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Artificial Intelligence in Business Management: A Literature Review on AI Applications on Risk Assessment in the Financial Industry

Ralf Wandmacher[1, 2, *], Christian Sturm[1, 2, *], Philipp Weber[1], Paul Kuhn[1]

[1]Department of Finance and Accounting, accadis Hochschule Bad Homburg, Bad Homburg v. d. Höhe, Germany

[2]Department of Entrepreneurship, accadis Institute of Entrepreneurship, Bad Homburg v. d. Höhe, Germany

Email address:
ralf.wandmacher@edu.accadis.com (Ralf Wandmacher), christian.sturm@acacdis.net (Christian Sturm)

[*]Corresponding author

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Abstract: Artificial Intelligence (AI) – simply referring to the intelligence exhibited by machines, as opposed to natural intelligence displayed by humans – is reshaping business, economy, and society. However, so far, knowledge in this field is still limited and highly fragmented, and primarily technical-oriented. In addition, the literature review demonstrates that academia has offered limited application-oriented research to support firms and managers implementing AI. This paper is based on a qualitative meta-analysis to identify the various areas of application of AI in financial risk assessment. The analysis identified *Credit Risk & Credit Scoring*, *Forecasting & Prediction*, *Security*, and *Fraud Detection* as major research areas of AI in finance. Furthermore, this paper identified how different AI applications are applied in business and demonstrated the impact of these applications. In addition, this research highlights promising AI applications for businesses and applications that are currently not suitable for implementation. Finally, promising research opportunities in AI-related business research are outlined. The description is necessary to advance the current technical-dominated research to include business-oriented research and application-specific research on artificial intelligence.

Keywords: Artificial Intelligence, AI, Finance, Systematic Literature Review, Risk Assessment

1. Introduction

Artificial Intelligence (AI) – simply referring to the intelligence exhibited by machines, as opposed to natural intelligence exhibited by humans – is reshaping business, economy, and society [58]. This simplified definition of AI fails to address the potential of artificial intelligence adequately. AI is well established in many industries and people's lives [63]. The implications – in particular for the economy – expected from the extensive implementation and application of AI are significant. Recent studies estimate that artificial intelligence will increase productivity and economic growth, adding $13 trillion to global output by 2030, which is equivalent to a 1.2 percent increase in GDP per year [10].

Academically, research on AI has proceeded in many research areas: computer scientists continuously develop more advanced deep-learning algorithms [9] and neuronal networks [53], social scientists discuss legal and ethical constraints and implications of AI [8, 11], and economists research the impact of AI for all stakeholder of the economic system [23]. However, this research focuses mainly on technical advancements in AI on specific applications (e.g., neural networks, machine learning, etc.) or on specific domains (e.g., decision support systems). So far, academia has offered limited application-oriented research to support firms and managers in implementing AI [75].

In addition to the limited application-oriented research, research on AI also lacks industry-oriented research [58]. An initial query on Scopus and Web of Science yielded more than

500.000 published articles on AI between 2018 and 2022. In comparison, in the same period, only around 3.500 of these articles – representing only 0.7 percent of the total AI research – focused on the financial industry.

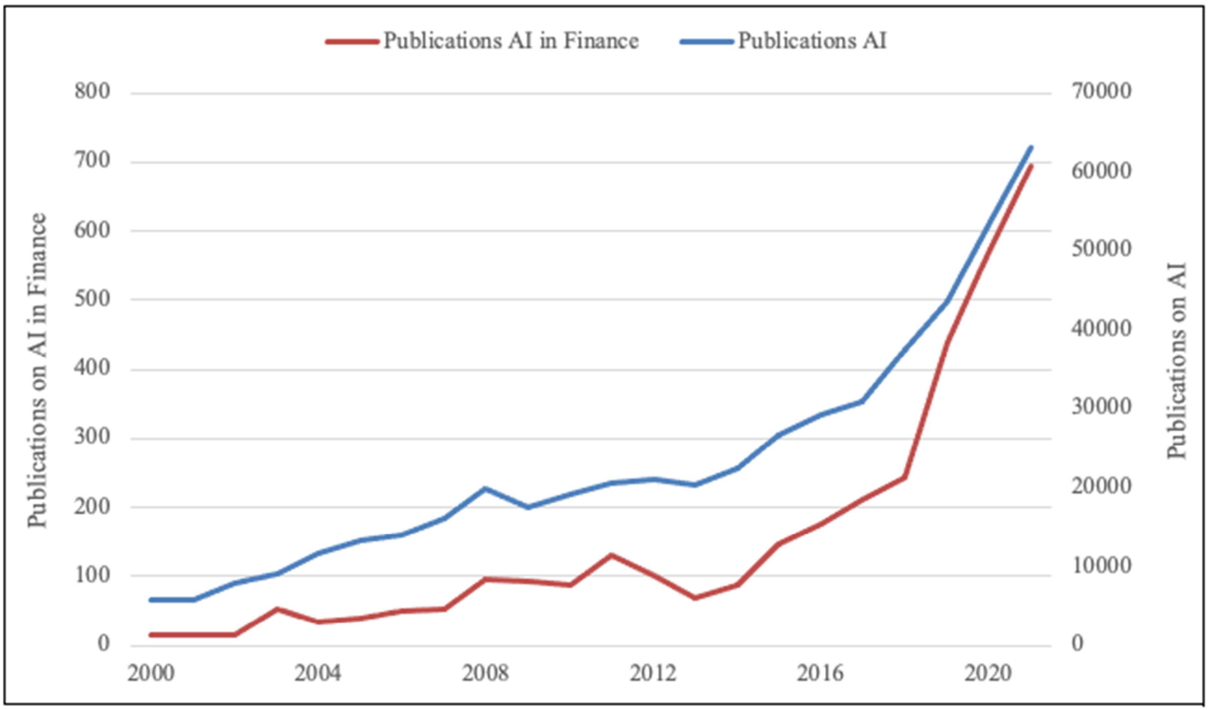

Figure 1. *Publications on AI and on AI in Finance (2000 to 2021).*

In the financial industry in particular, AI is causing a profound transformation [72]. AI is already applied in numerous areas in the financial industry, such as automated high-frequency trading, fraud detection, compliance monitoring, and others. In addition, financial authorities also rely on the new technology to analyze vast amounts of complex data to fulfill regulatory and supervisory obligations [7]. FinTech and BigTech companies are transforming the financial industry. AI is enabling these companies to enter the financial industry successfully, forcing traditional industry incumbents to adapt [7]. However, even though artificial intelligence is already applied in many areas, it is still in its infancy of the technology´s possibilities [43]. Against this background, this paper aims to identify the various areas of application of AI in the financial industry through a systematic literature review. The qualitative meta-analysis identified particularly the area of financial risk assessment, in which AI applications are already adopted. In the context of financial risk assessment and risk mitigation, this paper identified how different AI applications are applied and demonstrated the application´s impact. Furthermore, multiple promising research opportunities in AI-related business research are outlined. The outline is necessary to further advance the application-specific research on artificial intelligence. So far, the research has proliferated in recent years and generated a set of fragmented studies. However, the research is far from developing a robust corpus of literature, which fails to support organizations and management with concrete evidence of the benefits and implementation of AI.

2. Methodology

Research on artificial intelligence has received attention from academia and business in recent years. However, academia has offered limited application-oriented research to support the implementation of artificial intelligence in business. Although the areas of application and the numbers of publications are almost exponentially increasing, industry and application-specific reviews of AI research are currently lacking. Therefore, this study examines the application of artificial intelligence in financial risk assessment, following a systematic literature review methodology.

Table 1. *Overview of the Systematic Literature Review Process.*

Description	Scopus	Web of Science
Search Queries	469	222
Search Results		
Duplicates	302	
Articles not Publicly Available	27	
Articles for First Screening	362	
Articles Excluded	194	
Articles for Second Screening	168	
Articles Excluded	83	
Articles for Third Screening	85	
Articles Excluded	19	
Final Number of Articles	66	

This study follows the six-phase research design proposed by Jesson et al. [39], which includes: (1) setting the scope; (2) defining the review procedure; (3) identifying all relevant studies; (4) quality assessment; (5) data extraction and data synthesis; and (6) write-up [39]. The process started with a scoping review, a method to provide an initial overview of the available research and to identify existing knowledge gaps in the field (see Table 1).

In the second phase, the review procedures, including the scope of research with the including and excluding criteria, were defined. The study was limited to scholarly articles focusing on 'artificial intelligence (AI) in finance'. Furthermore, the inclusion and exclusion criteria were defined based on the suggestions by Jesson et al. [39]. The inclusion criteria focused on articles that (1) had a central focus on artificial intelligence in finance or a specific application of AI in finance and (2) a clear theoretical contribution. The exclusion criteria focused on eliminating articles that, (1) although referring to 'artificial intelligence in finance', did not thematically focus on the topic, or (2) insufficiently examine 'AI in finance' in general or a specific application of artificial intelligence in finance.

In the third phase, a systematic search was conducted in the two databases, Scopus and Web of Science. The investigation identified 469 scholarly articles in Scopus and 222 scholarly articles in Web of Science, published between 2018 and 2022. After eliminating all overlaps between the search queries, 389 scholarly articles were identified. The 389 results were summarized in an Excel sheet, specifying the title, author(s), year, and journal. Of these 389 articles, 27 were not available for download; thus, these articles were excluded. Finally, 362 articles remained in the selection for the initial screening of the abstract.

In the fourth phase, 168 scholarly articles were selected based on the thematic relevance of the abstract; the remaining were discarded as irrelevant. Thus, a total of 194 scholarly articles were excluded during the first screening. Afterwards, the 168 remaining articles were categorized based on the application of artificial intelligence in finance. In this context, seven significant areas of application of artificial intelligence in finance have been identified: *Credit Risk & Credit Scoring* (28), *Portfolio & Wealth Management* (10), *Decision-Making & Robo-Advising* (43), *Fraud Detection* (10), *Forecasting & Prediction* (45), *General Overview* (27), *Security* (3), and the additional theme of *Legal & Regulatory* (2) emerged.

Table 2. *Themes and AI Methods.*

Theme	Data Mining	Machine Learning	Neural Networks	Fuzzy Logic	Others
Credit Risk & Credit Scoring	3	15	4	0	6
Decision-Making & Robo-Advising	4	13	3	1	21
Fraud Detection	0	7	1	0	1
Forecasting & Prediction	1	24	14	4	2
General Overview	0	10	3	3	9
Portfolio & Wealth Management	0	6	1	0	3
Security	0	2	0	0	1

Notably, the central focus of most of these categories is the assessment or mitigation of risk. To further highlight this area of application of artificial intelligence in finance, the focus of this paper will be on the assessment and mitigation of risk through artificial intelligence in finance. Accordingly, only the categories *Credit Risk & Credit Scoring* (28), *Fraud Detection* (10), *Forecasting & Prediction* (45), and *Security* (3) will be further considered.

Subsequently, the remaining 85 scholarly articles were assessed based on the quality of their contribution. According to Corley and Gioia [17], the quality of a contribution should be assessed based on originality and utility. In this context, originality referrers to the degree of novelty of the presented insights of each contribution. The increase in knowledge can be either incremental – that is, the contribution incrementally improves understanding – or revelatory, in which case the contribution represents new and unique insights [17]. Utility referrers to the potential of each contribution to improve current practice or science [17]. Accordingly, scientific utility refers to improvements in conceptual rigor or the specification of ideas, whereas practical utility refers to the applicability of concepts to concrete problems of managers or practitioners [17]. In particular, as organization and management studies address academics and practitioners, Corley and Gioia [17] argue for theoretical prescience – the process of providing significant theoretical concepts for relevant managerial or organizational issues. The assessment of quality reduced the overall articles included in the literature review to the final sample of 66 articles relating to the risk assessment and risk mitigation – *Credit Risk & Credit Scoring* (20), *Fraud Detection* (8), *Forecasting & Prediction* (36), and *Security* (1) – through artificial intelligence in the financial industry.

In the subsequent phase (data extraction and synthesis), the Excel sheet – specifying the title, author(s), year, and journal – was extended to include the research methodology, findings, and main contribution. Afterwards, the extracted data from the articles was synthesized and analyzed. In this context, Jesson et al. [39] defined the synthesis as the process of organizing existing literature and deriving new connections.

The synthesis identified the main areas of application regarding assessing and mitigating risk in the financial industry through artificial intelligence. An organized synthesis, as well as a summary of applied techniques, is provided for each of these areas.

The last phase concludes the systematic literature review process and constitutes the following section.

3. Key Themes

Despite the ongoing interest, no uniform definition of artificial intelligence is yet established. However, the numerous definitions have several standard features that can be used to define AI: Artificial Intelligence can perceive the environment and its complexity [60, 68, 71], process – e.g., collect and interpret – data [42, 68, 71], and make decisions and take actions – including reason and learn – with a certain degree of autonomy [42, 60, 71], as well as achieve specific objectives [42].

The considered papers focus on different AI techniques, predominantly on Machine Learning, Data Mining, Neural Networks, and Fuzzy Logic. These techniques are distinct subcategories of artificial intelligence [27].

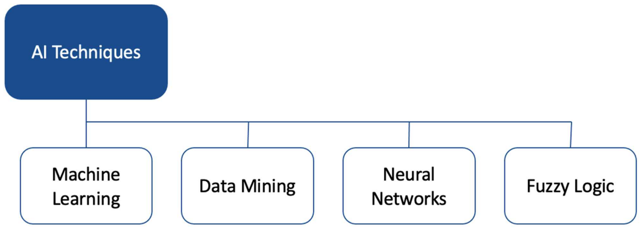

Figure 2. *AI Techniques.*

Machine Learning (ML) – as a subset of AI – performs experiential learning [30] by deploying computational algorithms to recognize patterns and regularities in data sets to make autonomous decisions [27]. The purpose is to allow machines to predict the output by a known input through the constant repetition and improvement of algorithms [30].

Neural Networks (NN) are a subset of Machine Learning and an essential element of deep learning algorithms [65]. Neural Networks consist of multiple node layers – including an input layer, numerous hidden layers, and an output layer [30]. This structure allows the different layers to respond to different input features to develop models without explicitly programmed instructions [30].

Fuzzy Logic describes a computational approach to imprecision and approximate reasoning [99]. In Fuzzy Logic, propositions are not defined by absolute values – such as true or false – but rather by the degree of affiliation [98]. Thus, Fuzzy Logic allows for making rational decisions in an environment of imperfect information [99]. In addition, another contribution of Fuzzy Logic is the ability to specify the imprecise [99].

Data Mining – just like the previously mentioned techniques – is also a subset of AI, deployed to generate knowledge from data based on new and non-trivial patterns, relations, and trends in data [21, 78]. Data Mining relies – especially for the pre-processing of data – on Machine Learning and statistical methods [78]. In general, the process of Data Mining includes "the collection and selection of data, the pre-processing of data, data analysis itself including the visualization of results, interpretation of findings, and the application of knowledge" [78].

3.1. Credit Risk & Credit Scoring

In modern economies, banks provide the financial infrastructure and manage financial flows. Accordingly, a primary function of the financial sector is the efficient processing of financial transactions. The efficient processing includes the provision of capital (loans) to corporations and households. Thus, banks assume the credit risk between debtor and depositor as well as the interest rate risk, resulting from the transformation of short-term deposits to long-term loans [1]. To evaluate the risk of a credit default, assessing the credit score is a central element of a bank's credit business [64]. In the past, the credit score assessment – i.e., the probability of whether debtors can comply with credit requirements – was determined by credit officers or expert-based credit scoring models [67]. However, recently the application of AI state-of-the-art technology – including machine learning, neural networks, and data mining – has attracted the interest of academia and practitioners. The raised interest is particularly evident in the number of literature reviews [6, 15, 47, 48, 64]. Nevertheless, this also indicates that the research on AI application in credit scoring is extensive and somewhat uncoordinated. In this respect, the different literature reviews primarily consider different institutional environments. Mhlanga [64] as well as Kumar et al. [47] examine the advantages and challenges of AI application-based credit scoring assessment for households excluded from traditional banking, Ariza-Garzon et al. [6] focus on the Peer-to-Peer lending market, and Ciampi et al. [15] on SME´s.

However, much of the current research is technically oriented and focuses exclusively on individual models and model improvement [4, 25, 26, 28, 35, 59, 66, 67, 84, 85, 86, 90, 93, 100]. Exclusively Lavrinenko & Shmatko [50] explore the application of AI in finance from a business perspective. This technically dominated research demonstrates the general lack of business and economic perspectives in the research of AI in finance.

3.2. Forecasting & Prediction

The research on AI in the financial industry is strongly focused on *Forecasting & Prediction* (36), specifically on *Stock Market* (17) *& Exchange Rate* (3) *Forecasting*, *Financial Crisis* (7) *& Bankruptcy* (3) *Prediction*, *Corporate Financial Risk Assessment* (2), and other (4).

The stock market is an essential element of the economy for public trading capital and ownership of firms. The stock market allows firms to raise capital for investment and growth and investors to invest capital potentially profitably. To reduce the investment risk associated with the stock market, practitioners and scholars have developed numerous models to predict stock prices [5, 29, 33, 36, 41, 51, 52, 55, 57, 69, 79-82, 88, 91, 92]. In academia, however, different opinions exist on whether the stock market developments can be predicted. In his influential research on the efficient market hypothesis (EMH), Eugen Fama states that the current stock price is based on all available information and that changes in stock prices result from newly available information [20]. Accordingly, the stock market cannot be predicted based on historical data to generate significant returns [96]. However, the application of state-of-the-art technology indicates something different. Current research indicates –the results are primarily experiential – that the application of machine learning (ML) and neural networks (NN), in particular, have the potential to predict stock market developments with high accuracy.

The efficient market hypothesis (EMH) applies not only to the stock market but also to financial tools in general, i.e., exchange rates [61]. Hence, exchange rates are based on all available information, and changes result from newly available information. Thus, exchange rates cannot be predicted according to the EMH [20]. However, here too, modern technology – in particular, machine learning (ML) and neural networks (NN) – is applied to predict changes in exchange rates relatively accurately [45, 61, 87]. The current research is based on both qualitative, and quantitative data. However, the prediction accuracy of the ML or NN models is currently only relatively higher compared to traditional models [45, 87]. Again, the rationale for predicting exchange rates is – exactly as with the stock markets – to reduce the risk associated with exchange rate fluctuations.

Financial crisis prediction (FCP) – or credit default classification – is applied to assess the credit risk of financial institutions to minimize the risk of credit default [62, 89]. Thus, the accuracy of the FCP has a significant impact on the profitability of financial institutions [89]. Traditional financial crisis prediction employed mathematical and arithmetic functions [62, 89]. In order to further enhance the financial crisis prediction of financial institutions, the attention has shifted toward the application of AI [13, 31, 54, 62, 74, 89, 95]. In particular, machine learning (ML) and neural networks (NN) have been tested in different organizational environments: in financial institutions [54, 62, 89, 95], in SME's [31], and in FinTechs [74]. The experimental results indicate that the tested models for financial crisis prediction are robust and efficient [89].

Besides financial crisis prediction, research has focused on bankruptcy prediction [46], as the economic effects of bankruptcies may cause major social problems – e.g., unemployment, economic recessions, and even a generic financial crisis [49]. To reduce the potential social and economic damage of corporate bankruptcy, statistical methods were deployed to develop predictive models [83]. Recent studies acknowledge that artificial intelligence models achieve greater efficiency in predicting financial risk and bankruptcy [46, 49, 83]. Again, machine learning and neural networks are applied and trained on quantitative and qualitative data. However, the current studies also suggest that the data needed for research is insufficiently available [49].

Predicting the financial risk of a corporation is gaining importance, particularly considering that – mainly as a result of the integration in the global economy – corporate capital is deeply connected with the financial markets [97]. Thus, the resulting dependency of corporations on the financial markets requires an assessment of corporate financial risks. Conventional financial risk prevention models (FRPM) are based on statistical analysis models [24]. As these models are highly complex, AI is being applied in current research, generating superior results [24, 32]. The experimental results indicate that the financial risk of a corporation can be assessed by corporate KPI´s as well as in combination with qualitative data [24, 32].

Other research topics on AI in the financial industry focus on M&A prediction [40] and on banking crisis prediction [77]. The application of machine learning is also applied to forecast environmental effects – such as geopolitical risks [73] – or customer behavior in regard to online banking [34].

Overall, current research on artificial intelligence applications in finance for forecasting and prediction is characterized by technical improvements of the various models and less by application-related requirements. In principle, the research emphasizes the importance of the models for the different areas – e.g., stock market forecasting or bankruptcy prediction – but lacks concrete recommendations for implementation. A fundamental issue in this context is data quality and availability.

3.3. Fraud Detection

Consumers as well as firms are affected by financial fraud. Whereas consumers are particularly affected by the unauthorized use of credit cards [14], the focus among firms is in particular on financial statement fraud detection [38, 56].

Within the economy, the annual report, including the financial statement, performs a fundamental function: to reflect the financial and operating results of a firm [38]. Accordingly, both documents serve as a reference to investors, shareholders, creditors, employees, and other stakeholders [37]. Since accounting fraud occurs less frequently than other financial crimes - such as misappropriation of assets or corruption - but causes significantly higher economic damage, it is essential to effectively reduce and prevent financial statement fraud [38, 56]. Current research is particularly focused on applying deep learning and neural networks to detect financial statement fraud [38, 56]. The models detect financial fraud with an accuracy of above 85% [38, 56], however, the empirical results also indicate that further research is necessary to eliminate current deficiencies regarding variable definition and sample selection [56].

In addition to financial fraud in firms, current research also examines how consumers are affected by financial fraud. Whereas firms are particularly affected by financial statement fraud [38, 56], consumers are affected by the unauthorized use of payment cards [14, 76]. According to the European Central Bank, in 2019, the total financial losses as a result of payment card fraud amounted to EURO 1.03 billion in the euro area only [19]. Due to the technological development, a physical payment instrument (card) is no longer necessary for a transaction [14]. Accordingly, payment card fraud is increasingly occurring online [76]. However, the currently rule-based expert fraud detection systems – which depend significantly on technical and business knowledge – increasingly experience difficulties in detecting complex fraud patterns in a timely and accurate manner [101]. Therefore, current research is assessing the application of machine learning and neural networks [14, 76, 101]. The experimental results indicate these models are significantly more efficient in detecting financial fraud [14], however, accuracy and processing times still must be further improved [14].

3.4. Security

Financial cybercrime – including money laundering, tax evasion, investment fraud, and others – poses a substantial risk to corporations and the economy. According to recent statistics, in 2021, the three most common cybercrimes – business email compromise (2.4 billion USD), confidence fraud and romance scams (956 million USD), and cryptocurrency (1.6 billion USD) – caused total economic damage of almost 5 billion USD in the USA only [22]. Currently, real-time analytics and interdiction methods are applied by financial institutions as protectionary measures against cybercrime [70]. New models to fight and prevent financial cybercrime are needed, particularly machine learning and deep learning models [70]. Current research focuses on stocks and securities fraud – i.e., market manipulation and inside trading [2], pump-and-dump schemes, fraud detection, and money laundering [12, 102]. This involves, in particular, machine learning and deep learning models to detect anomalies, patterns, and connections [70]. Other methods include recurrent neuronal networks to detect stock fraud [94] or social network analysis to detect money laundering [16, 18], which demonstrate positive results.

Nevertheless, research on AI applications in financial cybercrime detection encounters several challenges. The central challenge in the current research is the "access to labelled data to train and evaluate their model performance" [70]. Besides the availability and quality of data, future model construction, real-time application, and regulation are additional issues for future research.

4. Future Avenues of Research

The systematic literature review highlighted the current research on applying artificial intelligence in the financial industry, mainly focusing on the assessment and mitigation of risk. The literature addresses a diverse and highly relevant selection of themes, yet the existing literature remains highly fragmented.

Current research is almost exclusively technically oriented. The results are highly relevant, however exclusively experimental, as the application context is absent. Accordingly, the impact of research on the actual implementation of AI in the financial industry is minimal [76]. It is therefore necessary that research not only considers the improvement and optimization of AI applications, but also focuses on the application and implementation of these systems. This includes, in particular, the economic, legal, and ethical analysis of the impact of an AI implementation.

The future of AI depends on data and on data quality. The current research data is very homogeneous. In further research on AI – especially in the field of credit scoring – it is imperative that more heterogeneous data sets are applied. This dependence on data and the current homogeneous data sets may result in biases. Algorithmic biases may be part of the data model as shown in a study about a Robo-Debt scheme in Australia, e.g., data bias, method bias and societal bias [3]. The discussion about discrimination through data can be observed in a study about non-mortgage lending which finds the omission of gender increases discrimination [44].

The combination of other technologies with AI may be one of the most promising fields in finance. As AI needs data to learn, businesses and consumers need to be incentivized to provide data sets. This can be done by providing data security and by simplifying processes through data usage. Simultaneously, the data sets must be protected, and the result must be only accessible to each individual or business. The individuals and the business may have the right to share their results, but it is a right no obligation. A possible application could be credit scoring, which is important for financial transactions as well as for the closing of contracts.

The field of decentralized finance may be of interest to financial institutions, as a major cost factor for each financial institution is the equity cost of loans. If these loans could be automatically distributed and priced according to the real-time scoring of the counterparty through a decentralized marketplace with automated market making, the amount of equity needed could be optimized.

AI may be used for automatic decisions about financial investments, how products and services are getting paid, if or not loans are taken, and how future cash flows can be considered and monetarized. AI is also necessary in a society where machines and sensors communicate with each other, arrange transactions, and pay for and order products and services.

5. Conclusion

The primary contribution of the systematic literature review is the identification of the different application areas regarding the assessment and mitigation of risk in the financial industry through artificial intelligence. However, current research shows that almost exclusively technical aspects – including the improvement of AI – are at the forefront of research. Economic, legal, and ethical aspects regarding the application of AI are not considered at all or only to a rudimentary extent.

Furthermore, the literature analysis reveals a more fundamental problem: the insufficient definition of AI and the insufficient differentiation of the individual AI methods. In particular, the technification makes it difficult to clearly define and classify the different AI methods, which complicates the assignment to specific application and research areas. A more precise definition of artificial intelligence and a detailed differentiation of the individual methods would be beneficial for further research, but also for practitioners.

The aim for future research should be the inclusion of technology, economics, business methods, and ethics to work on the application in different use cases. The fundamental task for research is to unify research methods, e.g., pattern recognition should involve ethics and behavioral finance knowledge to optimize the data input for the opportunity of more relevant results.

The unification of research is fundamental to increase the quality of knowledge. Academic research may take the lead to classify and to structure the application of AI in business problems.

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