Applications of Artificial Intelligence in Sustainability Assessment and Risk Management in European Banking

Dominic Strube[1][a], Christian Daase[2][b] and Jennifer Schietzel-Kalkbrenner[3][c]
[1]*Hochschule Wismar, University of Applied Sciences, Technology, Business and Design, Wismar, Germany*
[2]*Institute of Technical and Business Information Systems, Otto-von-Guericke University, Magdeburg, Germany*
[3]*Berufliche Hochschule Hamburg, Hamburg, Germany*

Keywords: Credit Risk, Artificial Intelligence, ESG Assessments, Data Analysis, Sustainability.

Abstract: This article addresses the evolving dynamics of sustainability risks in the banking sector, with a particular focus on the integration of artificial intelligence (AI) in risk assessment and management. The impact of environmental, social, and governance (ESG) factors on creditworthiness evaluation is examined and highlights the complexities and challenges that financial institutions face in adapting their risk management frameworks to accommodate these sustainability risks. The paper underscores the difficulties banks face in effectively incorporating ESG considerations, primarily due to the absence of standardized methodologies and the intricate interplay between ESG components and banking risk elements. In this context, the potential of AI applications is critically assessed, especially those utilizing large datasets, to identify complex patterns and correlations that often elude human analysts. This investigation includes both the opportunities AI presents in enhancing the precision of risk assessments and the associated challenges, including issues related to the opacity and control of complex, self-learning AI models, as well as regulatory and privacy concerns. Finally, the article presents a schematic approach through which banks can actively integrate sustainability risks into their risk management strategies, emphasizing the need for ongoing research and development in this crucial area.

1 INTRODUCTION

In Europe, banks are increasingly facing the challenge of considering so-called *sustainability risks*. These risks, originating from environmental, social, or corporate governance sectors, can have negative impacts on a company's assets, finances, earnings, and reputation (BaFin, 2020). Due to these potential impacts, regulatory requirements demand that banks systematically identify, assess, manage, and monitor these risks. The European Banking Authority (EBA), as the overarching body, sets binding standards and guidelines for the banking sector. As early as 2020, the EBA published a guide on environmental and climate risks (European Central Bank, 2020). National supervisory authorities such as the German Federal Financial Supervisory Authority (BaFin) or the French Prudential Supervision and Resolution Authority (ACPR) issue their own standards and regulations, some of which are still optional, others mandatory. A central challenge for many banks is the lack of uniformity in these methods and a scarcity of robust data allowing for reliable assessment. Especially for smaller banks, these methods are particularly challenging due to insufficient data (Strube et al., 2023). Against this backdrop, this article explores how AI can contribute to assessing sustainability risks, particularly in terms of credit default risks. The goal is to optimize decision-making processes in credit granting and to identify at-risk credits early on. Our research questions (RQs) are:

RQ1: How do sustainability risks influence the creditworthiness of companies?

[a] https://orcid.org/0000-0003-3017-5189
[b] https://orcid.org/0000-0003-4662-7055
[c] https://orcid.org/0009-0009-3782-4963

Strube, D., Daase, C. and Schietzel-Kalkbrenner, J.
Applications of Artificial Intelligence in Sustainability Assessment and Risk Management in European Banking.
DOI: 10.5220/0012498700003717

In *Proceedings of the 6th International Conference on Finance, Economics, Management and IT Business (FEMIB 2024)*, pages 25-32
ISBN: 978-989-758-695-8; ISSN: 2184-5891

RQ2: To what extent is AI used in banks, and what challenges and potentials does the integration of AI offer in the risk management of banks?

RQ3: What might an AI-based model look like to effectively identify sustainability risks?

Section 2 begins with an introduction to the definition and typology of sustainability risks. This is followed in section 3 by an examination of the application of AI in banking and its specific use in capturing sustainability risks. The advantages and disadvantages of these technologies, especially in the context of banking data, are discussed in section 4. The fourth section presents which data can be used for an AI-supported assessment and concretize some use cases. The article concludes with a summary of the key findings.

2 BACKGROUND

Sustainability risks pertain to events or conditions associated with environmental, social, or corporate governance sectors (BaFin, 2020). The manifestation of these risks may have real or potential adverse effects on the net assets, financial condition, and operating results, as well as on the reputation of a company. The general consensus in science and practice for quantifying sustainability aspects includes consideration of the following criteria (Gleißner and Romeike, 2021):

Environment: This refers, among other things, to the eco-friendliness of a company's activities, including energy consumption, use of renewable energy, climate change strategies, and emission reduction.

Social: This includes the social impact of a company, both internally and external which examples. Such as human rights standards, prohibition of child and forced labor, equal opportunities, diversity, and promotion of further education.

Governance: This involves the structure and management of a company with respect to sustainable practices, including issues such as sustainability management, anti-corruption measures, quality management systems, financial sustainability, and risk management.

Sustainability risks are not a separate type of risk, but factors that influence existing risks such as credit risk, market price risk, liquidity risk, operational risk, , strategic risk or reputational risk (BaFin, 2020). In this article, the focus lies on analyzing credit default risk in the context of these interdependencies. Sustainability risks in the areas of climate and environment are also divided into physical risks and transition risks. Physical risks arise directly or indirectly from climatic changes, such as those immediately resulting from extreme weather events like storms, floods, or prolonged drought periods (Salisu et al., 2023). According to the latest estimates from the PESETA IV project (Projection of Economic impacts of climate change in Sectors of the European Union based on bottom-up Analysis) for instance, the economic losses due to drought periods in the European Union and the United Kingdom amount to about 9 billion euros annually. Spain suffers the greatest losses, with 1.5 billion euros per year, followed by Italy with 1.4 billion euros and France with 1.2 billion euros. Transition risks, on the other hand, are associated with political, legal, or technological changes aimed at mitigating climate change (Salisu et al., 2023). The pricing of CO^2, which can lead to increased operating costs, especially for companies with high emissions, is cited here as an example (Cammalleri et al., 2020). These discussed relationships are summarized in Figure 1.

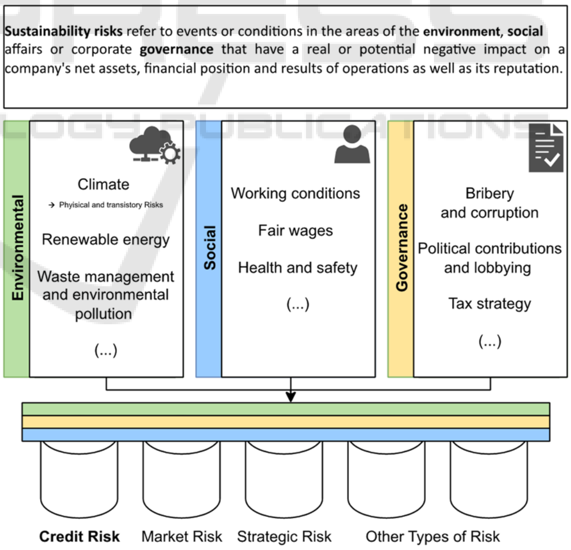

Figure 1: Exemplary presentation of the impact of ESG aspects on traditional risk categories.

Recently, political players in Europe have stepped up their efforts to create a regulatory framework to integrate sustainability risks into banks. In particular, the European Union (EU) and national financial regulators require banks to actively integrate sustainability risks into risk management using a wide range of methods. A study by Strube et al. (2023)

which 112 regional banks in Germany were surveyed on the topic of sustainability integration, shows that many banks still have considerable difficulties in effectively integrating sustainability risks into their risk management. Figure 2 indicates that 85.7% of respondents see the lack of standardized methods for identifying and assessing sustainability risks as the main obstacle. In addition to a lack of employee expertise (53.6%) and staff shortages (49.1%), the unwillingness of loan customers to cooperate (45.5%) and a lack of obligations to cooperate (37.5%) are also seen as obstacles to risk assessment. In addition, the participants emphasize a lack of general sustainability data and good technical systems for data collection and analysis. Overall, it is clear that the main barriers lie primarily in the complexity of the (still) difficult to grasp correlations between sustainability aspects and banking risks, as well as in a lack of data.

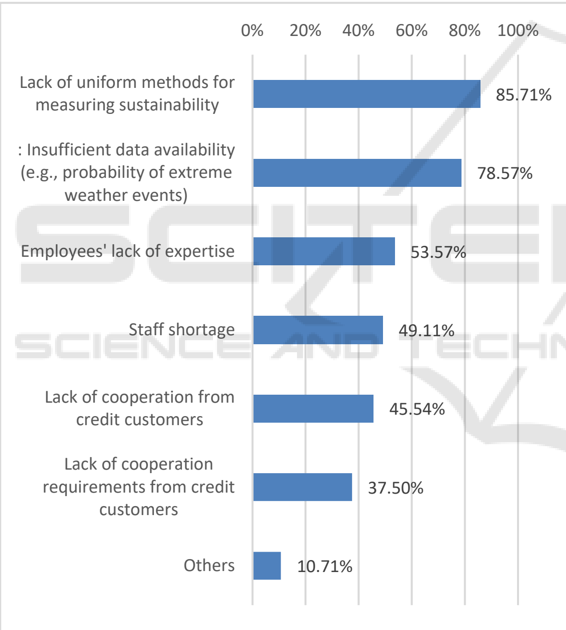

Figure 2: Challenges in the measurement of sustainability aspects (Strube et al., 2023).

Regarding RQ1, no conclusive evidence has been found to support the assertion that there is a direct correlation between sustainability aspects and the probability of default. Some studies indicate a positive correlation between a rating-score and financial performance indicators (Friede et al., 2015; Whelan et al., 2020). Also regarding small and medium enterprises (SME), a study with a 20-year data set from the Web of Science shows a positive correlation between sustainability and financial performance, a result confirmed by further research (Bartolacci et al., 2020; Hammann et al., 2009; Herrera Madueño et al., 2016). Additional investigations, such as those by Lucia et al. (2020), employing complex statistical models like random forests and inferential approaches, confirm a positive relationship between sustainable corporate practices and financial performance metrics, particularly equity and total capital returns. In addition, (Gupta et al., 2021) demonstrated, through the use of machine learning algorithms, that higher ESG performance correlates with improved profitability, as reflected in superior profit margins. These metrics significantly influence banks' accuracy of default calculations. Furthermore, many studies identify not only a positive impact on financial indicators but also a positive correlation between the probability of default on loans and bonds and companies with a sustainable orientation tend to pay lower risk premiums when borrowing, thus being more creditworthy (Bauer and Hann, 2010; Höck et al., 2020; Schneider, 2011; Weber et al., 2008). A study by Meles et al. (2023) examines the relationship between green innovation and lower default risk using a sample of European companies from 2003 to 2019, finding that green innovations reduce risk, especially in market-oriented countries and for non-publicly traded companies.

However, much of this research is based on evaluations by sustainability rating agencies, whose aim is to present the sustainability level of companies on the basis of a rating grade. Although the financial supervisory authorities recommend the use of such ratings, they do so with reservations (European Central Bank, 2020). There is a low concurrence between the various ratings, mainly due to the lack of standardized measurement procedures for ESG (Berg et al., 2019; Dimson et al., 2020; Strube and Daase, 2023). Therefore, the direct link between high ESG ratings and actual sustainability is uncertain. Additionally, studies show that larger companies tend to achieve higher ESG scores, which may reflect their more extensive resources and imply a systematic disadvantage for smaller firms in the rating process (Drempetic et al., 2020). This makes it difficult for banks, which often have a large number of SMEs in their loan portfolios. Moreover, it is questionable which aspects of the rating precisely influence the probability of default and to what extent. For example, a balanced gender quota leads to an improved rating (in the Governance category), but the direct link to financial stability is uncertain.

In summary, it is evident that sustainability aspects almost certainly have a significant impact on the probability of default on loans, but the specific connection between these factors is very unclear. The following will illustrate how AI can enhance the analysis and assessment of sustainability factors as well as the estimation of default risks by processing large volumes of data, recognizing patterns in complex information, and developing predictive models.

3 STATUS QUO OF AI IMPLEMENTATION IN BANKING: POTENTIAL AND LIMITATIONS

This chapter addresses the question of why and how AI is currently being used in banks. Given the abundance of data available in banks, such as economic indicators, account movements, and customer-specific data, banks are ideally suited for the use of AI to train algorithms for identifying patterns and connections. This includes applications like detecting criminal activities, customer-centric marketing, or improving the accuracy of credit ratings (Sadok et al., 2022). According to a study of PricewaterhouseCoopers (PwC) conducted in 2023, which surveyed 114 financial sector companies, including half banks, it was found that the financial services industry sees the greatest benefits in practical and operational improvements, with a clear focus on efficiency and cost reduction (Dagianis et al., 2023). Many processes in banks are very resource and labor-intensive. For instance, the credit granting process is a complex procedure that requires various interactions between the front and back-office areas and the credit customer, depending on the type of loan. The use of AI in the banking industry primarily offers the potential to reduce costs and increase revenues by automating repetitive processes. According to the study, AI applications in banks are primarily used in the areas of marketing, sales, IT, and risk management, particularly in managing social media channels (31%), analyzing network threats and malware detection (22%), and in fraud management and anti-money laundering checks (39% and 33%, respectively). In the credit granting process, it accounts for 19%. The integration of AI-based systems in risk modeling, which also includes the incorporation of sustainability aspects, is still in its early stages (14%). In traditional banks, the use of AI in the credit process is not yet particularly pronounced and is conducted through classical, statistical rating systems. Current initiatives regarding the use of AI to capture sustainability

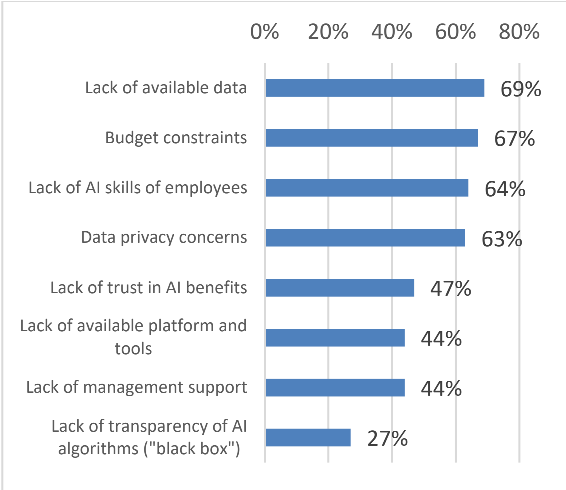

Figure 3: Reasons for not integrating AI (Berns, 2020).

aspects are few, including one by Deutsche Bank (2023), which is working on the introduction of machine learning procedures to classify its business operations as green through an auto-classification system, thereby relieving employees. BNP Paribas has made a database with various sustainability data available as open source and already recommends and uses the use of AI to analyze sustainability (Geng, 2023). The use of AI, despite its numerous application possibilities, also brings several challenges. Firstly, it is essential that in complex, self-learning models, the key parameters are made clearly understandable and controllable (Friedrich et al., 2021). However, with complex algorithms, it is often difficult to understand exactly how they come to a particular decision. This can pose a problem, especially in areas such as creditworthiness assessment, where decisions can have significant impacts on individuals or companies (Sadok et al., 2022). Moreover, banks are under strict regulatory supervision, which expects the internal logic of a rating system to be clear and transparent. If banks use systems that they cannot fully explain, this can lead to compliance issues. There is also the risk of making incorrect decisions. If the system is not fully understandable, there is a danger that faulty or biased decisions are made without being recognized (Sadok et al., 2022). If an algorithm overweights certain indicators of sustainability, such as CO^2 emissions, while neglecting other important aspects like water consumption, biodiversity preservation, or social responsibility, this can lead to a distorted assessment of sustainability. This could favor companies or projects that perform well in certain areas but have deficits in other dimensions of sustainability. For example, Amazon encountered a problem with its AI recruitment tool, which exhibited gender biases. It was discovered that this tool, intended to optimize the hiring process by identifying best resumes, favored men over women. The algorithm apparently detected and then optimized a gender imbalance in technical roles, thereby replicating a societal bias towards men in these positions a (Dastin, 2018).

In a further PwC study, financial companies were surveyed about the challenges they face in implementing AI. As illustrated in Figure 3, the dominant problems are data scarcity and financial constraints. It is somewhat unexpected that banks report a deficiency in data, considering their access to extensive datasets. Nonetheless, it is conceivable that a significant proportion of data within banking institutions may be present in an unstructured format, such as within text documents, electronic mails, or descriptions of transactions. Specifically in the context of sustainability data, there is an acknowledged shortfall, given that banks usually acquire only a restricted range of sustainability-related information directly from their credit recipients. This suggests that the institutions are struggling to acquire the large datasets needed for AI systems and to make the investments required for such technologies. Moreover, the survey reveals that internal expertise and data privacy concerns are significant internal barriers, while external factors such as trust in AI and the opacity of algorithms are weighted less, but remain important concerns for the acceptance and management of AI solutions (Berns, 2020).

4 APPLICATIONS OF AI-SUPPORTED RECORDING IN BANKS

4.1 Technical Requirements

In the previous two sections, we explored the important but complex interplay between sustainability factors, financial risk and AI in banking. It was shown that sustainability-related risks, particularly those related to climate change, almost certainly have an impact on the probability of default on bank loans. However, a systematic and comprehensive understanding of these relationships remains elusive. Artificial intelligence is proving to be an effective tool for deciphering these complex relationships. To date, the use of AI in banks has primarily focused on improving process efficiency, while its integration into risk modeling is a relatively under-researched avenue. This section aims to present different methods that could be used to address the challenges of incorporating sustainability factors into the risk management of European banking institutions.

Data Collection: As mentioned above, many financial institutions face the challenge of providing adequate ESG data. In the initial phase of ESG data collection, the focus is on obtaining relevant data. This is primarily documents and information provided by borrowers, usually in response to regular sustainability requests from financial institutions. In addition, both manual collection and automated web crawling and scraping enable the procurement of company data (Sadok et al., 2022). This includes the automated collection of standardized sustainability reports, information on corporate strategy and reputation. However, the integration of social media activities is not considered practicable, as these sources can be distorted or manipulative in the context of greenwashing. In addition, artificial intelligence can aggregate external data on physical risk indicators such as flood probabilities, meteorological data, groundwater levels and soil conditions. This data is available free of charge in many countries. The recording of potential transitional values, such as upcoming regulatory changes, can also be taken into account.

Data Storage: Cloud computing and related technologies are pioneers of big data applications. The provision of computing and storage resources has itself developed into a business model in recent years. The growing demands associated with big data analytics are increasingly exceeding the technical and financial capabilities of companies (Arostegi et al., 2018) and even scientific institutes (Dai et al., 2012). The motivation for a shift from the *infrastructure-as-an-asset* scheme, in which a company owns the required hardware, to *infrastructure-as-a-service* (IaaS), in which the computing power of external providers is used by transferring inputs and outputs over a network, is recognizable (Arostegi et al., 2018). The market mechanism behind this paradigm shift is a *pay-as-you-go model*, as only the service provided has to be paid for (Dai et al., 2012; Mashayekhy et al., 2014). For example, Commerzbank AG already uses cloud services to store and process large volumes of data (Tomak, 2019).

Data Evaluation and Analysis: An innovative approach would be to use AI to calculate the default probabilities of loans using both traditional rating data and sustainability data. The idea behind this is that AI can better identify and predict the links between a company's sustainability practices and its credit risk. This would mean that the AI would not only look at financial metrics but also ESG-related indicators to provide a more holistic assessment of creditworthiness. This approach could potentially provide more accurate predictions as it takes into account a broader range of risk factors. ESG factors such as environmental behavior, social responsibility and corporate governance can provide important indications of a company's long-term stability and risk profile. By combining this data with traditional financial metrics, AI could create a more comprehensive picture of credit risks, leading to more accurate and reliable default probabilities.

Transparency: As AI is increasingly used in applications that rely on private data of people in a society and impact human lives, the issue of trust in such systems led to the emergence of the term *explainable AI* or *responsible AI* (Daase and Turowski, 2023). Jobin et al. (2019) identify five principles for responsible AI with the ultimate goal of not only making AI applications understandable to the target audience, but also imposing general ethical rules on them. The principles include transparency, justice, non-maleficence, accountability, and privacy. Following these guidelines, data and solutions should avoid any kind of discrimination or bias, comply with legal regulations and ensure that private information is stored and processed in a way that makes people feel safe.

Data Augmentation: In order to make accurate predictions, ML models must be trained with suitable datasets from sufficiently large sample data. However, especially in the early phases of AI implementation, historical data in a suitably prepared form may only be sparsely available. Data augmentation is one way to close the gap between small datasets and sufficiently large training data for sophisticated ML models (Moreno-Barea et al., 2020). With this technique, the structure and statistical characteristics of real historical data can be modeled to generate new data that could also be real based on their properties.

4.2 Credit Risk Analysis Model

The technical prerequisites for using AI applications to evaluate credit default probabilities are illustrated in simplified form in Figure 4. Financial institutions may have access to internal data such as client information, technical capacities and personnel development. If the amount of data is not sufficient to train AI systems, these can be expanded in volume through augmentation. External data can also be included, which is particularly important with regard to ESG risks. This includes legal regulations, business trends that can influence the purchasing behavior of clients, climate data and demographics. After careful evaluation, the AI processing unit at the center, shown here schematically, can provide information on additional ESG risks alongside predictions on traditional credit default risks. Environmental changes, social upheavals and governance risks can thus be made comprehensible to the banking institution, thereby improving the evaluation process for the appropriateness of granting credits.

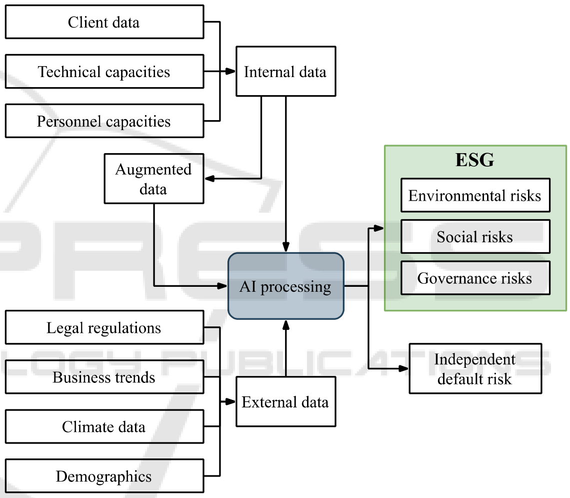

Figure 4: Schematic model for ESG risk predictions.

5 CONCLUSION

In conclusion, the integration of sustainability factors into the risk management practices of European banks presents a complex but increasingly essential challenge. As the awareness of sustainability risks grows, particularly in relation to climate change, their impact on the probability of default on loans becomes more evident. AI emerges as a promising tool in this context, offering innovative ways to decipher the intricate relationships between sustainability factors and financial risk. While the current usage of AI in banks mainly focuses on process efficiency, there is significant potential for its application in risk modeling, especially with respect to ESG data. This approach, however, is not without challenges. The scarcity of standardized and comprehensive ESG data, the complexity of AI models, and regulatory compliance issues pose significant barriers. Despite these challenges, AI can enhance the analysis and assessment of sustainability factors and improve the accuracy of default risk estimations by processing large data volumes and identifying patterns in complex information. AI offers a way to better understand and integrate these aspects into financial risk management, but its effective implementation requires the courage of banks to use these systems. Further research should focus on developing and validating AI models aimed at accounting for sustainability risks and assessing their impact on creditworthiness. Efforts to standardize ESG data for reliable comparability and thereby strengthen confidence in risk assessment are also necessary. Moreover, investigations into improving the explainability and transparency of AI applications in banks for credit granting decisions should be the subject of further research activities.

REFERENCES

Arostegi, M., Torre‐Bastida, A., Bilbao, M. N., & Del Ser, J. (2018). A heuristic approach to the multicriteria design of IaaS cloud infrastructures for Big Data applications. *Expert Systems*, *35*(5), Article e12259.

BaFin (2020). Merkblatt zum Umgang mit Nachhaltig-keitsrisiken, *2020*. https://www.bafin.de/SharedDocs/Downloads/DE/Merkblatt/dl_mb_Nachhaltigkeitsrisiken.pdf;jsessionid=E2FE3115144C8D0270ED0167BC4ED2AF.internet941?__blob=publicationFile&v=2

Bartolacci, F., Caputo, A., & Soverchia, M. (2020). Sustainability and financial performance of small and medium sized enterprises: A bibliometric and systematic literature review. *Business Strategy and the Environment*, *29*(3), 1297–1309.

Bauer, R., & Hann, D. (2010). Corporate Environmental Management and Credit Risk. *SSRN Electronic Journal.* Advance online publication.

Berg, F., K&ouml, lbel, J., & Rigobon, R. (2019). Aggregate Confusion: The Divergence of ESG Ratings. *SSRN Electronic Journal.* Advance online publication.

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

Cammalleri, C., Naumann, G., Mentaschi, L., & Formetta (2020). Global warming and drought impacts in the EU. https://joint-research-centre.ec.europa.eu/system/files/2020-05/pesetaiv_task_7_drought_final_report.pdf

Daase, C., & Turowski, K. (2023). Conducting Design Science Research in Society 5.0 – Proposal of an Explainable Artificial Intelligence Research Methodology. In A. Gerber & R. Baskerville (Eds.), *Lecture Notes in Computer Science. Design Science Research for a New Society: Society 5.0* (Vol. 13873, pp. 250–265). Springer Nature Switzerland.

Dagianis, K., Hecker, F., & Arbib, S. (2023). *Einblicke zur Künstlichen Intelligenz im deutschen Finanzsektor*. https://www.pwc.de/de/content/a57625e7-4f1e-4cda-a79e-428db2c9ac24/pwc-studie-ki-im-deutschen-finanzsektor.pdf

Dai, L., Gao, X., Guo, Y., Xiao, J., & Zhang, Z. (2012). Bioinformatics clouds for big data manipulation. *Biology Direct*, *7*, 43; discussion 43.

Dastin, J. (2018, October 10). Amazon ditches AI recruiting tool that didn't like women. *Global News*. https://globalnews.ca/news/4532172/amazon-jobs-ai-bias/#:~:text=Amazon%20has%20scrapped%20an%20AI,machine%20favoured%20men%20over%20women

Deutsche Bank. (2023, November 13). *Wie Künstliche Intelligenz das Bankgeschäft verändert*. https://www.db.com/what-next/digital-disruption/better-than-humans/how-artificial-intelligence-is-changing-banking/index?language_id=3

Dimson, E., Marsh, P., & Staunton, M. (2020). Divergent ESG Ratings. *The Journal of Portfolio Management*, *47*(1), 75–87.

Drempetic, S., Klein, C., & Zwergel, B. (2020). The Influence of Firm Size on the ESG Score: Corporate Sustainability Ratings Under Review. *Journal of Business Ethics*, *167*(2), 333–360.

European Central Bank. (2020). *Guide on climate-related and environmental risks*. https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.202011finalguideonclimate-relatedandenvironmentalrisks~58213f6564.en.pdf

Friedrich, L., Hiese, A., Dreßler, R., & Wolfenstetter, F. (2021). Künstliche Intelligenz in Banken – Status quo, Herausforderungen und Anwendungspotenziale. In P. Buxmann & H. Schmidt (Eds.), *Künstliche Intelligenz* (pp. 49–63). Springer Berlin Heidelberg.

Geng, C. (2023). *Accounting for AI risk in ESG investing – It's a black box*. https://www.bnpparibas-am.com/en-us/forward-thinking/accounting-for-ai-risk-in-esg-investing-its-a-black-box/

Gleißner, W., & Romeike, F. (2021). ESG-Risiken und ihre Quantifizierung. In O. Everling (Ed.), *Social credit rating: Reputation und vertrauen beurteilen* (1st ed., pp. 391–433). Springer Nature.

Gupta, A., Sharma, U., & Gupta, S. K. (2021). The Role of ESG in Sustainable Development: An Analysis Through the Lens of Machine Learning. In *2021 IEEE International Humanitarian Technology Conference (IHTC)* (pp. 1–5). IEEE.

Hammann, E.-M., Habisch, A., & Pechlaner, H. (2009). Values that create value: socially responsible business practices in SMEs – empirical evidence from German companies. *Business Ethics: A European Review*, *18*(1), 37–51.

Herrera Madueño, J., Larrán Jorge, M., Martínez Conesa, I., & Martínez-Martínez, D. (2016). Relationship between corporate social responsibility and competitive performance in Spanish SMEs: Empirical evidence from a stakeholders' perspective. *BRQ Business Research Quarterly*, *19*(1), 55–72.

Höck, A., Klein, C., Landau, A., & Zwergel, B. (2020). The effect of environmental sustainability on credit risk. *Journal of Asset Management*, *21*(2), 85–93.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399.

Lucia, C. de, Pazienza, P., & Bartlett, M. (2020). Does Good ESG Lead to Better Financial Performances by Firms? Machine Learning and Logistic Regression Models of Public Enterprises in Europe. *Sustainability*, *12*(13), 5317.

Mashayekhy, L., Nejad, M. M., & Grosu, D. (2014). A two-sided market mechanism for trading big data computing commodities. In *2014 IEEE International Conference on Big Data (Big Data)* (pp. 153–158). IEEE.

Meles, A., Salerno, D., Sampagnaro, G., Verdoliva, V., & Zhang, J. (2023). The influence of green innovation on default risk: Evidence from Europe. *International Review of Economics & Finance*, *84*, 692–710.

Moreno-Barea, F. J., Jerez, J. M., & Franco, L. (2020). Improving classification accuracy using data augmentation on small data sets. *Expert Systems with Applications*, *161*, 113696.

Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. *Cogent Economics & Finance*, *10*(1), Article 2023262.

Salisu, A. A., Ndako, U. B., & Vo, X. V. (2023). Transition risk, physical risk, and the realized volatility of oil and natural gas prices. *Resources Policy*, *81*, 103383.

Schneider, T. E. (2011). Is Environmental Performance a Determinant of Bond Pricing? Evidence from the U.S. Pulp and Paper and Chemical Industries *Contemporary Accounting Research*, *28*(5), 1537–1561.

Strube, D., & Daase, C. (2023). The Correlation of ESG Ratings and Abnormal Returns: An Event Study Using Machine Learning. In *Proceedings of the 5th International Conference on Finance, Economics, Management and IT Business* (pp. 76–81). SCITEPRESS - Science and Technology Publications.

Strube, D., Mayer-Fiedrich, M. D., & Streuer, O. (2023). Quo Vadis, Nachhaltigkeit? Eine empirische Untersuchung der Nachhaltigkeitsintegration im Kreditmanagement von Volksbanken und Sparkassen. *Corporate Finance*(09/10), 221–226.

Tomak, K. (2019). *Wie die Commerzbank aus Daten neue Produkte für ihre Kunden macht*. https://www.der-bank-blog.de/commerzbank-daten-bankprodukte/digital-banking/37655791/

Weber, O., Scholz, R. W., & Michalik, G. (2008). Incorporating sustainability criteria into credit risk management. *Business Strategy and the Environment*, n/a-n/a.