Utilization of AI in Credit Risk Analysis

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This research investigates how artificial intelligence could be utilized in credit risk analysis. Credit risk analysis is an essential part of credit ratings. This research concludes how to use artificial intelligence to minimize limitations of credit ratings and to facilitate and enhance the analyst's work when analysing credit risks. These themes will be considered with a literature review and credit risk manager's interview.

This research introduces one kind of credit rating process as a whole. The probability of default and expected loss are essential metrics when assessing credit rating. In addition to the probability of default and expected loss, credit risk analysis can comprise six segments: ownership and corporate structure, governance and management, business and competitiveness, industry and markets, financial structure and debt servicing capacity and sustainability risks.

Relevant sub-divisions of artificial intelligence are introduced to give an adequate overview of the capabilities of artificial intelligence. When introducing the limitations and deficiencies of credit ratings, this research analyses how to utilize artificial intelligence to enhance the credit rating process and eliminate the limitations of credit ratings. This research concludes that the limitations of credit ratings could be eliminated with credit rating artificial intelligence models introduced in the academic field.

This research introduces two artificial neural network models to facilitate the analyst's work and enhance the analysis. The first model helps analysts filter and adjust financial information to comparable. The second model helps analysts before the analysis when filtering if the target of the analysis can even get credit. This reduces the amount of analysis, and analysts can focus more on the rest of the analysis. The utilization of artificial intelligence in credit risk assessment has multiple limitations, such as information leak risks, ethical points of view, and the efficiency of cooperation between artificial intelligence and humans. The significance of the limitations explains the minimal use of artificial intelligence in credit risk assessments.

Key words: credit rating, credit risk assessment, artificial intelligence, artificial neural networks

Kanditutkielma

Oppiaine: Laskentatoimi ja rahoitus
Tekijä: Olivia Wahlberg
Otsikko: Tekoälyn hyödyntäminen luottoriskianalyysissä
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Tutkielma selvittää miten tekoälyä voitaisiin hyödyntää luottoriskianalyysissä laajemmin. Luottoriskianalyysi on tärkeä osa luottoluokitusten tekoa. Tutkielma analysoi, kuinka hyödyntää tekoälyä luottoluokitusten rajoitteiden minimoimiseksi ja analyytikon työn tehostamiseksi arvioitaessa luottoriskejä. Tutkielma on tehty kirjallisuuskatsauksen ja luottoriskipäällikön haastattelun pohjalta.

Tutkielma esittelee erään mahdollisen luottoluokitusprosessin kokonaisuudessaan. Maksukyvyttömyyden todennäköisyys ja odotettu tappio ovat tärkeitä mittareita luottoluokituksen arvioinnissa. Näiden mittareiden lisäksi luottoriskien arviointi voi koostua esimerkiksi kuudesta osasta: omistus ja yhtiörakenne, hallinto ja johtaminen, liiketoimintamalli ja kilpailukyky, toimiala ja markkinat, rahoitusrakenne ja velanhoitokyky ja kestävyysriskit.

Tekoälyn oleellisimmat osa-alueet on esitelty antamaan riittävä kokonaiskuva tekoälyn kyvyistä. Tutkielman esiteltyä luottoluokitusten rajoitteet ja puutteet, analysoidaan kuinka tehostaa luottoluokitusprosessia ja eliminoida luottoluokitusten rajoitteita tekoälyn avulla. Tutkielma päätyy lopputulokseen, että luottoluokitusten rajoitteita voitaisiin eliminoida akateemisella alalla esitettyjen luottoluokituksen tekevien tekoäly mallien avulla.

Tutkielmassa esitellään kaksi neuroverkkomallia edistämään ja tehostamaan analyytikon työtä ja analyysiä. Ensimmäinen malli auttaa analyytikkoa haravoimaan ja muuntamaan taloudellisia raportteja vertailukelpoisiksi. Toinen malli olisi analyytikon avuksi ennen analyysiä, kun arvioidaan, mitkä analyysit kannattaa edes tehdä ja kenellä ei ole mitään mahdollisuutta saada esimerkiksi lainaa. Tällöin analyysien määrä vähenee, ja analyytikko pystyy tekemään muut analyysit huolellisemmin. Tekoälyn hyödyntäminen luottoriskianalyysissä sisältää paljon rajoitteita, kuten tietovuotoriskin, eettiset näkökulmat ja tekoälyn ja ihmisen välisen yhteistyön tehokkuuden. Rajoitteiden merkittävyys selittää tekoälyn vähäisen hyödyntämisen luottoriskianalyyseissä tähän mennessä.

Avainsanat: luottoluokitus, luottoriskianalyysi, tekoäly, neuroverkot

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1 Introduction

The primary role of financial institutions is to provide a marketplace for surplus and deficit institutions to allocate capital to the most helpful use. Banking is the most known financial actor. Banking splits into commercial banking, which includes daily banking services, and investment banking, which consists of services for governments, companies, and other corporations. Investment banking raises governments, companies, and other corporations' debt and equity financing. (Hull 2018, 26-32.)

Credit risk management can be viewed from different perspectives. Banks analyse the probability their customers can repay loans and define interest rates for them according to the analysis. In addition to traditional bank-based credit risk management, other financial institutions and companies, such as insurance companies and large corporates, implement credit risk analysis. Insurance companies can in addition to insuring, guarantee a loan. The loan guarantee mitigates the credit risk incurred by the lender and improves credit availability and terms for the borrower. Large companies analyse if their customers can pay receivables from sales and other debts back. Financial institutions might also analyse their investment portfolio's credit risk to optimize their risk preferences. (Olli, interview, 2024.)

This research focuses on analysing companies' credit risk. In this context, the entity carrying out the analysis is a financial institution, such as a bank, insurance company or large corporation. The borrower and subject of the analysis is the company. Additionally, this research addresses the credit ratings provided by credit rating agencies. In this case, the company is also the subject of the credit rating.

Companies raise capital to invest and grow their business. Liabilities of companies' balance sheet consists of equity and debt. The two ways for companies to raise capital are to raise equity capital or credit capital. Credit capital consists of long and short-term loans, bonds, and other instruments with forehand set rates, maturities, and payback periods. Loan maturity refers to the period from when the loaned amount is paid back. Credit risk analysis is an essential part of corporate debt raising. Through credit risk analysis, investors, financial institutions, and other lenders aim to minimize their expected losses when they are loaning to companies. (Bhimani et al. 2019, 388.)

When an investor loans the company, the borrower (in this case, the company) is committed to paying the loaned money back during a certain period. The loaned capital can be paid back in one time as a whole or divided into several payments. Bonds are also fixed income for investors. The most significant difference between loans and bonds is the company issuing a bond and investors being able to sell the bonds on the secondary market. A company's interest rate depends on its assumed capability to repay the borrowed money. (Welch 2022.)

Credit risk describes the probability a company fails to pay its debt back and faces insolvency under the given terms (Win 2018). When the market believes a company will be able to pay its debt back in the future, its credit risk is lower, and when the company is not likely able to pay its debt back, its credit risk is higher. Credit risk rises at the same time as the uncertainty of the repayment rises. If the company has a high credit risk, the investors have a high risk of not getting their money back. It may not be worth it to the investor to invest, if the probability of repayment is low. The interest rates for companies with high credit risks are higher due to risk and profit correlating. The interest rates are the investors' reward for taking the risk. (Welch 2022.)

Credit risk assessment is the basis for corporate lending, and its success defines the success of banks (Savvides 2011). Credit risk has been the most common cause of bank failure in banking history (Tomić-Plazibat et al. 2006). Credit risk analysis is an essential factor in the financial field because its outcome is a way to obtain the credit rating of the company under analysis. Credit rating agencies are essential to the stability of financial markets due to markets and investors' trust in their ratings.

AI offers companies new tools in almost every field and has been used to improve, for example, technological in-house systems. However, there are risks when using AI in the corporate world because some AI tools are still relatively new, and companies are not fully aware of their capabilities. One of the most significant risks when using AI in the corporate world is information leak risk. On the other hand, technology is constantly evolving, and companies are in the middle of change. New AI systems are built constantly, and the fear of being left behind in technological development is real (Sinha et al. 2021, 15). (Sestino and De Mauro 2022; Giudici and Raffinetti 2023; Locatelli et al. 2022, 1.)

This research focuses on the utilization of AI in credit risk management from the point of view of companies' credit risk analysis when it comes to credit ratings. The motivation of this research is to find out if AI can enhance and complement human-based credit analysis. Human-based analysis refers to the analysis made by analysts in this research. Based on the motivation, this research investigates how to connect AI to human experiences and intuition and human-based credit risk management systems to obtain more accurate credit ratings for companies.

1.1 Research Gap and Research Questions

There is previous research of utilizing AI in credit risk management with individuals' financial inclusion and mortgages. There are also multiple academic research modelling credit rating AI models (Wang and Ku 2021; Locatelli et al. 2022). Instead, there is not much previous research on enhancing particularly human-based credit risk analysis with AI when it comes to assessing companies' credit risks. The utilization of AI is not generalized in the field of credit risk management, mostly due to data security risks. The institutions should develop their own in-house AI systems to utilize AI in credit analysis, which would be expensive. Also, there would be no certainty if these systems even work or would implement current human-based analysis. AI and human-based credit risk analysis are combined in this research. The research question of this research is:

1. How human-based credit ratings could be enhanced with AI?

The research question hypothesis is that using AI in credit ratings would make human-based credit risk analysis and credit ratings more efficient and precise. However, when AI is implemented into the assessment process, there are risks of the accuracy of credit ratings. This research considers how AI could be utilized in human-based credit ratings while ensuring the ratings implemented with AI are authenticated correctly.

1.2 Structure and the Limitations of this Research

This research is a qualitative study based on previous research and one interview. The human-based credit analysis process is not widely researched in the academic field. The human-based credit risk assessment determined in this research is based on the interview of Kaisa Olli, Credit Risk Manager at Garantia Insurance Company Ltd. The interview is based on Kaisa Olli's own expertise and general experience in credit risk management,

as well as her background as a Master of Science in Economics and Business Administration. Therefore, the interview does not refer to any practices or principles applied at Garantia Insurance Company.

This research analyses AI and human-based credit risk assessment first separately. The credit risk rating section includes an introduction to the theme, the sub-divisions of human-based credit risk assessment, and the deficiencies of credit ratings. The AI section introduces the main sub-divisions of AI and how AI has been used in the financial field. Later, this research combines these two main themes and analyses qualitatively previous research where AI and credit risks have been combined. Based on the literature and the interview, this research ends to the conclusion of how to use AI to develop human-based credit risk analysis and if it is even possible to implement AI into human-based credit risk analysis.

The figures from Figures 2 to 5 were made with the R-studio. This research's main limitation is the limited literature on human-based credit risk analysis. This research does not observe differences between different economic regions. Instead, it explores how human-based credit risk analysis could be enhanced in theory based on previous research and an interview with a credit risk expert.

2 Credit Ratings

The companies' assumed capability of carrying out debts is defined by credit ratings. Credit rating is the main method created to qualify and predict a company's ability to repay debt. Irresponsible lending and misclassifications of credit ratings can lead to huge disasters, as the financial world saw during the subprime crisis (Agarwal et al. 2014). After the subprime crisis, financial institutions had to create better credit risk management practices. Those with dedicated credit risk assessment structures and credit risk management cooperation with the government achieved better overall performance during and after the financial crisis (Cousin et al. 2024).

Most of the public credit ratings are made by credit rating agencies. The leading credit rating agencies in the world are Standard & Poor's and Moody's. Rating categories are letter combinations from AAA to D. AAA or Aaa is the best, and D is the worst credit rating available. D means the corporate under analysis is in default. Below, you find the table of Moody's and Standard & Poor's rating categories. The bottom rating grades are called speculative grades, and the top grades are generally called investment grades. The investment rates, which are the compensation for the risk, increase when the credit rating decreases. To sum up, credit ratings are tools for lenders to estimate the risk of borrowers' default and to set the interest rate to the right level compared to the estimated risk level. (Welch 2022.)

	Investment Grades →				← Speculative Grades					In Default
Standard & Poor's	AAA	AA	A	BBB	BB	B	CCC	CC	C	D
Moody's	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	D
	Higher interest rates →									

Table 1 Moody's and Standard & Poor's Credit Rating Categories. Conforms to the table presented by Welch (2022)

2.1 Probability of Default (PD)

The probability of default (PD) is a measure of the probability the borrower fails to pay its debt according to the agreed terms. The probability of default is a major factor when assessing a company's credit rating. Credit rating agencies, such as Standard & Poor's and Moody's, usually use PD when assessing credit ratings. Financial institutions have constantly developed new metrics to estimate PD and rating agencies have their own models to estimate the probability of default. Li et al. (2023) presents the default-prediction single-index hazard model (DSI) for estimating the corporate probability of default and the reasons for its capabilities compared to traditional models. PD refers to the likelihood that a borrower will default on its debt obligations within a specific period. PD is commonly expressed as a percentage or a decimal: the higher the PD, the higher the risk of default. Depending on the rating agency, a certain percentage (or decimal) corresponds to a certain credit rating. (Ding et al. 2012; Kong et al. 2008; Li et al. 2023; Olli, interview, 2024.)

2.2 Expected Loss (EL)

The expected loss is the key metric when estimating the part of debt an investor is expected to lose (Venter and De Jongh 2024). Expected loss is often utilized when estimating the risk premium for the debt, and it can be calculated from the Probability of Default (PD), Exposure at Default (EAD), and Loss Given Default (LGD), as the metrics below show. (Van Gestel et al. 2009)

$$PD \times EAD \times LGD = EL$$

PD is presented as a percentage or decimal, as explained in the previous chapter. EAD is the amount the creditor has claims against the debtor at the time of calculation. EAD decreases at the same pace as the debtor pays the debt back. LGD is the percentage of the debt that may result in the creditor's loss. The debtor's survival despite the default, for example, liquidation opportunities and securities, reduces LGD. (Van Gestel et al. 2009.)

2.3 The Assessment of Credit Risk

Credit risk assessment is quite a significant part of defining the credit rating. Accurately completed credit risk assessment is important for banks to limit credit losses (Salihu and Shehu 2020). Credit risk assessment includes analysis of corporates' qualitative and

quantitative information from the financial reports from the history of corporates' operations (Tomić-Plazibat et al. 2006). The most proper way to predict corporates ability to pay its debt back in the future is with cash flow projections (Savvides 2011). Anyway, all the qualitative and quantitative sub-divisions impact critically on the credit risk assessment.

Many factors must be considered when assessing credit risk, and different rating agencies can categorize the process differently. The next two chapters present one method for assessing credit risk, which is divided into six segments.

2.3.1 Qualitative Assessment of Credit Risk

Five of the six segments are part of the qualitative analysis: ownership and corporate structure, governance and management, business and competitiveness, industry and markets, and sustainability risks (ESG). With ownership and corporate structure, an analyst defines if the company is part of a group and if it is a subsidiary or parent corporation and clears out the loans of the group's other companies. Also, the analyst analyses who exercises the company's controlling interest. The owner's financial situation is under analysis, as if the owners would be able to help the company if its covenants are close to being not fulfilled or if the company fails to pay its debt. When it comes to governance and management, the main question is who sits in the management group and on the board of directors and if they use their authority legally and report in accordance with current standards. Analyst investigates the company's potential ethical problems, potential legal proceedings, and the company management's risk appetite. When assessing a company's credit risk, the risk appetite is not necessarily seen as good quality. Great risk appetite can mean more risk without better profits when invested in debt capital due to the profit being locked into forehand set interest rates. (Olli, interview, 2024.)

With business and competitiveness, an analyst evaluates a company's business models, competitive ability, and competitive position in the market. The definition of the customer base and the company's operations compared to its competitors are relevant. In the part of industry and markets, the analyst defines a company's industry's cyclical sensitivity and sights of future growth. The markets, geographical area of operations, and the company's position in the market where corporate operates are also under analysis. The last qualitative segment is sustainability risks. Sustainability risks consist of

environmental risks (E), social risks (S), and governmental risks (G). Analyst defines probabilities of the realization of sustainability risks and the impacts in the matter of realization. The sustainability risks are complex and have an impact on all the other segments under the assessment. After the corporate sustainability reporting directive (CSRD) set by the EU (2022/2464) comes into force, it can facilitate the assessment of credit risks regarding sustainability risks. (Olli, interview, 2024.)

2.3.2 Quantitative Assessment of Credit Risk

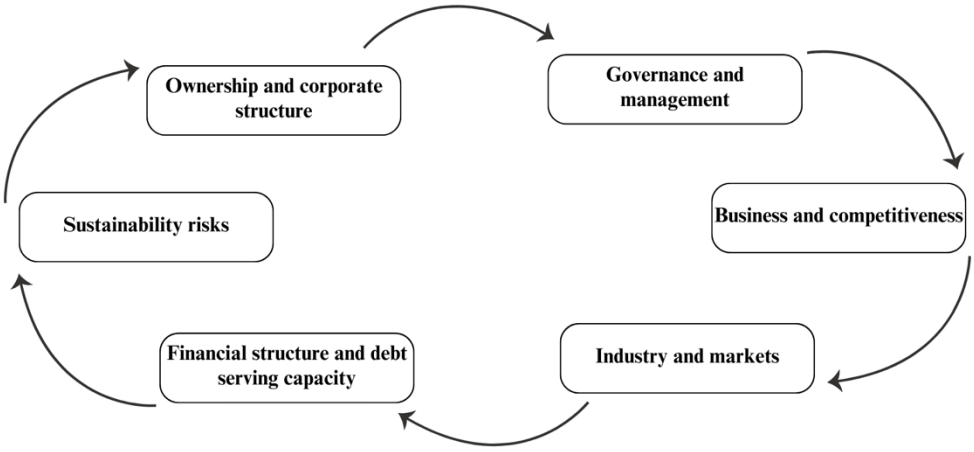
The quantitative assessment of credit risk consists of analysing the financial structure and debt servicing capacity. As a single section, these define the analysis's outcome critically. Financial structure and debt serving capacity include assessing the adequacy of cash flow and balance sheet position. Analysts also inspect the company’s balance sheet and financial solidity, indebtedness and debt maturity, liquidity risk, and the risk of loan interest and exchange rates (Olli, interview, 2024).

Assessing a company’s financial situation over several financial years in the entity is an important part of understanding its financial capability. Information from several years provides a good overall picture of the company’s financial operations and is crucial when assessing its overall financial capability. However, Free Cash Flow (FCF) is quite an important individual item when assessing a company’s credit risk. While a company may have the incentive to manipulate certain items in the income statement or balance sheet, free cash flow is typically an element that cannot be easily altered or adjusted by the company. In addition, free cash flow is a key metric when evaluating the company’s capability to pay its debt and further evaluating the company’s creditworthiness, especially in the long term. To sum up, it is important for the analyst to determine whether the company is able to generate enough free cash flow to repay its debt. (Olli, interview, 2024.)

An important part of the quantitative assessment of credit risk is the financial information available of the companies. Companies do not willingly offer financial information that would decrease their credit rating. In addition, smaller companies do not need to report as extensively, and in such cases, interviews with the company’s management serve as a crucial source of information for analysts (Olli, interview, 2024).

Because of its nature, quantitative analysis is more precise than qualitative analysis. Numbers are easier to predict and assess, and if the company has prepared its financial reports according to current standards, analysts can trust on the accuracy of the reports under analysis. However, all segments of credit risk assessment impact each other (Olli, interview, 2024). The analysis must be conducted without separating any sub-divisions from one another, as the figure below shows. Also, predictions are an important part of assessing corporates' probability of default from both the qualitative and quantitative points of view (Olli, interview, 2024).

Figure 1 An example of the possible classification of credit risk assessment



2.4 Deficiencies of Credit Ratings

Credit ratings are generally well-known measures among investors and other financial actors. Due to its simplicity and comparability, it is a useful source when assessing prices to, for example, companies' bonds. However, there are limitations concerning credit ratings that limit its usefulness. Welch (2022) determines four limitations of utilizing credit ratings. The first limitation is the credit ratings do not consider systematic risk of the market. Credit rating does not include the risk of many companies defaulting at the same time, for example, due to a common crisis. Instead, credit risk ratings consider only the issuer's risk of default. (Welch 2022.)

Secondly, credit rating agencies are not responsible for their ratings, even if they mislead investors (Welch 2022). Liberti and Petersen (2019) splits the information affecting

lending practices and financial decision-making into hard and soft information. There are also findings that the company's relationship with the lender plays a role when determining the company's costs of debt and access to credit (Petersen and Rajan 1994). From this can be concluded that the credit rating agencies' responsibility freedom allows credit rating agencies to be more easily affected by soft information and their relationship to the issuer. As a result, the ratings could not be correct, which distorts the market.

Thirdly, the credit rating agencies are paid by the investment banks when rating their securities. Rating agencies would be motivated to assess the ratings of the institutions that pay for them more optimistically than otherwise. A great example of the realization of the side effects of optimistic ratings is the financial crisis in 2008-2009 (Eichengreen et al. 2012). Credit rating agencies earned a great sum of money when assessing bonds issued by investment banks optimistically to provide the investment banks higher ratings. The consequences of the third issue could be classified into the same category as the second issue. In conclusion, credit ratings are not fully independent as far as they are assessed by humans. (Welch 2022.)

The last issue of credit risk ratings determined by Welch (2022) is the ratings' change over time. Bonds move up and down approximately 3-10% per year after being issued (Welch 2022). This complicates the aftermarket and can also distort the market and the prices of the bonds, especially if the issuer's financial situation changes.

3 Artificial Intelligence (AI)

Artificial Intelligence is defined as a machine's ability to learn, conclude, plan, and create, which are typical human skills. Technical systems collect data and information to solve problems, observe their environment, and draw observational conclusions via AI. The use of Artificial Intelligence has increased for the past few years, and the European Parliament predicts that AI will significantly change everyday life, including the financial field, in the future. (European Parliament 2023.)

Artificial intelligence covers a wide range of different technological systems. AI uses multiple different methods and models to deal with all the varieties of problem types it is trained (Sinha et al. 2021, 9). The most significant sub-divisions of AI from the point of view of this research are presented in this chapter.

3.1 Generative AI vs. Operational AI

Generative AI is a type of machine learning architecture that can create seemingly new content, such as texts, images, and audio. It is trained using several computational techniques, such as generative adversarial networks (GAN) and reinforcement learning from human feedback (RLHF). When trained with these methods, the model can learn relationships and patterns from the training data to produce novel data instances. (Feuerriegel et al. 2024.)

Large language models (LLMs) are a type of generative AI that creates new text and recognizes text fed to it. Chatbots are an example of LLMs. (Chen et al. 2023.)

Operational AI is a part of a company's day-to-day operations, for example, predicting from data and optimizing systems. Operational AI is also known as Traditional AI. For example, traditional AI can be utilized in supply chain management for optimising and automating supply chains (Helo and Hao 2022). There is also a positive correlation between a country’s AI supply chain interaction and sustainable development (Wang 2024).

Expert systems are an example of operational AI. Expert systems give out results based on the values fed to the model. Those models use only the data originally fed to them when giving out results for new problems. (Miller 2019; Sadok et al. 2022)

The most well-known form of AI is generative AI, which was first presented to the public in the form of chatbots. Nevertheless, operational AI has been widely used to enhance business operations and technological development compared to generative AI, but the role of generative AI is constantly growing in the business field (Chen et al. 2023).

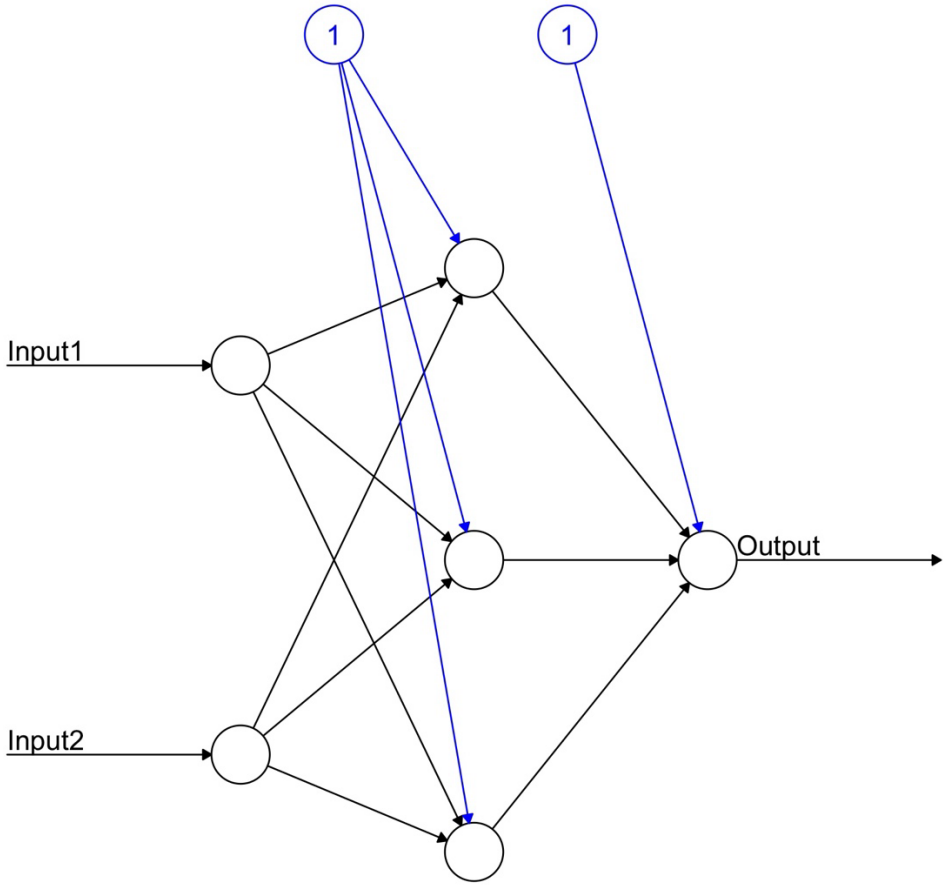
3.2 Machine Learning (ML)

Machine Learning is a widely utilized AI method. AI methods are models that solve problems given to them. ML models require large amounts of data and are trained with this data. From the training data, ML models observe certain formulas. When the model is fed a value, it gives an answer based on formulas it has created from the training data. (Campesato 2020, 18-19.)

Machine learning is divided into supervised learning, unsupervised learning, and reinforcement learning. Supervised learning requires a specific, well-labelled dataset to train the model. Unsupervised learning does not require a well-labelled dataset to find probable patterns and outcomes. Reinforcement learning is applied when the amount of data is not enough to train the model or when the variability of the data is not sufficient. With reinforcement learning, the model takes feedback during training and adapts the feedback to its logic. (Sinha et al., 2021, 9.)

Artificial Neural Networks (ANNs) are one kind of ML model. The implementation of ANN models has increased during the last decade due to its versatility. ANN tries to simulate biological neural networks. The simplified ANN model consists of three layers: the input layer, the hidden layer, and the output layer. Each layer is connected to each other with weighted links, and each layer consists of a group of neural nodes. As simplified, each neural nod includes some kind of metric, and each nod impacts the output. Complex models have more hidden layers, and the metrics affecting the output increase, which makes the model more complicated. When creating an ANN model, the input data is divided into training, validation, and testing subsets. The ANN model learns the logic of the data from the training subset. A validation subset is used to ensure the model has learned the right logic. The ANN model uses the testing subset to make independent predictions based on the learned logic. (Salihu and Shehu 2020; M. Wang and Ku 2021; Reis and Quintino 2023.)

Figure 2 A simple ANN model



3.3 Strong and Weak AI

Artificial Intelligence splits into Strong AI and Weak AI when it comes to AI techniques. The most significant difference between Weak and Strong AI is the expected results and how they are viewed. With weak AI, the focus is on whether the system performs correctly, whether the result is correct, or if it carries out its task the same way as humans would. Strong AI aims to perform its tasks the same way as humans and its purpose is to implement human thinking. (Campesato 2020, 4.)

Weak AI is currently more widely used in the world. Strong AI systems are more difficult to create, and there are ethical issues when creating strong AI systems. (Sinha et al. 2021, 9.)

3.4 Artificial Intelligence in Business and Finance

The nature of corporation defines how expensive and difficult in-house AI systems are to build. For that reason, there is much variation in the implementation of AI in different industries. The role of AI is continuously growing in the business field. This chapter

relates previous research and case examples of how AI has been utilized or could be utilized in the financial field and credit risk management. Companies have utilized AI technologies in their projects and ERP systems. AI is going to change the structure of the economic industry, and people need to adapt to it. Also, AI is going to have a huge impact on employee's tasks and working environments and the implementation of AI requires new regulations in the industry. (Lausberg et al. 2024; Xu et al. 2024.)

AI adoption improved bond credit ratings in Chinese A-share listed firms. It also improved firms' information transparency and productivity. In conclusion, AI adoption improved firms' operations, which, by implication, improved financial measures. When financial measures improved, credit ratings also increased. (Xu et al. 2024.)

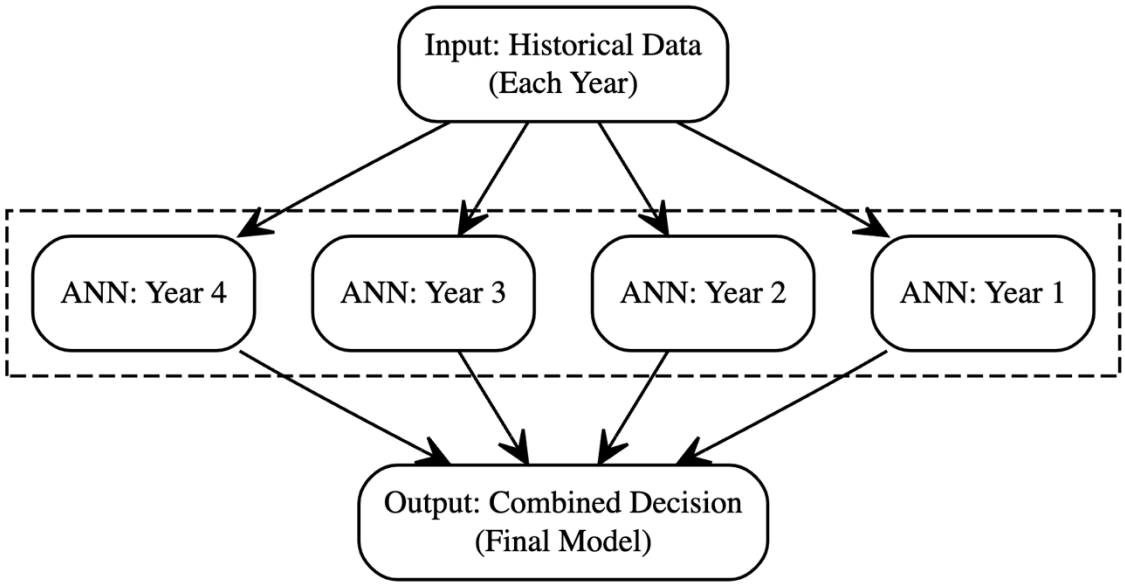
AI can be utilized in credit risk management to expand banking services to the unbanked and underbanked population. Alternative data, such as satellite images, public data, registered from companies, and social media data, allows machine learning techniques to be utilized when assessing the creditworthiness of individuals. AI agents can collect and analyse big data from alternative data sources to create machine learning algorithms to assess the creditworthiness of the unbanked and underbanked populations. To make use of AI in credit risk management and to expand banking services, financial institutions must invest in evaluating AI and especially machine learning systems. (Mhlanga 2021.)

AI has also been utilized to facilitate people's access to mortgages. Experian, a consumer credit reference agency, implemented AI to make more precise predictions of people's spending habits and to reduce the time it takes to apply for mortgages. The AI system optimizes the mortgage process by analysing thousands of mortgage applications and then determining the most efficient workflows between different groups. The lenders would be able to estimate the applicant's ability to pay the debt back based on other customers' data that fits the applicant's profile. (Marr et al. 2019, 221.)

When it comes to corporates' credit ratings, Wang and Ku (2021) introduced Parallel Artificial Neural Networks (PANN) as a tool to predict credit ratings. PANN is trained with historical financial data and, according to Wang and Ku (2021), results based on credit rating history, predicts more accurate ratings, at least compared to traditional methods. PANN works with quite the same principles as Experian when expanding people's access to mortgages. PANN is a combination of several independent artificial neural networks (ANNs), each utilizing data on the financial performance of each year in

the company's history. PANN has superior performance with data from the real world. (Wang and Ku 2021.)

Figure 3 The Parallel ANN model (Wang and Ku 2021)



AI has improved business operations in different fields (Helo and Hao 2022; Xu et al. 2024). With the help of AI, banks can utilize more and different kinds of datasets, which provides a base for better credit risk predictions (Sadok et al. 2022). The implementation of AI can enhance the credit application process (Salihu and Shehu 2020). There are multiple ways to utilize AI by different AI models (Wang and Ku 2021; Locatelli et al. 2022). The examples introduced in this chapter underline AIs, and especially expert systems', capabilities to make business operations more precise and efficient. The utilization of AI has increased companies' productivity and will increase even more in the future when AI models are trained and developed even more to respond better to the demands of companies. However, AI has not been used to its full potential in the field of credit risk management and credit risk ratings. The next chapter will consider how AI could be utilized in credit risk management and, more specifically, in human-based credit ratings.

4 Enhancing Credit Risk Analysis with AI

This chapter answers to the research question of how credit rating agencies could enhance and complement human-based credit risk analysis with AI. Also, this chapter considers tools to minimize the credit rating limitations Welch (2022) determined. The methods presented previously in chapter 3.4 and the themes that came up in the interview act as a base for the analysis. The aim of the analysis is to conclude if these methods and themes could be generalized to apply human-based corporates' credit ratings and Welch's (2022) limitations of credit ratings. The hypothesis is that by utilizing AI in credit risk analysis, experts would be able to focus on their expertise, and statistical and repetitive tasks would be made by AI.

Because of the nature of credit risk management when it comes to credit risk ratings, the utilization of AI is seemingly limited. The field heavily depends on a few big operators such as Standard & Poor's and Moody's. The credit risk assessments and ratings are quite established. The potential of AI to change the industry significantly soon is not likely, but AI could enable improvements to credit risk assessments, such as making credit risk assessments more precise and enhancing credit risk assessments. AI will probably not replace humans in credit analysis for a long time ahead, but it could help experts find and filter relevant financial information about companies under credit risk analysis. (Olli, interview, 2024.)

4.1 Expanding Companies Access to Credit

As chapter 4.1 defines, financial institutions can make use of AI when assessing the creditworthiness of individuals, for example, when it comes to lending and mortgages. This can also be extended to include smaller companies struggling to get credit (Mhlanga, 2021). Considering the nature of AI, the methods Experian used could possibly be expanded to increase companies' access to credit. It would require large amounts of data on different companies' financial management in multiple different financial situations. Expert models could be trained with this data, and when assessing a company's credit risk, the model could estimate the company's payback capability. The model could estimate the company's payback capability by matching the company to the same profile companies in the data. The expert model could possibly use the same methodology as Experian in the case example.

Instead, it is not likely that financial institutions would invest large amounts of money to make it easier for companies to get more debt by AI, at least before industry leaders take that step (Locatelli et al. 2022, 2; Olli, interview, 2024). The expert models yet presented, could not implement current credit risk rating systems (Mhlanga 2021; Wang and Ku 2021). Instead, they would do the rating itself without human-based analysis. It would be difficult for financial institutions to trust this kind of systems yet. Consequently, the next parts will discuss how to implement current credit rating systems with AI.

4.2 Making Credit Ratings More Precise with AI

One of the current changes in the field of credit risk management is the large amount of information available of companies. It requires a lot of resources from credit risk analysts to obtain all the financial information about companies under analysis, but at the same time, it is crucial for financial institutions to obtain all the information to maintain their competitive position (Locatelli et al. 2022, 30). According to Locatelli et al. (2022, 40), financial institutions could exploit advanced ML techniques to obtain more precise ratings. Advanced ML models could provide online ratings calculated in real-time for financial institutions to automate the rating process and update automatically, surprising changes in the market (Locatelli et al. 2022, 30-31).

The PANN model Wang and Ku (2021) presented could be extended into an online model. In this case, the PANN model would continuously calculate credit ratings based on historical financial data and new financial data when new data is released. Since the PANN model does not have a human effect on credit ratings, financial institutions could hardly fully trust this kind of online rating, at least not yet. Instead, online models could be utilized to minimize the risk of using outdated ratings and ensure the ratings are independent.

As narrated in chapter 2.3, Welch (2022) determined four limitations regarding credit ratings. The first limitation is credit ratings not considering systematic risk of the market. The first limitation is part of the nature of the ratings and cannot be eliminated with AI, at least in a beneficial way. The best way to make use of the first issue is for all actors in the financial field to acknowledge it.

According to Welch (2022) the second limitation of ratings is rating agencies not being responsible for their ratings. The third issue is the analyst’s potential readiness to assess

the ratings optimistically to receive higher rewards (Welch 2022). If the online model acts independently from the analyst, could financial institutions compare the analyst's rating and the model's ratings to ensure the analyst's rating is unbiased. This would be the answer to Welch's (2022) second and third limitations of the use of credit risk ratings. The fourth limitation Welch (2022) presented was the ratings change over time. If making use of the online ratings, when the model changes the company's credit risk rating, the analyst should also reassess the rating.

Training advanced ML models to create online ratings would make credit risk assessment more precise and limit the possibilities of dependent ratings. Even though Welch's (2022) first issue cannot be eliminated, the three other issues could, in theory, be eliminated with the help of AI. Anyway, in this case, the analysis would be made twice, and it would not facilitate analysts' work. The next chapter considers how to facilitate analysts' work with the help of AI.

4.3 Enhancing Human-Based Credit Risk Ratings with AI

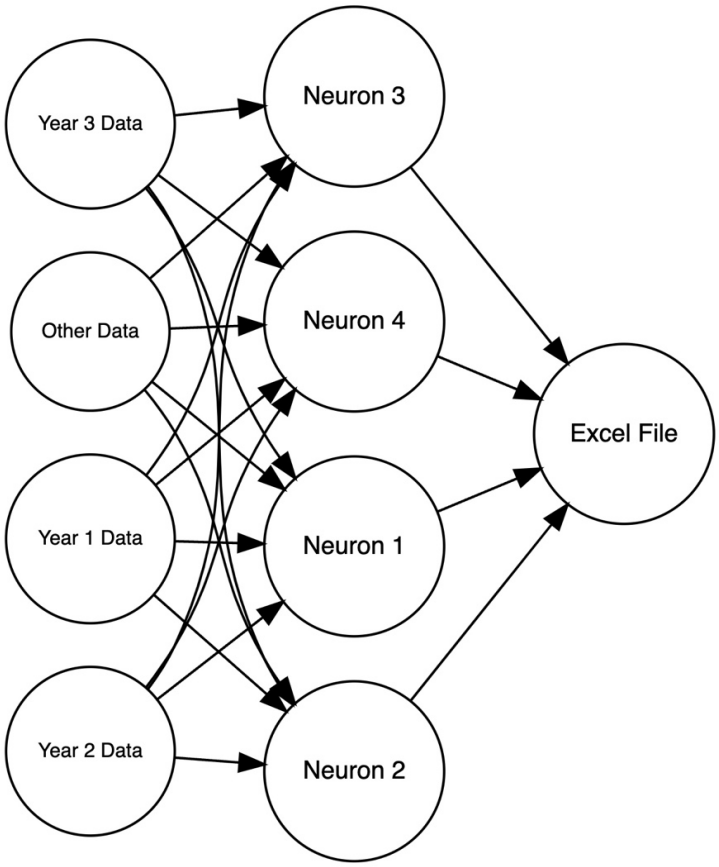
The definition of significant items in accounting is open to various interpretations. When assessing credit risks, analysts spend a lot of time searching for relevant information from the material. They need to separate poor profitability from a worse business cycle or other temporary poor results. To get an adequate overview, analysts need to inspect, interpret, and adjust comparable a company's financial and sustainability reports from multiple previous years. (Olli, interview, 2024.)

Artificial Neural Networks (ANN) was defined in chapter 3.2 (Wang and Ku 2021). Wang and Ku (2021) presented how ANN could be utilized in the form of PANN. Previously presented methods lacked when, instead of implementing human-based analysis, these methods would redo the analysis. ANN could be utilized to help analysts get an adequate overview of the financial situation of the company under analysis.

As Wang and Ku (2021) related, ANNs consist of the input layer, hidden layers, and output layer. The main difference between operational AI systems, such as expert systems, and artificial neural networks is that expert systems use only the training data when giving out results (Sadok et al. 2022). Instead, ANN systems learn continuously from examples in addition to training data fed to it when training the model (Sadok et al. 2022). In addition to expert systems, ANN can adapt the data and feedback as it is given

more inputs. ANN model could be trained to give out, for example, a company's comparable long-term financial information in Excel format when fed all the financial data available of the company. In addition to the training data, the ANN model could be trained with the help of analysts. For example, the model would give out an Excel file of the company's financial information as defined earlier, and the analyst verifies the accuracy of the information in Excel and gives feedback to the model. If the file is incorrect, the model should redo the Excel based on the analyst's feedback.

Figure 4 The first ANN model based on my idea

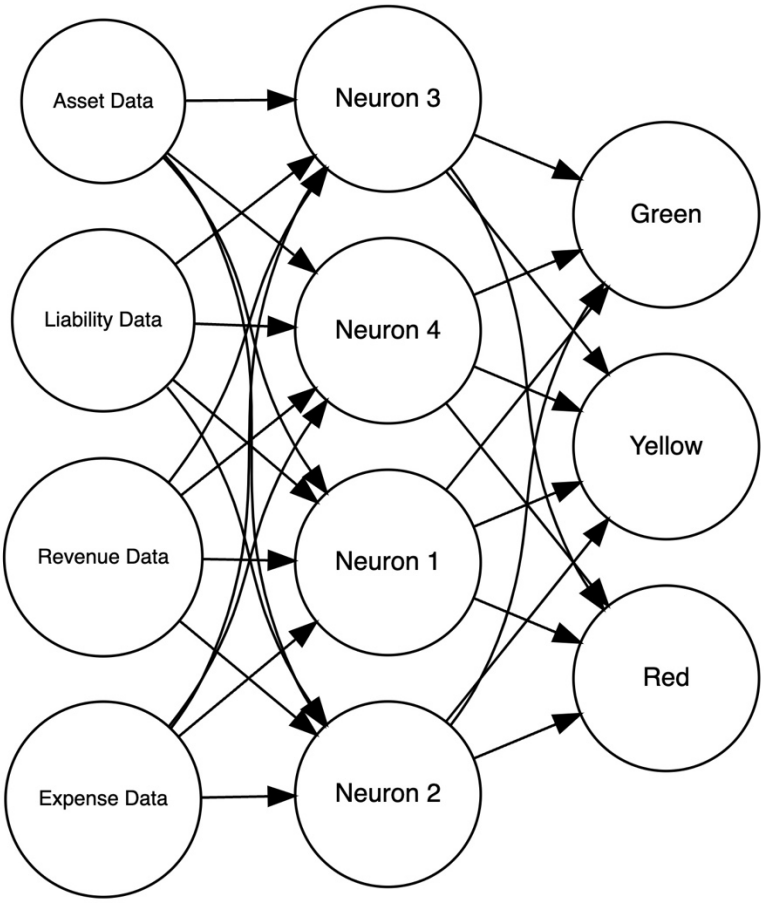


Based on the ANN output, the analyst could assess the quantitative credit risk more effectively when not having to put that much time into producing comparable financial information. The ANN model would evolve over time, and the aim is to get a model that gives out an accurate Excel file with all the relevant financial information on the first try. Anyway, even during the training process the analysts save resources when not having to transform the information to comparable form themselves, instead only giving feedback and comparing original information to the file ANN created.

As mentioned in chapter 4.2 and according to Olli (2024), there is also a lot of qualitative information available on companies, especially listed ones, and it takes a lot of resources from analysts to reach all the relevant information. Generative AI has been utilized in the form of Large Language Models (LLM) in business and finance (Chen et al. 2023). According to Chen et al. (2023), LLMs can be used to analyse a company's public information. Based on the public information, LLMs could give valuable insights into companies' operations. AI could be generalized to companies' research, both qualitative and quantitative information, in the same ways as Chen, Wu and Zhao (2023) presented, AI could be utilized in financial and business research. For example, LLMs could be trained to recognize relevant companies' information. The model could find the relevant points from the company's data and analysts could ensure that no important items or information has been overlooked.

According to Olli (2024) AI could maybe be utilized at the start of the analysis when assessing if it is relevant even to assess credit risk. Olli (2024) threw the idea of a theory where an AI model could do a preliminary assessment of the company's overall position before the analyst starts the analysis. The principle Olli (2024) presented could benefit, for example, banks, insurance companies, and big corporations assessing credit risk when potentially lending, guaranteeing a loan, or selling on credit. The principle could be implemented with the ANN model determining if the company under analysis is, for example, green, yellow, or red. If the company under analysis gets a green assessment from AI, its financials and other metrics are great according to AI. Yellow, on the other hand, means that AI is not sure if the target is great or not, and it requires more specific analysis. Red ones are bad investments, and lending to them is not profitable under any circumstances, according to AI. Green and yellow targets would, for example, be analysed by analysts and red ones would receive immediate negative decisions. This kind of model would reduce analysts work and the green and yellow analysis could be made more efficiently.

Figure 5 The second ANN model based on my idea



The principle Olli (2024) suggested could be implemented with the same kind of artificial neural network (ANN) model as presented earlier. However, instead of an Excel file, the input includes qualitative reports as well as financial information. The output is either green, yellow, or red.

4.4 Limitations of Using AI in Credit Risk Ratings

The use of AI in credit risk ratings is still quite limited today (Sadok et al. 2022). In addition to the conservative nature of the field, other limiting factors make credit risk agencies suspicious of AI (Olli, interview, 2024). Based on previous research, information leak risks, challenges between AI and human cooperation, and ethical issues when implementing AI in credit ratings are among the most significant limitations (Bundy et al. 2023; Giudici and Raffinetti 2023).

Previous research supports the claim of uncertainty related to AI. Failures of AI implementation are unavoidable when introducing chatbots and other AI systems to customers (Song et al. 2023). Cummings et al. (2024) presents an accident caused by AI. According to Cummings et al. (2024) the autonomous car dragged the pedestrian for 8

seconds after the pedestrian was thrown on the autonomous car's way by another car. This example underlines the imperfection and vulnerability of AI can cause serious damage. For that reason, the limitations and risks of AI need to be taken seriously.

When assessing the limitations of utilizing AI in credit ratings, a relevant question is the risks of utilizing AI in human-based credit risk analysis. Information leak risk is quite a significant risk due to the extent of the damage caused when possibly implemented. Banks are responsible to protect customers' data (Sadok et al. 2022). Because of the nature of AI, credit rating agencies must create in-house AI systems when implementing AI in their operations. For example, ML systems can leak the information fed to it because they use all the information and feedback fed to it to develop their operations (Sadok et al. 2022). For that reason, these models embrace all the information fed to them as part of their operations and may use the information to the next user's problems.

In-house AI systems restrict unintentional information leaks, but they do not solve all problems related to information leak risks. In addition to implementing the in-house AI systems, those systems need to be protected well to prevent misuse of the data in the systems. As the utilization of AI is expanding in the financial field, the ML and AI models should include certain metrics to evaluate the trustworthiness of AI applications (Giudici and Raffinetti 2023). Giudici and Raffinetti (2023) suggest these models should include sustainability, accuracy, fairness, and explainability (S.A.F.E.) as key metrics. The advance of the metrics Giudici and Raffinetti (2023) presented is the stability of it despite the irregularity in data. In addition, all four metrics are based on one integrated statistical method, the Lorenz curve, which provides a better assessment of the AI method's trustworthiness when compared to other metrics (Giudici and Raffinetti 2023).

On the other hand, the in-house AI systems, created especially for credit rating agencies to meet their needs, are quite expensive when compared to AI systems available to all. The next question is when companies have invested in expensive in-house AI systems, if AI can even help humans to make more precise analyses. The cooperation between humans and AI is the key factor when assessing if humans can make use of AI in their analysis.

Humans do not fully understand AI, and AI is not capable of implementing human reasoning about mental characteristics, which is crucial for rich social interactions (Bundy et al. 2023). Analyst interviews with the company's management, as a resource for the

analysis, cannot be yet replaced with AI systems due to the psychological understanding needed in the interview. Bundy et al. (2023) present “Cognitive Artificial Intelligence” as a potential tool to improve human-machine cooperation, especially learning methods and the relationship between reasoning and learning. There is a need for advancements in cognitive science and AI to enable more realistic interaction between humans and AI (Bundy et al. 2023). When implementing AI to human-based credit risk analysis, the analysts working with AI systems should be trained to understand AI’s capabilities and the best ways to cooperate with AI to get the best results. The key for analysts is to understand they are chatting and giving feedback to machines instead of humans. Even if the chatting is human-likely, the machine does not receive or analyse the information the same way as humans.

The ethical point of view is also a significant limitation when implementing AI into the credit risk assessment. Even if the academic field has introduced different credit rating AI models, the models have not been implemented in the real world. The models presented would do the whole analysis without the help of analysts. The issue is the analysts not being able to ensure the steps of analysis because the model gives out only the credit rating or some other kind of assessment of the credit risk of the target under analysis. Sadok et al. (2022) relates to “black boxes” when referring to not knowing what variables AI algorithms use for their predictions. The opacity of the AI models causes major ethical and legal limitations (Sadok et al. 2022).

When using big data, the data includes many different variables. In addition to relevant variables such as a company’s previous repayment capability, data may include information about targets’ social networks. Due to the opacity of AI models, analysts cannot be sure which variables the model uses. The credit rating made by AI could possibly rely on non-relevant measures. Humans can filter relevant information from non-relevant information, but AI cannot recognize the differences between variables in the data. (Sadok et al. 2022; Reis and Quintino 2023.)

If the financial institute utilizing AI violates the law in operation, which includes AI, there is also an issue from the legal point of view. AI cannot be legally responsible, but no one else can take responsibility for illegal actions on AI's behalf. Even if the last responsible is the financial institution, there is an ethical issue in punishing someone else for machines' actions. Also, the use of LLMs and general AI includes special limitations.

Generative AI can give fictitious and illogical responses, which misleads users. In addition, generative AI can answer differently to questions with the same meaning depending on the changes in the prompt base. Generative AI requires further development before it can be implemented into the operations of financial institutions. (Chen et al. 2023.)

Credit ratings determine if the target gets, for example, a loan, and the results of analysis are big factors when assessing, in this case, companies' access to credit. Due to credit analysis' great influence, credit rating agencies must be sure their analyses are made ethically and correctly. Utilizing AI to make the whole assessment or determine the rating would not ensure that the analysis is made ethically and correctly, at least for now. The limitations of using AI in credit ratings are still more significant than the potential benefits of the implementation. In addition to the risk of information leaks and expenses of creating new AI systems, there is no certainty if the AI systems even enhance companies' operations. The ethical issue of credit rating agencies trusting AI to make the analysis correctly when the agencies give up on traditional and established practices is significant and not compensable. These limitations contribute to the minor use of AI in credit risk operations so far.

5 Conclusions

5.1 Summary

This research investigated how to enhance and complement credit risk analysis with AI. The research question was: How can credit rating agencies enhance and complement human-based credit ratings with AI? The main viewpoint of this research was how to enhance and complement human-based credit risk analysis with AI. This research also considers how to eliminate the limitations of credit ratings, Welch (2022, 6.2) determined, with AI.

The conclusion to the research question was not that simple. Several credit rating AI models have been presented in the academic field. The AI models yet presented focus on automating the whole credit risk assessment process. This research focuses on enhancing and complementing especially human-based credit risk assessment with AI.

Academic credit rating AI models have not been utilized in the real world because there are too many risks when letting AI do the whole rating instead of an analyst. Implementing AI in credit rating agencies and analysts' daily operations has multiple limitations, such as ethical concerns, information leak risks, and the expenses of creating the models despite the uncertainty of AI systems working correctly. Implementing AI into credit risk operations would increase technological control of credit risk management tools to prevent data leaks and misuse.

This research concludes that three of four Welch's (2022) credit rating limitations could be in theory eliminated with AI. Credit rating agencies could implement credit rating AI models yet presented to get an impartial and continuous rating, considering current changes in the financial markets affecting the credit rating. This research concludes the ways to eliminate Welch's (2022) credit rating limitations would redo the analysis. For that reason, these models would not facilitate the analyst's work.

This research describes two ANN models which could facilitate and enhance analyst's work with credit risk assessment. The first model would be useful when filtering relevant financial information from all the data available of the company under analysis. The second model would be useful before analysis when allocating resources and filtering, which analysis are crucial to make. The second model would not particularly enhance

credit ratings. The second model could significantly enhance credit risk assessment in some cases, such as banks, insurance companies, and big corporations assessing credit risk when potentially lending, guaranteeing a loan, or selling on credit.

In conclusion, the credit rating limitations determined by Welch (2022) cannot be eliminated without duplicate analysis for now. Instead, this research introduces ways that analysts could benefit from AI while analysing companies' credit risks.

The most significant advance in enhancing human-based credit risk assessment with AI compared to credit rating AI models is the transparency of the process. When AI does only simple and repetitive tasks, analysts have more resources for the analysis, but at the same time, the analysis process is explainable. The same limitations and risks of utilizing AI in credit risk management apply even if the credit risk assessment process is enhanced only particularly with AI. Even though the risks and limitations are not that significant when utilizing AI particularly in the credit rating process, the utilization of AI in the credit ratings requires more research before implementing the models presented to the real world.

5.2 Suggestions for Further Research

This research considers only the quantitative assessment of credit risk analysis when utilizing AI. Further research could also include qualitative parts. Also, this research does not consider the regulation of AI in the financial field. AI has been widely regulated, especially in the EU, and the regulations limit its potential utilization. Therefore, the regulation of AI and the potential utilization of AI considering the regulation should also be investigated more widely.

This research includes references from multiple continents, making it global. Instead, credit risk ratings depend on the economics and principles of the area in which financial institutions operate. Also, some continents are more advanced in using AI, so the utilization of AI in credit risk ratings cannot be directly generalized globally. Further research should focus on utilizing AI in human-based credit risk ratings by continent or economics.

In addition to how different continents could utilize AI, different financial institutions could also be separated. This research does not consider the differences between each financial actor or the purposes of their acts. To maximize the advantage of AI, it should

be targeted to meet the needs of each actor. Further research should also consider how different financial actors could utilize AI to fulfill their needs.

This research includes limited ethical dilemmas regarding the use of AI in credit ratings. Further research should consider ethical points of view more broadly. Even though this research supposes credit rating AI models to be more independent than human-based ratings, this assumption has not been investigated broadly yet. Further research should conclude whether AI is independent when it comes to credit ratings.

References

Agarwal, S. – Amromin, G. – Ben-David, I. – Chomsisengphet, S. – Evanoff. D.D. (2014) Predatory Lending and the Subprime Crisis. *Journal of Financial Economics,* Vol. 113(1), 29–52.

Bhimani, A. –Horngren, C. T. – Datar, S. M. – Rajan, M. V. (2019) Management and Cost Accounting. 7th edition. Pearson, Harlow.

Bundy, A. – Chater, N. – Muggleton, S. (2023) Introduction to 'Cognitive Artificial Intelligence.' *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* Vol. 381(2251), 1-7.

Campesato, O. (2020) Artificial Intelligence, Machine Learning and Deep Learning, Mercury Learning & Information, Dulles.

Chen, B. – Wu, Z. – Zhao, R. (2023) From Fiction to Fact: The Growing Role of Generative AI in Business and Finance. *Journal of Chinese Economic and Business Studies,* Vol. 21(4), 471–496.

Cousin, J. G. – Dereeper, S. – Essama Zoh, G. (2024) Impact of Credit Risk Management on Provisioning Expectations: Evidence from U.S. Banks during the Subprime Crisis. *Finance Research Letters,* Vol. 62(4), 1-8.

Cummings, M. M. – Wheeler, B. – Kliem, J. (2024) A Root Cause Analysis of a Self-Driving Car Dragging a Pedestrian. *Computer,* Vol. 57(11), 31–40.

Ding, A. A. – Tian, S. – Yu, Y. – Guo, H. (2012) A Class of Discrete Transformation Survival Models With Application to Default Probability Prediction. *Journal of the American Statistical Association,* Vol. 107(499), 990–1003.

Eichengreen, B. – Mody, A. – Nedeljkovic, M. – Sarno, L. (2012) How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads. *Journal of International Money and Finance,* Vol. 31(5), 1299–1318.

European parliament. (2023) Mitä tekoäly on ja mihin sitä kaytetään? <https://www.europarl.europa.eu/pdfs/news/expert/2020/9/story/20200827STO85804/20200827STO85804_fi.pdf > retrieved on 30.10.2024

EUR-Lex (2022) Directive (EU) 2022/2464 <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022L2464> retrieved on 30.10.2024

Feuerriegel, S. – Hartmann, J. – Janiesch, C. – Zschech, P. (2024) Generative AI. *Business & Information Systems Engineering,* Vol. 66(1), 111–126.

Van Gestel, T. – Baesens, B. (2009) Credit Risk Management: basic concepts: Financial Risk Components, Rating Analysis, Models, Economic and Regulatory Capital. Oxford University Press, Oxford.

Giudici, P. – Raffinetti, E. (2023) SAFE Artificial Intelligence in Finance. *Finance Research Letters,* Vol. 56(9), 1-14.

Helo, P. – Hao, Y. (2022) Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study. *Production Planning & Control,* Vol. 33(16), 1573–1590.

Hull, J. C. (2018) Risk Management and Financial Institutions. 5th edition. John Wiley & Sons, Hoboken, New Jersey.

Kong, D. – Tiong, R. L. – Cheah, C. Y. – Permana, A. – Ehrlich, M. (2008) Assessment of Credit Risk in Project Finance. *Journal of Construction Engineering and Management,* Vol. 134(11), 876–884.

Korinek, A. (2023) Generative AI for Economic Research: Use Cases and Implications for Economists. *Journal of Economic Literature,* Vol. 61(4), 1281–1317.

Lausberg, I. – Vogelsang, M. (2024) AI in Business and Economics. De Gruyter, Berlin/Boston.

Li, S. – Tian, S. – Yu, Y. – Zhu, X. – Lian, H. (2023) Corporate Probability of Default: A Single-Index Hazard Model Approach. *Journal of Business & Economic Statistics,* Vol. 41(4), 1288–1299.

Liberti, J. M. – Petersen, M. A. (2019) Information: Hard and Soft. *The Review of Corporate Finance Studies,* Vol. 8(1), 1–41.

Locatelli, R. – Pepe, G. Salis, F. (2022) Artificial Intelligence and Credit Risk: The Use of Alternative Data and Methods in Internal Credit Rating. Springer International Publishing, Cham.

Marr, B. – Ward, M. (2019) Artificial Intelligence in practice: How 50 successful companies used artificial intelligence to solve problems. 1st edition. John Wiley & Sons, Chichester.

Mhlanga, D. (2021) Financial Inclusion in Emerging Economies: The Application of Machine Learning and Artificial Intelligence in Credit Risk Assessment. *International Journal of Financial Studies,* Vol. 9(3), 39-55.

Miller, T. (2019) Explanation in Artificial Intelligence: Insights from the Social Sciences. *Artificial Intelligence,* Vol. 267(2), 1–38.

Olli, Kaisa (2024). Interview on credit risk analysis. Conducted on 1.11.2024, by Olivia Wahlberg

Petersen, M. A. – Rajan, R. G. (1994) The Benefits of Lending Relationships: Evidence from Small Business Data. *The Journal of Finance,* Vol. 49(1), 3-37.

Reis, B. – Quintino, A. (2023) Evaluating Classical and Artificial Intelligence Methods for Credit Risk Analysis. *Journal of Economic Analysis,* Vol. 2(3), 94-112.

Sadok, H. – Sakka, F. – El Hadi, M – Maknouzi, E. (2022) Artificial Intelligence and Bank Credit Analysis: A Review. *Cogent Economics & Finance,* Vol. 10(1), 1-12.

Salihu, A. – Shehu, V. (2020) A Review of Algorithms for Credit Risk Analysis. *Proceedings of the ENTRENOVA,* Vol. (9), 134-146.

Savvides, S. C. (2011) Corporate Lending and the Assessment of Credit Risk. *Journal of Money, Investment and Banking,* Vol. (20), 124-128.

Sestino, A. – De Mauro, A. (2022) Leveraging Artificial Intelligence in Business: Implications, Applications and Methods. *Technology Analysis & Strategic Management,* Vol. 34(1), 16–29.

Sinha, S. – Huraimel, K. A. (2021) Reimagining businesses with AI. John Wiley & Sons, Hoboken, New Jersey.

Song, M. – Xing, X. – Duan, Y. – Mou, J. (2023) I Can Feel AI Failure: The Impact of Service Failure Type and Failure Assessment on Customer Recovery Expectation. *Industrial Management & Data Systems,* Vol. 123(12), 2949–2975.

Tomić-Plazibat, N. – Aljinović, Z. – Babić, Z. (2006) A Multi-Criteria Approach to Credit Risk Assessment. *Computers in Business,* Vol. (7), 76-81.

Venter, J. H. – De Jongh, P. J. (2024) Trading Option Portfolios Using Expected Profit and Expected Loss Metrics. *Risks,* Vol. 12(8), 130-148.

Wang, H. (2024) Linking AI Supply Chain Strength to Sustainable Development and Innovation: A Country-level Analysis. *Expert Systems,* Vol. 41(5), 1-15.

Wang, M. – Ku, H. (2021) Utilizing Historical Data for Corporate Credit Rating Assessment. *Expert Systems with Applications,* Vol. 165(3), 1-12.

Welch, I. (2022) Corporate Finance. 5th edition. Anderson Graduate School of Management University of California, Los Angeles.

Win, S. (2018) What Are the Possible Future Research Directions for Bank's Credit Risk Assessment Research? A Systematic Review of Literature. *International Economics and Economic Policy,* Vol. 15(4), 743–759.

Xu, G. – Li, X. – Li, S. – Tong, Y. (2024) Artificial Intelligence Adoption and Credit Ratings*. *Asia-Pacific Journal of Accounting & Economics,* Vol. (11), 1–15.

Appendices

Appendix 1 Interview Questions

- Millainen prosessi luottoriskien analysointi on käytännössä ja millaisia vaiheita siihen liittyy? / What kind of process is the credit risk analysis in practice and what stages are involved?

- Mitkä osat tästä prosessista on ihmisen tekemää analyysiä ja millaisia viitekehyksiä analyysille on? / Which parts of this analysis are made by humans ans what kind of frameworks exist to the analysis?

- Mistä analyytikot keräävät dataa analyysiä varten? / From where analysts collect data for the analysis?

- Perustuen kokemuksiisi luottoriski päällikkönä, voisiko tekoälyä hyödyntää joissain luottoriskianalyysin vaiheissa tulevaisuudessa? Ja jos voi, missä vaiheissa sitä voisi hyödyntää ja uskotko sen voivan vaikuttaa analyysien laatuun tai niiden tekemisen tehokkuuteen? / Based on your experiences as credit risk manager, could AI be utilized in some steps in yhe credit risk analysis in the future? And if so, in which steps it could be utilized, and do you believe it could affect to the quality of analysis or to the effectiveness of doing them?