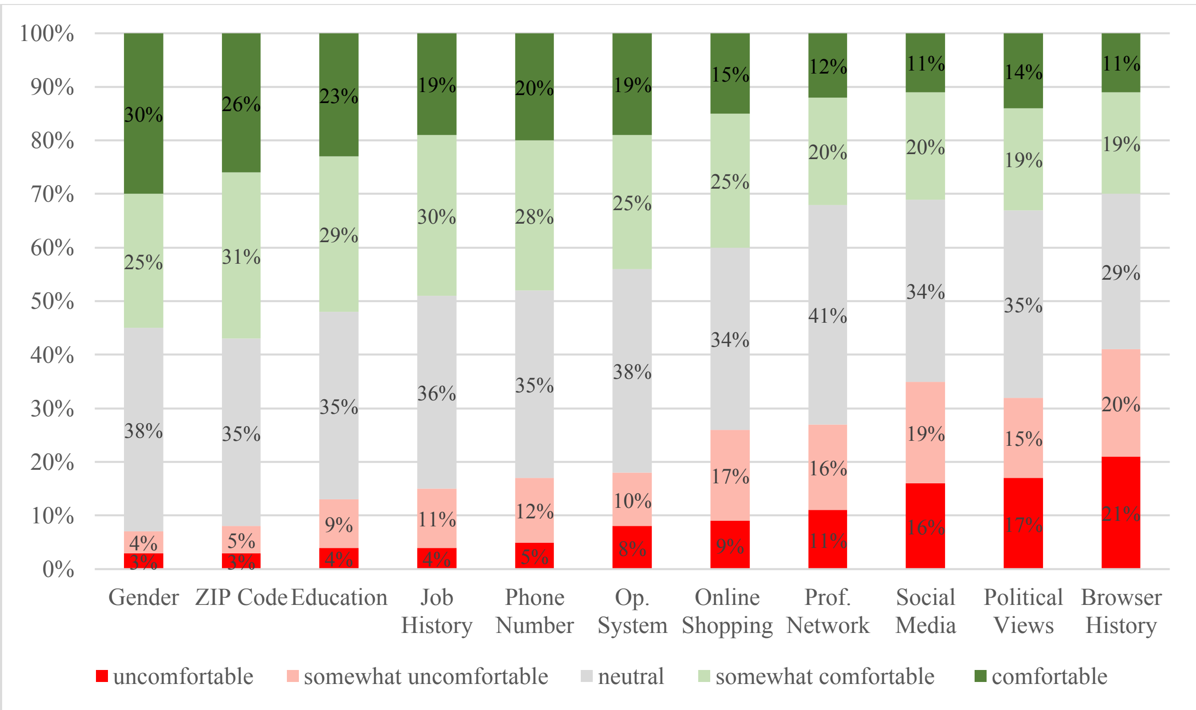
Table 9: Chi² results (additional)

	Value	df	p-value	CohensW
χ^2 Social Media	16.348	7	0.0221**	-
Fisher-Test	-	-	0.0345**	0.2149
χ^2 Bank (Traditional or Digital)	0.4216	4	0.981	-
χ^2 Education	1.5225	2	0.4671	-

**5% significance level

<u>Willingness to share data: customer perspective</u>

Figure 9: Answer distribution of non-traditional data



Quantitative data examined which data customers were willing to share with their banks. As Figure 9 shows, the majority of participants arranged their willingness to share different data types in the middle. This indicates that participants tend to have no extreme opinions on sharing non-traditional data.

Data points which participants were at least somewhat comfortable to share were gender (55%), ZIP code (57%) and education (52%). Data where participants felt at least somewhat uncomfortable to share were browser history (41%) and political views (33%). The two most controversial data points were sharing social media or professional network data where 34% felt rather uncomfortable to share this data while 32% felt rather comfortable. The same applied to professional networks, where 27% voted rather comfortable and 29% rather uncomfortable. Another prominent finding is that participants were similarly likely to disclose their operating system (45%) as their Online Shopping data, with a 5% difference.

Moreover, the more controversial the data point (E.g., social media or political views), the more ambivalent the opinions. For instance, 32% of respondents stated they felt somewhat uncomfortable sharing their political views with their banks. At the same time, 33% felt at least somewhat comfortable sharing this information.

4.4. Future scenarios

To synthesize the quantitative and qualitative data as well as findings from the literature review, the following chapter proposes possible future scenarios based on insights gained.

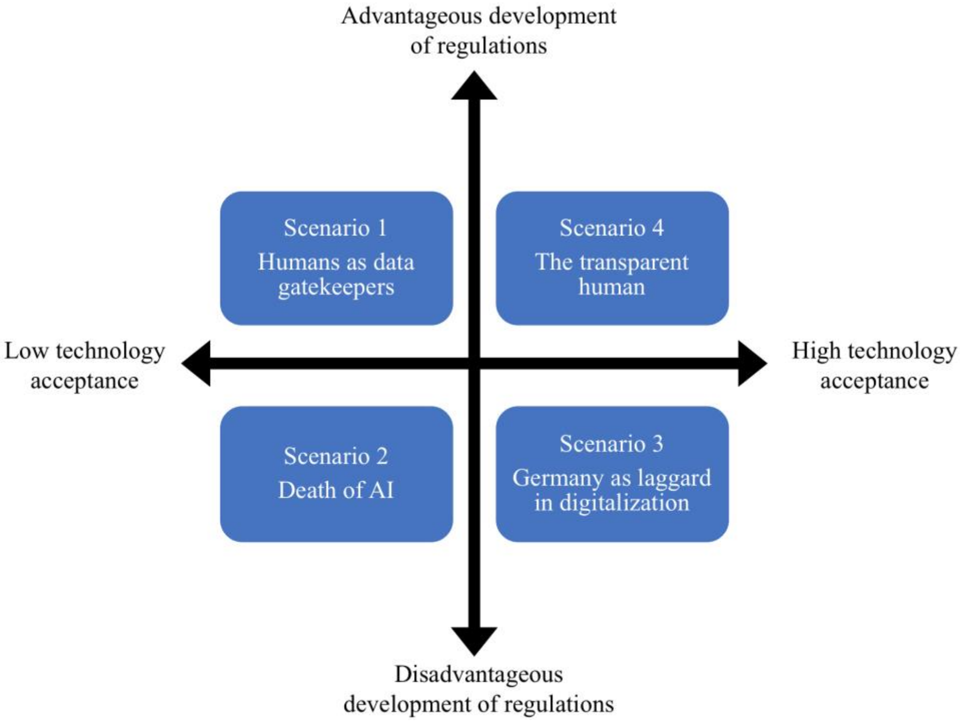
To assess future scenarios, the 2 x 2 matrix approach was chosen. This method is useful when only two criteria are sufficient to predict future developments (Schwartz, 1996). According to Schwartz, all important driving forces have to be noted first. DF's are identified by conducting a STEEP[6] analysis. Afterwards, all DF's are evaluated based on their degree of uncertainty and importance.

As a result, regulatory developments and customer adoption constitute the axes of the matrix. The first was used as it was most named as a barrier by experts and the latter was based on customer opinions assessed in the survey. These factors produced four possible future scenarios.

The four scenarios offer a more differentiated outlook on the future than other methods producing three outcomes usually based on a base case, a pessimistic scenario and an optimistic. The foregoing method is prone simply to choosing the middle scenario. Moreover, this approach ensures that the two top DFs are incorporated in all scenarios (Amer et al., 2013).

[6] Social, Technological, Economic, Environmental, Political

Figure 30: 2x2 matrix



Scenario 1 – Humans as data gatekeepers

With advantageous regulatory developments in the EU and Germany, AI-driven creditworthiness assessments will no longer be seen as high-risk applications. Banks have greater regulatory scope for action and increase their spending in testing and implementing models driven by non-traditional data. The level of digitization in the bank's credit department is increasing. However, customer skepticism about sharing non-traditional data with banks will prevail. This future scenario emphasizes banks as incentive-providing entities. Banks have to grant customers convincing arguments for sharing their data. Interviewee 7 describes this scenario as follows: *"We still haven't reached the point where people know the value of their data. It has to be clear: I am sharing this data and in return I receive something beneficial. We have to address [...] this delta with granting transparency."*

In this scenario, customers are the driving forces for adoption. If incentives cannot emphasize the benefits of sharing data, banks risk developing services not accepted by the market.

Scenario 2 – AI wipe-out

The third quadrant implicates a scenario where scoring that includes non-traditional data becomes impossible. Disadvantageous regulatory developments restrict using AI in credit scoring. Moreover, low technology acceptance will have a negative impact on the adoption on consumer level. Customers are skeptical of banks and fear data misuse. Alternative assessment solutions would not be accepted by the market and banks gain no advantage from using AI in credit scoring. Furthermore, trust in new technologies is low on all sides, therefore *"humans remain unbeatable" (Interview 6)* when it comes to assessing credit risk. These developments paired together will lead to a wipe out of AI in credit scoring. Banks will go fully back to manual credit assessments and will completely rely on human decisions. Banks that have already invested in new models and systems are left with sunk costs. Fixed costs for manual processing remain high. The negative attitude of customers is also reflected in other areas.

Scenario 3 – Germany as laggard in digitalization

High technological acceptance but disadvantageous regulatory developments will lead to barriers being aggravated. The EU AI Act will still rate AI-driven credit assessments in the high-risk category. However, the hardening of barriers stems primarily from German legal regimes. Compared to other European countries, German institutions continue to practice an *"extreme interpretation" (Interview 7)* of EU guidelines, specifically GDPR enforcement. In this scenario, regulatory developments hinder innovation within credit departments. Banks will allocate financial resources to innovation associated with other departments. A delta forms between customer readiness to disclose more data and services offered by banks. Risks emerge both at the micro level of the banks and at the macro level of the country. Germany falls behind in digital transformation in the credit sector, while other European countries start to offer more assessments based on non-traditional data. The impact of this scenario is high, as German banks' reputations in terms of technological advancement will suffer. Threats grow from FinTechs exploiting the delta. However, Fintechs will *"sooner or later be caught up with regulations" (Interview 9)* and developments will impact the Start-Up scene.

Scenario 4 - The transparent human

The last scenario includes advantageous regulatory developments and high acceptance among customers. The scope of action widens for banks, allowing them to test and implement models driven by non-traditional data. Loans will be granted solely based on machine-made decisions. Without stop parameters, banks *"operate opportunistically [...], what is legally allowed is tested and used" (Interview 1*) and can collect large amounts of data, similar to tech corporations. Assessment criteria include data collected from smart devises. Moreover, social media networks are accessible, and banks work closely with third-party data collectors to get a comprehensive picture of their customers. In this scenario the possibility of a situation similar to China is highest. Developments largely depend on the extent to which ethical guidelines play a role. Gains from this scenario relate to the ability to provide financial resources to people who were previously excluded. However, state power will rise in this scenario. People risk becoming slaves of their data. Every action must be weighed against the possibility: could this information be used against me? Therefore, the question of ethical boundaries remains.

5. Discussion

The discussion is divided into two parts. First, findings from the literature, the survey and the expert interviews are merged. In this way, a comprehensive picture can be drawn. Then, the scenarios developed are discussed. This involves evaluating the plausibility of each scenario and deriving implications.

5.1. Discussion of triangulation

The drive to compete in AI and significantly shape global policies has led to a global AI race. As expounded in the literature review, studies suggest that the EU is on the verge of losing to its main competitors China and the US. The German banking landscape has some backlogs too. As one study revealed, 9% of executives surveyed believed their company was not well positioned to implement and use AI (PwC, 2020). These findings coincide with the results of the expert interviews. **A low degree of advancement was identified** and barriers like regulatory requirements, data availability, and lack of trained personnel were cited. Regulatory requirements in particular play a major role in the area of credit scoring, as it is considered a high-risk application. In conclusion, future adaptions of the EU AI Act and data privacy legislations will significantly influence how AI is incorporated in credit scoring as well as how comfortable banks feel to pilot projects in this area.

Nevertheless, high risks might raise customer skepticism as well. Taking the quantitative data collected into account, a comprehensive picture of customer acceptance emerges. Experts pointed to people's lack of willingness to share data as one barrier. Qualitative data suggest a differentiated view of this barrier. On one hand, perceived usefulness and risk affect the decision to accept a non-traditional assessment. Alternatively, certain benefits[7] were connected

[7] Time saving, access to financial resources independent from financial history

with a non-traditional assessment. These findings indicate non-static willingness to share information, which is congruent with expert opinions. Even though customer skepticism forms a barrier, this barrier can be overcome, such as by consciously highlighting *"the value of data transparency" (Interview 2)* or disclosing data protection practices. Moreover, the survey demonstrated that on average a high percentage of people are indifferent about sharing specific data points. These findings indicate that customers either do not have enough knowledge to form an opinion or they do not care. These wavering opinions were also congruent with the experts. The "inconsistency" mentioned whereby people share personal data with rather untrustworthy firms while simultaneously being hesitant to share it with regulated institutions was noteworthy.

Additionally, experts mentioned two data points retrieved from the survey too. Interviews indicated professional history and address as data points customers would be willing to share with their bank and 57% of respondents were at least somewhat willing to share their ZIP code. The willingness to share professional history depended on the type of information. For instance, people were more willing to share their professional history than sharing professional networks like LinkedIn. When exploring potential stop parameters, several experts pointed towards the German ADG. However, customer data showed that gender and ZIP code were the two data point with the highest willingness to share. This potentially highlights people's lack of knowledge, leading to inconsequent sharing habits with different institutions. For instance, when people share their ZIP code, they might not be aware that living in a low-price area could lead to discrimination. This further strengthens the need for robust models controlling for biases and strong ethical guidelines.

Looking at developments in China, no tendencies towards a big-brother-like scenario were detected by experts. Looking into the distant future, two experts stated that they believed credit assessment with rewards and punishments was possible. Predicting this scenario largely depends on one's stance towards state power in the future. As researchers like Harari suggest, AI benefits totalitarian systems (Harari, 2018). In Germany, any rise in state power is viewed with suspicion due to "*Stasi history, as well as a different mindset because of our democratic values" (Interview 2).* AI advancement therefore remains a balancing act, specifically with respect to credit. In general, experts favor a hybrid-scenario where bank personnel still have high decision-making authority. While assessment based on non-traditional data can be considered, the final decision is based on human intervention (Interview 9).

Lastly, motives identified like risk optimization and cost reduction are ultimately dependent on the bank's business model. It is not clear that banks should increase pilot programs with alternative models based on our findings. With commercial clients, every mistake carries a significantly higher risk because the transaction size is higher.

5.2. Discussion of future scenarios

To decide which of the scenarios is most likely to occur, the theoretical foundation of the Potential Surprise Theory by Ernest Shackle was used. PST focuses on plausibility instead of probability. According to Shackle, probability is problematic because it implies that all plotted potential outcomes together have a probability of 100%. However, if new developments or insights require adding another outcome, probabilities of former scenarios have to be reduced. This problem is referred to as the additivity problem. By choosing plausibility, the problem is circumvented. PST allows to add or reject scenarios based on the researcher's subjective determinations about the future (Derbyshire, 2017).

Following Shackle, the four scenarios will be evaluated according to their degree of surprise on a scale from zero to five (Derbyshire, 2017). Zero refers to a scenario being highly plausible and five being implausible. The evaluation is based on current conditions. To assign a value to each scenario, we draw upon findings from the literature and the qualitative and quantitative data. Table 10 provides an overview of the four scenarios, their surprise scale values and arguments that determined the scale position.

Table 10: Scenario analysis assessing the least surprising scenario

Scenario	Surprise scale	+ Arguments strengthening plausibility & - Arguments weakening plausibility
Humans as data gatekeepers	2	+ Some banks already start to test (E.g. Interview 5 or Deutsche Bank[8]) + Role of human as data gatekeeper is already common in other areas, E.g., using Google or Amazon[9] - Other areas like asset management or compliance already higher advanced, potential spill over to credit - Relaxation of regulatory enforcements unlikely in the near future
AI wipe-out	5	- Pressure from FinTechs, other countries and incumbents already piloting with AI in credit scoring - Savings potentials favor piloting with alternative scoring models - In low-volume area automation easier to implement - Qualitative data do not indicate any trend in terms of declining willingness to disclose data
Germany as laggard of digitalization	1	+ Survey reveals tendency that people are not as consistent when it comes to sharing their data + Strict interpretation of EU-guidelines + Findings from global AI-race, suggesting a weak position of Europe in terms of AI
The transparent human	4	- 80% of experts believe China-like scenario is unlikely - All experts believe there will be built in stop-parameters - Current EU AI Act prohibits Social Scoring - Current government form and Germany's historical imprint limits state power + 2 experts suggest that a big-brother-like scenario could occur in the distant future

Looking at all four scenarios, the third has the lowest value on the surprise scale. It describes Germany as laggard of digitalization. The most important factor that makes this scenario the least surprising pertains to the conditions that presently exist. For instance, experts stressed that Germany is already starting to fall behind, while *"[...] Spain or France are more advanced in terms of technologies like AI" (Interview 5)*. From a customer perspective, the survey showed that opinions towards sharing non-traditional data are not as extreme as expected. Moreover,

[8] In December 2022 Deutsche Bank announced a collaboration with NVIDIA to foster innovation in the area of AI. Targets: "advanced risk management, voice AI, better fraud detection and advanced customer service" (Deutsche Bank, 2022)

[9] From additional findings

regulatory developments were identified as the strongest barrier, making AI advances rather unlikely.

The scenario of humans as data gatekeepers was given a 2 on the surprise scale. What makes this scenario not surprising is that humans already act as data gatekeepers in other industries. For instance, companies like Google collect vast amounts of data on their customers. In this case it is up to the individual to define what they want to share. Moreover, legal structures like the GDPR favor this scenario. GDPR grants each individual the right to declare which data they are willing to disclose and how long this data is allowed to be stored. However, tendencies towards advantageous regulatory developments for AI are not evident at the moment.

A scenario where AI in credit scoring is completely eradicated was considered to be rather surprising with a value of four. As other countries already deploy AI more extensively and FinTechs continue to challenge the old ways of banking, a complete ban appears impossible. Moreover, Expert five confirmed AI-driven models are being used and also Deutsche Bank recently announced to work alongside with Nvidia to accelerate AI-innovation, including in assessing credit. Hence, even though occurring slowly, first steps towards non-traditional scoring models are being made.

The most surprising scenario is the fully transparent human where 80% of experts stated that under current conditions a China-like scenario is impossible. The other 20% referred to a possibility, not taking current conditions into account. As the EU AI Act has prohibited social scoring, an extreme scenario like this is not feasible in the near future.

6. Conclusion

After discussing the findings, the following chapter provides an overall conclusion. Implications for future research and managerial implications are discussed as well as a critical appraisal of this work.

6.1. General conclusion

The literature suggested that the EU, including Germany, may be losing ground to the US and China in terms of AI development. This led to the question of whether this is also the case in the area of credit scoring and to what extent non-traditional data is used by German banks. This research question was addressed with a mixed-method approach.

Expert interviews were conducted to determine the current state of development of AI-driven scoring models at German banks. In addition, questions were asked about possible future developments. To measure acceptance by potential customers, a survey was conducted and analyzed. An adapted TAM framework was used as the basis, as well as queries to determine willingness to share various data points for credit scoring. Lastly, scenario analysis was conducted, leading to a least surprising future scenario.

All the data pointed towards **low advancement of AI in credit scoring in the German market.** Non-traditional data is rarely incorporated in scoring models. While clear motives for deploying AI-driven scoring models were identified (like risk optimization and cost reduction), regulatory barriers hinder banks from exploiting these advantages. Furthermore, lack of available data and qualified personnel with AI knowledge make it difficult to advance the technology.

This finding was supplemented by the user perspective whereby **no strong rejection attitudes can be identified** with regard to use of alternative scoring methods. Instead, a tendency towards neutrality was observed, which can be attributed to customers having not enough knowledge to answer questions or their having no opinion about them.

Looking at future developments, the findings indicate development of a big brother-like scenario as unlikely. More likely is the scenario where German banks have to be aware of not falling behind in implementing new technologies for credit scoring.

The overall findings complement other studies examining the use of AI across departments in banks. This dissertation serves as an important contribution to classify AI-advancement for the specific use case of lending. Nonetheless, these findings constitute rudimentary research that is still at an early stage. Other factors influencing future developments need to be examined on both the banking and customer side.

6.2. Managerial implications

One implication for managers in banking is to establish collaborations with insurers. Pilot projects could benefit from knowledge exchange between the two industries. For both parties, accurate risk assessment is vital and experts suggested that the insurance industry already tests possible solutions. In addition, strategic partnerships can be valuable to overcome barriers. For example, to mitigate lack of IT expertise, partnerships like Deutsche Bank's with NVIDIA can be advantageous.

Secondly, with perceived usefulness and drivers for customer adoption, the indicators are apparent. For instance, banks should focus on ensuring that customers know their data is in safe hands and communicate advantages of the regulated banking sector more effectively. As experts stated, banks have an advantage in terms of being well prepared to meet regulatory requirements and keep data save. This advantage can be used effectively when new competitors enter the market.

Lasty, the scenarios developed can help managers to understand potential challenges for each possible scenario. Managers should pay close attention to scenarios that are less surprising and should evaluate implications for their institutions. This analysis can serve as a basis for decision-making when it comes to deciding on pilot projects.

6.1. Future Research & Limitations

For qualitative insights, ten interviews were conducted. Interviewees had either a banking or consulting background. To gain a more multilayered picture, experts from other areas could have been consulted. For instance, perspectives from regulatory bodies, preferably from Germany, the EU and outside the EU, would have been beneficial. Additionally, political perspectives from ruling parties could have enriched research further. Due to the time constraints associated with this work, these discussions were not feasible.

The interviews also revealed a distinction in AI progress for banks focused on retail clients versus those with commercial customers. Future research could look at each banking vertical in more detail and ascertain relevant drivers. Additionally, the interviews could have had a wider scope and compared individual EU member states. For instance, one interviewee suggested that the level of development in Spain was already higher than in Germany[10].

The TAM framework was adapted from online banking. The factors influencing adoption of online banking might not be fully transferable to credit scoring. From a customer's point of view, research on AI in the credit area is still in its infancy and survey respondents do not fully grasp the various implications. In the future, a more robust framework determining customer adoption of AI in financial services should be developed. In this work, the focus was on the three dimensions commonly assessed in banking research (risk, perceived usefulness, and need for interaction). Further testing and including more dimensions influencing the intention to adopt will increase the validity of the model.

Another limitation lies in the conservative attitude of Germans towards taking out loans. While the average level of debt of an American household in 2021 was $96,371 (Horymski, 2021), Germans owe, on average, 31,100€ (Statista Research Department, 2022). The tendency towards neutral views could relate to the fact that some of the respondents never came into contact with the topic of credit before or that they were generally debt-averse, biasing responses. Future research could filter respondents according to their credit situations to develop cohorts with greater similitude.

Lastly, this dissertation revealed that customers need to perceive alternative assessment mechanisms as useful and that they should be able to understand the benefits of sharing information. Future research could focus on understanding which advantages[11] contribute most to the decision-making processes of customers.

[10] Interview 9
[11] E.g., lower interest rates, time savings, access to financial resources with limited banking history

7. References

Amer, M., Daim, T. U. & Jetter, A. (2013). A review of scenario planning. *Futures*, *46*, 23–40. https://doi.org/10.1016/j.futures.2012.10.003

Aust, S. (2021, October 1). *What is SCHUFA? Understanding credit score in Germany*. EVERESTATE. Retrieved January 19, 2023, from https://www.everestate.com/blog/credit-score-germany

Authers, J. (2018, September 7). Financial crisis 2008: A reporter's memories from the front lines. *Financial Times*. https://www.ft.com/content/c2d50f1c-b18c-11e8-8d14-6f049d06439c

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R. & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Barreto, I. (2009). Dynamic Capabilities: A Review of Past Research and an Agenda for the Future. *Journal of Management*, 36(1), 256–280. https://doi.org/10.1177/0149206309350776

BBC News. (2020, January 16). A quick guide to the US-China trade war. *BBC News*. https://www.bbc.com/news/business-45899310

Bertelsmann. (n.d.). China's Social Credit System. *Bertelsmann-Stiftung*. Retrieved November 3, 2022, from https://www.bertelsmann-stiftung.de/fileadmin/files/aam/Asia-Book_A_03_China_Social_Credit_System.pdf

Ceron, R. (2019, December 5). *AI, machine learning and deep learning: What's the difference?* Servers & Storage. https://www.ibm.com/blogs/systems/ai-machine-learning-and-deep-learning-whats-the-difference/

Chan, L., Hogaboam, L., & Cao, R. (2022). *Applied Artificial Intelligence in Business: Concepts and Cases (Applied Innovation and Technology Management) (English Edition)*. Springer.

Chan, T. F. (2018, May 22). China's social credit system has blocked people from taking 11 million flights and 4 million train trips. *Business Insider Nederland*. https://www.businessinsider.nl/china-social-credit-system-blocked-people-taking-flights-train-trips-2018-5?international=true&r=US

Castro, D. & McLaughlin, M. (2021, January). *Who is Winning the AI Race: China, the EU, or the United States? - 2021 Update*. Center for Data Innovation. Retrieved January 9, 2023, from https://www2.datainnovation.org/2021-china-eu-us-ai.pdf

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Reed Business Education.

Clover, C. (2016, January 19). China: When big data meets big brother. *Financial Times*. https://www.ft.com/content/b5b13a5e-b847-11e5-b151-8e15c9a029fb

Curran, J. M., & Meuter, M. L. (2005). Self-service technology adoption: comparing three technologies. *Journal of services marketing*, 19(2), 103-113. https://doi.org/10.1108/08876040510591411

Dai, X. (2020). Toward A Reputation State: A Comprehensive View of China's Social Credit System Project. *Social Credit Rating*, 139–163. https://doi.org/10.1007/978-3-658-29653-7_7

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Deutsche Bank. (2022, December 7). *Deutsche Bank und NVIDIA schließen neue KI-Partnerschaft*. Retrieved December 29, 2022, from https://www.db.com/news/detail/20221207-deutsche-bank-partners-with-nvidia-to-embed-ai-into-financial-services?language_id=3

Derbyshire, J. (2017). Potential surprise theory as a theoretical foundation for scenario planning. *Technological Forecasting and Social Change*, *124*, 77–87. https://doi.org/10.1016/j.techfore.2016.05.008

Dick, S. (2019). Artificial Intelligence. *Harvard Data Science Review*, 1(1). https://doi.org/10.1162/99608f92.92fe150c

Doran, D., Schulz, S. & Besold, T. R. (2017). What Does Explainable AI Really Mean? A New Conceptualization of Perspectives. arXiv (Cornell University). http://export.arxiv.org/pdf/1710.00794

European Commission. (2021). Regulation of the European Parliament and of the council laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain union legislative acts. In *EUR-Lex* (2021/0106/COD). Retrieved December 23, 2022, from https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52021PC0206

European Parliamentary Research Service. (2022, November 29). *What Think Tanks are Thinking*. European Parliament. Retrieved January 12, 2023, from https://www.europarl.europa.eu/RegData/etudes/BRIE/2022/739219/EPRS_BRIE_TT_739219_Deglobalisation_final.pdf

Future of Life Institute (FLI). (2022, November 28). *The Artificial Intelligence Act*. The Artificial Intelligence Act. Retrieved November 24, 2022, from https://artificialintelligenceact.eu

German Parliament. *Data protection regulations in the area of Business Activities of Banks and Savings Banks.* (2008). Deutscher Bundestag (WD 3-3000-317/08). Retrieved January 20, 2023, from https://www.bundestag.de/resource/blob/422740/b152c5809b4fbb4390deb8ba7c7adaf6/wd-3-317-08-pdf-data.pdf

Harari, Y. N. (2018, May 18). *Why fascism is so tempting -- and how your data could power it* [Video]. TED Talks. https://www.ted.com/talks/yuval_noah_harari_why_fascism_is_so_tempting_and_how_your_data_could_power_it

Hentzen, J. K., Hoffmann, A., Dolan, R. & Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. *International Journal of Bank Marketing*, *40*(6), 1299–1336. https://doi.org/10.1108/ijbm-09-2021-0417

Horymski, C. (2023, February 24). Credit Scores Steady as Consumer Debt Balances Rise in 2022. *Experian*. Retrieved February 28, 2023, from https://www.experian.com/blogs/ask-experian/consumer-credit-review/

Isaacson, W. (2012). The real leadership lessons of Steve Jobs. *Harvard business review*, 90(4), 92-102.

Jack, E. P., & Raturi, A. S. (2006). Lessons learned from methodological triangulation in management research. *Management Research News*, 29(6), 345–357. https://doi.org/10.1108/01409170610683833

Johns, R. (2005). One Size Doesn't Fit All: Selecting Response Scales For Attitude Items. *Journal of Elections, Public Opinion & Parties*, *15*(2), 237–264. https://doi.org/10.1080/13689880500178849

Lam, T. (2021). The People's Algorithms: Social Credits and the Rise of China's Big (Br)other. *The New Politics of Numbers*, 71–95. https://doi.org/10.1007/978-3-030-78201-6_3

Leon, P. G., Ur, B., Wang, Y., Sleeper, M., Balebako, R., Shay, R., Bauer, L., Christodorescu, M., & Cranor, L. F. (2013). What matters to users? *Proceedings of the Ninth Symposium on Usable Privacy and Security - SOUPS '13*. https://doi.org/10.1145/2501604.2501611

Li, D., Tong, T. W. & Xiao, Y. (2021). Is China emerging as the Global Leader in AI? *Harvard Business Review*, *18*. https://hbr.org/2021/02/is-china-emerging-as-the-global-leader-in-ai

McLaughlin, M., & Castro, D. (2021, January). *Who is winning the AI race: China, the EU, or the United States?* https://www2.datainnovation.org/2021-china-eu-us-ai.pdf

McKinsey. (2021, March). *AI-powered decision making for the bank of the future*. McKinsey & Company: Global Banking & Securities. https://www.mckinsey.com/~/media/mckinsey/industries/financial%20services/our%20insights/ai%20powered%20decision%20making%20for%20the%20bank%20of%20the%20future/ai-powered-decision-making-for-the-bank-of-the-future.pdf

O'Reilly III, C. A., & Tushman, M. L. (2008). Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Research in organizational behavior*, 28, 185-206.

Ostrom, A. L., Fotheringham, D. & Bitner, M. J. (2019). Customer Acceptance of AI in Service Encounters: Understanding Antecedents and Consequences [Springer Nature Switzerland AG 2019]. In *Handbook of Service Science, Volume II (Service Science: Research and Innovations in the Service Economy) (English Edition)* (2nd edition., 77–103).

PwC. (2020, May). *How mature is AI adoption in financial services?* PricewaterhouseCoopers GmbH. https://www.pwc.de/de/future-of-finance/how-mature-is-ai-adoption-in-financial-services.pdf

Quan-Haase, A., & Young, A. L. (2010). Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging. *Bulletin of Science, Technology & Society*, *30*(5), 350–361. https://doi.org/10.1177/0270467610380009

Raso, F. A., Hilligoss, H., Krishnamurthy, V., Bavitz, C., & Kim, L. (2018). Artificial intelligence & human rights: Opportunities & risks. *SSRN Electronic Journal*, (2018-6).

Rowley, J. (2012). Conducting research interviews. *Management Research Review*, 35(3/4), 260–271. https://doi.org/10.1108/01409171211210154

Russell, S. J. & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach*. Prentice Hall.

Schufa Credit Score Report in Germany. (2020, January 2). *Banks Germany*. https://banks-germany.com/schufa-credit-score

Schwab, K. (2017). *The fourth industrial revolution*. Currency.

Schwartz, P. (1996). *The Art of the Long View: Planning for the Future in an Uncertain World* (1.). New York: Double Day.

Snapes, L. (2022, October 14). Kanye West: bank JP Morgan Chase cuts ties with rapper. *The Guardian*. Retrieved November 10, 2022, from https://www.theguardian.com/music/2022/oct/14/kanye-west-bank-jp-morgan-chase-cuts-ties-with-rapper

Stanford Institute for Human-Centered Artificial Intelligence (HAI). (2021). *Global AI Vibrancy Tool: Who's leading the global AI race?* Stanford University. Retrieved January 14, 2023, from https://aiindex.stanford.edu/vibrancy/

Statista Research Department. (2021, November 15). *Mean individual debt level in Germany from 2006 to 2022*. Statista. https://de.statista.com/statistik/daten/studie/353616/umfrage/individuelle-schuldenhoehe-in-deutschland/

Sulaiman Abdallah Alsheibani, Yen Cheung, & Chris Messom. (2018). Artificial intelligence adoption: AI-readiness at firm-level. *Pacific Asia Conference on Information Systems*, 37.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, 18(7), 509-533.

Wachter, S., Mittelstadt, B., & Floridi, L. (2017). Transparent, explainable, and accountable AI for robotics. *Science Robotics*, *2*(6). https://doi.org/10.1126/scirobotics.aan6080

Wholey, J. S., Hatry, H. P., & Newcomer, K. E. (2010). *Handbook of Practical Program Evaluation*. John Wiley & Sons.

Wolford, B. (2020, May 26). *Do consumers know their GDPR data privacy rights?* GDPR.eu. Retrieved December 28, 2022, from https://gdpr.eu/consumers-gdpr-data-privacy-rights/

8. Appendices

Appendix A: Interview 1

Occupation: Innovation Manager

Q	How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)
A	2
Q	Is your organization using AI in credit scoring? (Yes/No) If no, are you planning to incorporate it? No, but we are actively discussing it and have it on the agenda
Q	What are the most important motives for implementing AI in credit scoring?
A	• Reducing the workload for employees • Simplification of the decision: many regulatory provisions, difficult for employees to keep on track with newest regulations
Q	Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service
A	1. Compliance 2. Credit/Asset Management/Customer Service is not used
Q	What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?
A	• IT infrastruture is still poled towards old systems • Human talent: hard to get data scientists, ml engineers, difficult to draw towards banking
Q	US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit?
A	No
Q	China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?
A	• Hopefully not, but not completely unrealistic • Some measurements are already leaning towards it • Could be a scenario in 20 years

Q Which non-traditional data are customers most likely to share with their bank?

A
- Rent payments/ phone payments could be used
- Everything that insurances are using could be very interesting for banks
- Everything related to financial aspects
- Social Media low tolerance to share

Q Will there be built in stop parameters (|E.g., Health Care data excluded)

A
- In an ideal scenario each person can decide themselves
- Banks will use whatever the regulatory instances allow/prohibit

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- To make human completely redundant: next 10-12 years will be difficult in terms of firm credit
- In retail/standard credit employees might become redundant (E.g. China Alipay)

Appendix B: Interview 2

Occupation: Director Financial Services Technology

Q How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)

A 1-2

Q What are the most important motives for implementing AI in credit scoring?

A
- Cluster Analysis -> finding new factors (non-traditional)
- Time saving
- Differentiation between commercial and retail business

Q Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service

A
1) Compliance
2) Customer Service
3) Asset Management ((especially Portfolio Analysis/Scenario Analysis/ Pricing history etc.)
4) Credit

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Blackbox
- Data privacy difficult for smaller institutions
- AI talent: many talents are leaning towards start-ups/fintech, hard for banks to reach right candidates. Better for young talents very difficult with senior talents

Q	US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit?
A	• Thinking of Asia with regard to credit or insurance who use Facebook/Twitter for data gathering: if you can proof the influence of a factor with a non-biased analysis / how robust is my model -> then Yes!
Q	China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?
A	• Social Scoring is not seen negatively by Chinese people • Historical differences between China and Germany make comparison of systems difficult • China's reputation has suffered during the last years, now less likely European countries adapt parts of the scoring methods • AI could be beneficial to combat criminal behavior
Q	Which non-traditional data are customers most likely to share with their bank?
A	• Data from insurance (in a limited way) • What is the value of my data? • Transactional data
Q	Will there be built in stop parameters (E.g., Health Care data excluded)
A	• The bigger my data pool and there are no legal restrictions: first analysis, looking at responsible AI
Q	Will we still need bank employees in AI-driven credit scoring, or will they become redundant?
A	• No, looking at insurance (E.g., lemonade) there are already insurers that provide fully AI-driven services • Smaller credits will be provided with AI (E.g., Chatbot) • The more complex (E.g., commercial credit) bank employees are still important • Employees who did credit up to 100.000 might get retrained for advisory of larger credit volume • Deposit Insurance Fund • How many advisors do I have at the moment, what are 10% smallest credits, provide working teams who then find AI driven solutions • Whole process must be automized, it is not enough to simply develop a scoring model

Appendix C: Interview 3

Occupation: Senior Consultant

Q How would you rate the advancement of AI in credit scoring in Germany?
(From 1 being not advanced at all to 5 being very advanced)

A
- Some companies are testing
- 2-3

Q What are the most important motives for implementing AI in credit scoring?

A
- Cost reduction
- Automation (reducing manual work)
- Make better decisions

Q Please rank banking areas regarding their adoption of AI from highest to lowest.
Asset Management, Credit, Compliance, Customer Service

A
1. Customer Service
2. Asset Management
3. Compliance
4. Credit

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Knowlegde & human talent
- Data quality
- Regulatory barriers
- Explainable decisions/ black box

Q US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
Are people who make their beds less likely to default on credit?

A
- Technically it is feasible
- Would mean a lower risk

Q China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?

A
- Not likely in the near future
- Culture in EU is very different
- People might protest

Q Which non-traditional data are customers most likely to share with their bank?

A
- Anything related to financials
- Tracking data from devices (how many steps taken, location)
- Employment history (E.g., LinkedIn)
- difference between actively or passively sharing data

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A
- Yes
- Health data as hard stop (E.g., being able to predict likelihood of a heart attack)

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- Special cases will still demand bank employees
- Low-volume decisions bank employees will become redundant (E.g., until 10.000 Euros)

Appendix D: Interview 4

Occupation: Senior Consultant (Financial Services consulting)

Q How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)

A 2-3

Q What are the most important motives for implementing AI in credit scoring?

A
- Risk minimization
- More personalized products

Q Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service

A
1. Customer Service
2. Compliance
3. Asset Management
4. Credit

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Regulatory barriers
- Explainable decision/black box
- Data availability
- Customer skepticism

Q	US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit?
A	Is there a correlation? If yes, from a rational perspective it could make sense
Q	China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?
A	• Hopefully unlikely, no trend in that direction • Need rewarding and punishing factor -> not necessary in Germany as (most) people follow the law
Q	Which non-traditional data are customers most likely to share with their bank?
A	• ZIP • Look at what insurers assess • Age
Q	Will there be built in stop parameters (E.g., Health Care data excluded)
A	• Factors that could lead to a certain discrimination (problem of bias in data)
Q	Will we still need bank employees in AI-driven credit scoring, or will they become redundant?
A	• In small volume loans: will become redundant • High volume (E.g., mortgage) bank employee still important

Appendix E: Interview 5

Occupation: PO Big Data & AI

Q	How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)
A	4
Q	Is your organization using AI in credit scoring? (Yes/No) If no, are you planning to incorporate it? Yes
Q	What are the most important motives for implementing AI in credit scoring?
A	• Risk minimization • More efficient

- Time saving
- Cost reduction

Q Please rank banking areas regarding their adoption of AI from highest to lowest.
Asset Management, Credit, Compliance, Customer Service

A
1. Compliance
2. Credit Scoring
3. Customer Service
4. Asset Management

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- AI is not always better
- Old data infrastructure with poor data quality ("technical debt")
- Regulatory barriers

Q US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
Are people who make their beds less likely to default on credit?

A
- There has to be a causal relationship (backed by large-scale studies
- Reliability of a person is an important parameter, so in case there is a causal relationship yes

Q China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?

A
- (hopefully) unlikely

Q Which non-traditional data are customers most likely to share with their bank?

A
- Data already shared with insurer
- Difficult: data from private life

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A
- Critical data that could lead to discrimination from ADG (religion, disability, sexual orientation)
- Customer have to understand the benefit of sharing the data

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- No, employees rather have different tasks (E.g., analyzing more complicated cases)

Appendix F: Interview 6

Occupation: Managing Director Credit Risk

Q	How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)
A	2
Q	Is your organization using AI in credit scoring? (Yes/No) If no, are you planning to incorporate it?
A	No, but have a team piloting projects
Q	What are the most important motives for implementing AI in credit scoring?
A	/
Q	Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service
A	1. Asset Management 2. Customer Service 3. Compliance 4. Credit
Q	What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?
A	• Regulators demand accountability • Lack of data availability - "We have not many credit defaults. This is something we are proud of. However, this A) lowers our motives to incorporate AI and B) makes it difficult to develop models as there are less default use cases to train AI" • Budget restrictions
Q	US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit?
A	• No statistical evidence that there is a correlation • Without evidence doesn't make sense to use it
Q	China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?
A	• Maybe in the distant future (+20 years) • Difficult to implement in Germany, already difficult to incorporate useful measurements like highway cameras

Q Which non-traditional data are customers most likely to share with their bank?

A
- Logical inconsistency -> not willing to share data with their bank but other institutions
- How many bank accounts
- Don't think that on a voluntary basis customer want to share much

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A
- Difference between retail and commercial clients
- Anything discriminatory

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- Human stays most reliable
- However, might be different in +20 years
- At the end human will have the final decision making power

Appendix G: Interview 7

Occupation: Speaker of the management board

Q How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)

A 3

Q Is your organization using AI in credit scoring? (Yes/No)
If no, are you planning to incorporate it?
No, as we are focusing on credits for large-scale projects, which is a highly individual business

Q What are the most important motives for implementing AI in credit scoring?

A
- Cost reduction
- More objective risk assessment (taking out the human factor)
- Reduction of Alpha and Beta mistake (Alpha = bad credits are not being recognized; Beta = good credits are not realized). If decision is not precisely calibrated risks might be hindered but opportunities will pass by

Q Please rank banking areas regarding their adoption of AI from highest to lowest.
Asset Management, Credit, Compliance, Customer Service

A
1. Compliance
2. Asset Management
3. Credit
4. Customer Service

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A

- War for talent
- Regulatory: Germany is a special case. EU decides something, Germany executes on a highly granular level
- People responsible for developing solutions or consult banks have never actually worked in a bank
- AI creates power shifts and dependencies

Q US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
Are people who make their beds less likely to default on credit?

A

- It can be useful
- Shows reliablility of a person

Q China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?

A

- China: Aggressive shift
- Germany: successive measures that grant more authority to the state
- Scenario can become reality

Q Which non-traditional data are customers most likely to share with their bank?

A

- Blood type
- Religion
- Car brand
- Housing situation (Flat vs house, tenant vs owner)
- Vacation destinations

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A

- People will share if the benefit is clear
- Likely the state will still provide restrictions

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A

- Yes, it is possible

Appendix H: Interview 8

Occupation: Digital Value Creation Manager

Q How would you rate the advancement of AI in credit scoring in Germany?
(From 1 being not advanced at all to 5 being very advanced)

A 2

Q What are the most important motives for implementing AI in credit scoring?

A
- More personalized product offers
- Better risk assessment
- Automation
- Greater efficiency

Q Please rank banking areas regarding their adoption of AI from highest to lowest.
Asset Management, Credit, Compliance, Customer Service

A Not enough insights in all these areas to rank

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Data Quality and availability
- Regulatory: EU AI Act
- Digital talent: difficult for banks to acquire data scientist

Q US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
Are people who make their beds less likely to default on credit?

A
- Might be useful but unrealistic scenario

Q China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?

A
- Technically feasible
- EU regulatory point towards more conservative direction, therefore rather unlikely

Q Which non-traditional data are customers most likely to share with their bank?

A
- Address
- Employment history (E.g., LinkedIn)
- Age
- SCHUFA score
- Information from previous credits
- Credit card payments from previous banks
- But only if customer

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A
- Everything that is allowed will be tested
- Likely that there will be regulations on exlainability (which factor contributed how much?)

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- Special cases will still demand bank employees
- Low-volume decisions bank employees will become redundant (E.g., until 10.000 Euros)

Appendix I: Interview 9

Occupation: Senior Economist

Q How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)

A 2

Q Is your organization using AI in credit scoring? (Yes/No)
If no, are you planning to incorporate it?
No, but several AI pilot projects

Q What are the most important motives for implementing AI in credit scoring?

A
- Cost reduction

Q Please rank banking areas regarding their adoption of AI from highest to lowest.
Asset Management, Credit, Compliance, Customer Service

A
1. Compliance
2. Customer Service
3. Asset Management
4. Credit Scoring

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Budget restrictions (low margins)
- Regulatory
- Lack of Resources

Q US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
Are people who make their beds less likely to default on credit?

A
- Not useful
- These kind of data are none of the bank's business

Q China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?

A
- Highly unlikely because of EU AI act

Q Which non-traditional data are customers most likely to share with their bank?

A
- Health data: already shared with insurances

Q Will there be built in stop parameters (E.g., Health Care data excluded)

A Yes. Dependent on: Parties in the government, DSGVO and preferences/history of a country/culture. Regulatory will have high impact on stop parameters

Q Will we still need bank employees in AI-driven credit scoring, or will they become redundant?

A
- No, depends on type of credit
- High-volume credits bank employees will still be important
- AI-models need to be built by humans and have biases

Appendix J: Interview 10

Occupation: Director Analytics Practice

Q How would you rate the advancement of AI in credit scoring in Germany? (From 1 being not advanced at all to 5 being very advanced)

A 2

Q What are the most important motives for implementing AI in credit scoring?

A
- Cost reduction
- Usage of new data sources
- Reducing discrimination
- Innovation pressure

Q Please rank banking areas regarding their adoption of AI from highest to lowest. Asset Management, Credit, Compliance, Customer Service

A
1. Customer Service
2. Asset Management
3. Compliance
4. Credit

Q What are barriers which might hinder the development of AI banking applications in Germany? What can be done to overcome these barriers?

A
- Regulatory (GDPR in Germany, AI act in EU)
- Lack of Human capital
- Explainabilty & interpretability
- Consumer expectations (consumers favor regulatory guidelines how to use AI)
- Benefits of AI and providing data is not clear to customer

	• Legacy IT system in banks is not sufficient, difficult to renew IT infrastructure
Q	US Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring? Are people who make their beds less likely to default on credit?
A	• If linked to reliability and having finances in order then yes
Q	China is extensively using behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for the elderly, spreading false information etc.) Can a scenario like this become reality for Germany as well?
A	• There is a tendency in Germany to look and discuss new models • On the other hand, ethical questions are leading the discussion • Therefore, rather unlikely
Q	Which non-traditional data are customers most likely to share with their bank?
A	• If you have a certain benefit (E.g., special product offering or interest) customers are more likely to share their data • Account history to categorize data • There are no limits to what people are willing to share on the internet, but when it comes to sharing it with a financial institution they get skeptical
Q	Will there be built in stop parameters (E.g., Health Care data excluded)
A	• Data from ADG (Eng. Anti-discriminatory law) E.g., Origin, Religion, Disability, sexual identity
Q	Will we still need bank employees in AI-driven credit scoring, or will they become redundant?
A	• Not for all banks will become redundant • Difference between retail and commercial credit

Appendix K: Interview Questions

Block	Question
Adoption of AI at firm level Based on Alsheibani, Cheung & Meesom (2018)	**Q1** Is your Institution currently using AI in Credit Scoring?
	Q2 Please rank the following Banking Areas in their adoption speed of AI Applications from highest to lowest -> Asset Management, Credit, Cybersecurity, Compliance, Customer Service
	Q3 What are the most important motives to implement AI in credit scoring?
	Q4 Using AI in Credit Scoring will provide relative advantage in comparison to my competitors (Consent Likert Scale)
	Q5 What are barriers which might hinder the development of AI applications?
	Q6 How would you rate the advancement of AI in Credit Scoring in Germany?
Comparison between Germany and China Based on chapter 2.1. & Raso et al. (2018)	**Q7** A famous quote by Admiral McRaven states "If you want to change the world, start off by making your bed". Making your bed is supposed to be correlated with productivity, a greater sense of well-being, and stronger skills at sticking with a budget. Can such conclusions be useful for credit scoring?
	Q8 China is already making use of behavioral parameters to assess credit worthiness. The Chinese government goes so far as to use a social scoring that rewards or punishes certain behaviors (E.g., caring for elderly, spreading false information etc.). Can a scenario like this become reality for Germany as well?
	Q9 Which non-traditional data are most likely to be included first?
	Q10 Will there be built in stop parameters (E.g., certain data that will be excluded?)

L: Quantitative Survey

Question	Answer	Source
Demographic Questions (Age, Gender, Education)		Sulaiman et al., (2018)
How often do you use Social Media? (Facebook, Instagram, Snapchat…)	8-point Likert Scale (never to multiple times per day)	Quan-Haase & Young (2010)
Which type of bank are you mainly using?	a) Traditional Bank b) Digital Bank	-
Imagine the following scenario: You have recently moved to Germany and your new job is outside the city. You need to buy a car to get to work. To do this, you apply for a loan from a reputable German bank. Due to your insufficient credit history, the bank offers you an alternative credit check (as described previously). The payment and interest conditions remain the same. State the likelihood of approving to this assessment.	Likert Scale: 1-5	-
State your approval to the following statements: *Usefulness* I believe this credit assessment is useful/has a higher quality/is more efficient	Likert Scale: 1-5	Curran & Meuter (2005)
Need for interaction Personal contact to a bank advisor is important to me. Bank employees help me solve problems a machine could not. I value personal contact to my bank advisor	Likert Scale: 1-5	Curran & Meuter (2005)
Risk I assume that my credit check is secure and private. My interests come first. My data will be treated confidentially	Likert Scale: 1-5	Curran & Meuter (2005)
How comfortable are you with sharing the following data points with your bank?	Likert Scale 1-5 (very comfortable – very uncomfortable)	Leon et al., (2013)