Artificial Intelligence and Machine Learning usage in credit risk management

A study from the Swedish financial services industry

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Abstract

Credit risk management is a fundamental process established in almost every financial institution. There are various tools and methods that financial institutions can use in order to mitigate risks among their loan takers. Credit scoring is a standard method used to evaluate risks among loan applicants, and it can be done by traditional statistical methods as well as Artificial Intelligence- and Machine Learning methods. This thesis presents a survey result among different Swedish financial institutions on their use of Artificial Intelligence and Machine Learning solutions in credit risk management. The results find that Artificial Intelligence and Machine Learning is moderately used with ambitions to further increase the use. The credit risk management process still heavily relies on traditional statistical credit scoring methods as there are regulations, end user perspectives, ethical dilemmas, and IT aspects that still need to be addressed in order to fully enable an implementation of Artificial Intelligence and Machine Learning in this area. A combination of traditional statistical and Artificial Intelligence and Machine Learning solutions is seen as an optimal way forward.

Acknowledgements

We would like to send a big thank you to our supervisor Gert Sandahl who has made this thesis possible by contributing with his long experience giving us advice, ideas, and guiding us in the right direction during the writing process.

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Abbreviations

AI Artificial Intelligence

ML Machine learning

Glossary

Artificial intelligence - The Financial Stability Board (2017) defines AI as computer systems that can execute complex tasks that would generally require human intelligence.

Big Data - Big data is defined as a fast volume expansion of complex data, high in velocity and variety (TechAmerica Foundation 2012).

Big data analytics - IBM (2021) defines big data analytics as an analytic technique used for processing large quantities of big data sets.

Credit risk management - Credit risk management is the practice of identifying and mitigating loss by understanding limits of financial institutions loss reserves at any given time to maximize risk-adjusted returns (BIS 2000).

Creditworthiness - is a loan applicant's ability to pay off their debt.

Credit scoring - According to Mpofu & Mukosera (2014), credit scoring is used to evaluate the creditworthiness of a loan applicant. Usually, a numerical value with specific creditworthiness is associated with an individual and it describes the potential borrowers' ability to repay the loan. Credit scoring is based on several variables, such as income, financial history, employment, and demographics (Mpofu & Mukosera 2014).

Machine learning - ML is described as a subcategory of AI and is defined as creating algorithms that automatically develop and optimise themselves through experience without human intervention (Financial Stability Board 2017).

Table of contents

1. Introduction

1.1 Background

Financial institutions' primary source of income comes from loans (Samreen & Zaidi 2012). There is a risk that borrowers do not pay back their loans and therefore financial institutions have built methods that evaluate a loan applicant's ability to repay their debts to mitigate these risks. The most common method for credit risk management is traditional credit scoring (Eddy & Bakar 2017). It classifies the loan applicants based on a set of variables, and the result indicates whether the applicant will be granted a loan and if so, how much (Samreen & Zaidi 2012). Regardless of the banks' strict credit scoring policies, a certain amount of loan takers still face problems related to the repayment of their debts which can cause distress for financial institutions (Samreen & Zaidi 2012).

The recent development of Artificial Intelligence (AI) and Machine Learning (ML) technologies has been introduced in credit risk management leading to several benefits and concerns. AI and ML has led to significant improvements in analyzing large amounts of unstructured raw data collected from various sources and converting it into useful information (Financial Stability Board 2017). According to Plaschke, Ishaan & Whiteman (2018), new technology provides cheaper, better, and faster ways of dealing with finance functions' activities. This technology has gained traction, and organizational focus has shifted towards exploring these automation tracks further in-depth. The predictive algorithms in finance can recognize different financial patterns and make predictions (Financial Stability Board 2017). The acceleration of digital solutions has enabled AI and ML implementation in various ways, optimizing financial institutions' credit risk management (Mckinsey 2018).

1.2 Problem Discussion

During the last two decades, the amount of collected and available data has grown exponentially (Mckinsey 2018). This data, if analyzed and interpreted correctly, can lead to significant improvements when it comes to decision making. There is a large interest in the financial services industry to utilize this information and thereby improve their efficiency (Mckinsey 2018). The financial services industry is increasingly adopting AI and ML solutions to complement other tools in order to evaluate large amounts of data, identify relationships, and make predictions (Financial Stability Board 2017). The Financial Stability Board (2017) further states that the implementation of AI and ML has come from the desire to reduce costs, improve productivity, and improve risk management. In particular, according to existing research by the Bank of England (2019) and Biallas & O'Neill (2020), automation in risk management has seen a large increase in AI and ML solutions in the United States and the United Kingdom due to an increasing regulatory burden and unreliable credit risk models in the aftermath of the financial crisis from 2008 (Mckinsey 2018).

Another reason is risk management's close connection to financial institutions' core business activities. Financial institutions have primarily focused on innovation where AI and ML serve as tools to follow regulatory compliance and automate "dull" tasks (Financial Stability Board 2017). Existing research shows that traditional statistical credit scoring models are still extensively used in credit risk management. In our research we want to analyze to what extent AI and ML solutions are being used in the Swedish financial services industry.

1.3 Purpose

The purpose of this thesis is to describe to what extent AI and ML is implemented in the Swedish financial services industry (specifically when it comes to credit risk management) and to what degree it is in accordance with the existing research in the area.

1.4 Research question

This thesis addresses the following research question

1. To what degree has the Swedish financial services industry started to use AI and ML in credit risk management?

1.5 Limitations

This thesis does not address different credit scoring methods from a mathematical perspective, and it does not cover AI and ML from a computer science perspective either. The study is geographically limited to the financial services industry in Sweden and it covers both private and corporate lending.

2. Literature

As a starting point for this thesis, a literature review of previous research in the area of AI and ML use in the financial services industry was made. Findings from the literature review were used to refine the research question and to analyze the results to make conclusions.

2.1 Big data

According to TechAmerica Foundation (2012), big data is defined as a fast volume expansion of complex data, high in velocity and variety. Big data comes with challenges and opportunities that require advanced technologies such as AI and ML to analyse it and draw conclusions in order to make predictions (TechAmerica Foundation 2012).

According to the Federal Trade Commission (2016), using big data analytics is a cost-effective and robust way of collecting information. By using big data analytics, companies can optimize their business operations by better understanding clients' needs and environment while simultaneously mitigating risks (Federal Trade Commission 2016). Big data analytics can thus help make predictions that otherwise would not be possible with only human capacity.

When it comes to financial risks such as credit risks, there are examples of financial institutions using big data analytics to compile public record information such as bankruptcies and personal property ownership (Federal Trade Commission 2016). This information has been used to improve the evaluation of an individual's creditworthiness.

2.2 Artificial Intelligence and Machine Learning

In order to make big data comprehensible and useful, it requires AI and ML techniques to be implemented (Financial Stability Board 2017). The Financial Stability Board (2017) defines AI as computer systems that can execute complex tasks that would generally require human intelligence. ML is described as a subcategory of AI and is defined as creating algorithms that automatically develop and optimize themselves through experience without human intervention (Financial Stability Board 2017). ML algorithms can find hidden patterns and provide companies with comprehensible summaries of substantial datasets that in turn can be used as a basis for decision making (Financial Stability Board 2017). However, human intelligence has general knowledge as well as the ability to see a broader picture with context taken into account. Therefore, most industries are not planning to entirely replace human intelligence, but rather see AI and ML as complementary to human intelligence (Financial Stability Board 2017).

2.3 Credit Scoring

According to Mpofu & Mukosera (2014), credit scoring is used to evaluate the creditworthiness of a loan applicant. Usually, a numerical value with specific creditworthiness is associated with an individual and it describes the potential borrowers' ability to repay the loan (Mpofu & Mukosera 2014). Thereby the financial institutions such as banks strive to reduce their credit risks. According to Mpofu & Mukosera (2014) the credit scoring model is based on several variables, such as income, financial history, employment, and demographics. There is a wide range of credit scoring methods from traditional-based to AI and ML-based (Mpofu & Mukosera 2014). The objective with all credit scoring models is to forecast the individual loan applicant's ability to pay back the loan.

2.3.1 Traditional-based credit scoring models

Traditional-based credit scoring relies on quantified customers' characteristics stored in a database and is analyzed by using traditional statistical methods to identify the level of risk associated with a loan applicant (Vidal & Barbon 2019). This statistical credit scoring does not require large amounts of information as it bases the credit scoring estimates only on variables that have a proven direct correlation with the ability for repayment (Abdou & Pointon 2011). A loan applicant's total credit score is a sum of points defined by answering different questions which classifies the loan applicant into a category, approved or rejected (Abdou & Pointon 2011). According to Eddy & Bakar (2017), the traditional-based credit scoring method (primarily the logistic regression) is used by the majority of financial institutions.

The traditional-based credit scoring models require that a loan applicant has enough relevant historical credit information in order to be evaluated. In the cases of lack of such historical credit information a potentially creditworthy loan applicant may be rejected (Financial Stability Board 2017).

2.3.2 AI and ML in credit scoring

Financial institutions rely on credit scoring tools to provide them with a clear view of individuals' creditworthiness which serves as a foundation for accurate credit evaluations and decisions (Financial Stability Board 2017). AI and ML algorithms can optimize these credit decisions by making the process faster and cheaper while potentially mitigating the credit risks. According to the Financial Stability Board (2017), some financial institutions use unstructured and semi-structured datasets such as social media- and phone activity, to give them better insight into potential borrowers' creditworthiness. This differs from the traditional credit scoring models where the lenders decide if someone is creditworthy based on a predefined set of variables. If the potential borrowers lack enough historical credit information, their loan application may be rejected. Thereby this method leaves out many potential borrowers who may be creditworthy (Financial Stability Board 2017). Fintech is an example of start-up financial institutions that use AI and ML to target customers who may be rejected by financial institutions that use traditional credit scoring models (Financial Stability Board 2017). Leo, Sharma & Maddulety (2019) explain that AI and ML methods for creditworthiness evaluation can result in a more significant and more profitable loan portfolio for financial institutions.

However, the use of AI and ML in deciding a borrower's creditworthiness is problematized by O'Neil (2016), as the advanced algorithms of this type usually only provide "yes" or "no" answers and are not understandable for the loan officer. The AI and ML algorithms are developed and maintained by experts which can make them not easily understandable for end-users. O'Neil (2016) further explains that each of these algorithms is a simplification of reality as it includes a subset of all variables that could be taken into consideration by a human. The algorithms can also become outdated over time as society and people's preferences change (O'Neil 2016). O'Neil (2016) further describes several examples where AI algorithms have interpreted data in ways that has led to unjustified discrimination that in many cases was considered illegal.

According to Golbayani (2019), the fundamental problem in risk management is related to rare events that can trigger significant losses. These types of rare events happen infrequently, and no traditional mathematical framework allows real-time detection and analysis of these events (Golbayani 2019).

According to Aziz & Dowling (2019), AI-based credit scoring methods are considered to have more accurate results than the traditional ones. However, when it comes to user-friendliness, understanding the results, and the required skills for AI implementation (Aziz & Dowling 2019), the traditional statistical-based credit scoring models are still the preferred alternative (Eddy & Bakar 2017).

2.3.3 Combined traditional and AI approach for credit risk management

The traditional-based credit scoring is based on concrete numerical values of variables and cannot incorporate a considerable amount of additional (non-numerical) personal data about a loan taker that could improve the decision making (Abdou & Pointon 2011). AI methods can interpret large volumes of non-numerical data which makes them suitable for this type of credit scoring (Financial Stability Board 2017).

A study performed by Son, Byun & Lee (2016) analyzed different groups of loan takers over a 13-year period. It shows that AI and ML models perform better than the traditional models for credit risk prediction. However, the traditional credit scoring models do provide a better understanding of the results (Son, Byun & Lee 2016). In order to gain benefits of both the traditional and AI-based methods, Altman, Marco & Varetto (1994) suggest further investigation of a combined approach for predictive analysis.

Jarrahi (2018) proposes a so-called human-AI symbiosis where human intuition and AI analytics complement each other in order to improve decision making. He further explains that both humans and AI algorithms can become smarter over time as they benefit and learn from each other.

2.4 Legal Aspects of the AI and ML usage in the financial services industry

According to the Swedish government office (Regeringskansliet 2018), there are some general risks of using AI such as cyberattacks, data manipulation, and disinformation. The risks with AI are technical and ethical when it comes to its use, especially in public service (Regeringskansliet 2018). Therefore, the Swedish government office (Regeringskansliet 2018) and the European Banking Federation (2019) require AI algorithms to be transparent and understandable as it imposes moral and juridical challenges when it comes to constitution and automation of authorities' decisions. Financial institutions are subject for strict regulations including explanations to why a loan applicant has been rejected. Transparency and explainability are essential in the future development of AI and ML (European Banking Federation 2019) to prevent discrimination based on race, gender, education level, etc. (Zest AI 2020).

The European Parliament (2020) has concluded that the development of AI systems, if designed and implemented correctly, is not in conflict with the GDPR (General Data Protection Regulation). Further, the European Parliament (2020) claims that it needs to be clarified which AI applications may impose risks on personal integrity and thereby be a subject for a preventive assessment by the authorities.

As AI is a relatively new and evolving technology, it is essential to ensure that the laws and regulations are developed to enable and fit AI models in the European financial services industry (European Banking Federation 2019). It is essential to maintain a high consumer protection level while creating a technology-neutral regulation to develop AI in the financial services industry (European Banking Federation 2019).

3. Method

3.1 Research approach

This thesis describes the use of AI and ML in the Swedish financial services industry.

The research question evolved from being general to focusing on developing the research based on gathered data that has been derived from the studied scientific papers.

The methodology is primarily based on a quantitative approach. The approach is characterized by collecting numerical data which in our case has been gathered through a survey and by examining the scientific papers charting their findings. The gathered data is analyzed in order to find relationships between different variables (Patel & Davidson 2019).

The thesis has characteristics of being inductive, generalizing conclusions from the individual respondents in previous surveys (Bank of England 2019; Biallas & O'Neill 2020). Later these conclusions were analyzed in the context of Swedish financial institutions.

3.2 Theoretical Framework

The literature study is primarily based on literature, scientific papers, government reports and web pages about AI and ML use in the financial services industry. It was collected through the electronic databases, primarily from the University of Gothenburg databases GUP (2021) and GUPEA (2021), E-books, and Google Scholar (2021).

The literature study was also assembled by extending the search to different central banks' surveys to gain inspiration about AI and ML use cases in the financial services industry (Biallas & O'Neill 2020; Bank of England 2019). During the research, a critical approach was made to the gathered information by conducting a critical analysis of the sources and previous surveys performed in the subject (Patel & Davidson 2019, p. 68). This was done by analyzing references to the studied research papers, context of the research, academic institutions, and the studied companies' information.

3.3 Data collection

This section describes the methodology for the collection of primary and secondary data as well as the theoretical framework of how the survey has been conducted.

3.3.1 Primary data

The collected primary data has been described as empirics in this thesis. The advantage of collecting and using primary data is the possibility to formulate questions in a way that is directly related to the research question.

3.3.1.1 Survey

The primary data used in this thesis is primarily collected through a survey with closed-ended questions with “Yes” and “No” answering alternatives and a third alternative “I don’t know” which serves as a neutral stance.

Opened-ended questions have no predetermined response alternatives. The considered response is the respondents own answer. This could be problematic because the answers can have many variations or be too broad, which complicates analysis and interpretations of the data that could lead to many different conclusions about the gathered data (Bryman & Bell 2018).

The close-ended questions are expressed with a set of predefined answer alternatives among which the respondents can select one (Ejlertsson 2014). The close ended questions clearly reflect the respondents’ position concerning the research question. The advantage of using a survey containing close-ended questions is the possibility to distribute it among a population who can answer the questions without a personal interview. It also requires less time and effort to perform the survey and analyze the results compared to qualitative personal interviews (Ejlertsson 2014).

Initially, a set of open-ended questions were defined to be used in qualitative interviews with professionals working in Swedish financial institutions. The proposed methodology was to distribute the questions to relevant professionals through our personal network and follow up with personal interviews. The approach was not successful as it required much time from the respondents to answer and lack of knowledge about all of the questions. As a consequence of this, our approach needed to be redefined.

Following that, the focus shifted from a qualitative approach to a quantitative approach which consisted of a new survey with a set of close-ended research questions that covered credit risk models as well as the use of AI and ML in credit risk management. The selected respondents were limited to individuals in different management positions working in financial institutions in the Swedish financial services industry.

The construction of the close-ended survey questions had a high degree of standardization by sending out the survey equally to every respondent with a set of predefined answers: “yes”, “no” or “I don’t know”. The close-ended questions further simplified the analysis of the results. Answering “yes” or “no” indicated a clear answer to the question. Moreover, answering “I don’t know” indicated a neutral stance to the question (Patel & Davidson 2019, p. 73). The survey also guaranteed the anonymity of the respondents’ identity as well as their company.

The survey questions were developed to fit the Swedish financial institutions that are approved by Finansinspektionen (Sweden's financial supervisory authority) (FI 2018). The categorization of firms in this thesis was an adaption of the European Union's categorization of SME (European Commission 2020). The financial institutions were classified into four categories by analyzing each company's total revenue for the financial year 2019. The defined categories were: large financial institutions (revenue above 10 billion SEK), medium financial institutions (revenue between 1 billion SEK and 10 billion SEK), small financial institutions (between 100 million SEK and 1 billion SEK), and micro-sized financial institutions (under 100 million SEK). The sample was structured to cover an equal share of all sizes. This has been our studied population, which is a small fraction of the whole financial services industry in Sweden.

When searching for relevant literature, the main focus was on keywords such as “Big Data”, “Artificial Intelligence” and “Machine Learning”, which helped the authors narrow down the survey questions. These questions were relevant for getting a picture of AI and ML’s state in different financial institutions when it comes to the credit risk management process. The survey questions were also influenced by previously conducted surveys performed by Bank of England and the World Bank (Bank of England 2019, Biallas & O’Neill 2020).

Considerations were also made to the number of questions and the time consumption that could lead to a loss of interest or patience from the respondents and the survey cancellation as a result (SCB 2016). Extensive surveys can intimidate the intentional respondents (Bryman & Bell 2018), therefore the authors of this thesis made an effort to shorten the survey. The questions selected in the survey were considered necessary for the analysis. Unnecessary information that does not fit the proposed research area or does not provide value to the analysis was removed to simplify the survey (Bryman & Bell 2018).

In the following step, the survey was sent out through Google Forms (2021) to professionals in management positions such as Credit Managers, working in the Swedish financial services industry. The search and selection of the survey participants was done via the platform LinkedIn (LinkedIn 2021) and it was based on their current role in their organization, narrowing down functions related to AI, credit analysis, and credit risk management.

In total, approximately 135 professionals in the Swedish financial services industry received the survey. The sample was determined to cover different organizations' sizes to understand whether there are any differences between smaller and larger financial institutions when it comes to AI and ML usage.

The survey results were received through Google Forms (2021). Out of 135, 37 (27%) professionals responded. After analyzing the responses, the answers were consolidated into 25 unique answers due to multiple answers from the same company or unclear answers. In the cases of multiple responses from the same company, one response was selected to be used in the analysis. The selection was based on the role and professional background information such as education and employment history of the respondent (LinkedIn 2021).

The survey was distributed to the same amount of different company sizes to get an even distribution among Swedish financial institutions. Still, the most considerable response rate was among medium-sized companies compared to other categories. Thereby the results could be interpreted as somewhat skewed towards medium-sized companies.

After the survey, some of the respondents were contacted via LinkedIn (2021) to get more detailed information about their survey answers. A few of them responded with complementary in-depth comments about the use of AI and ML in their respective organizations as well as their professional opinion on the subject. Thereby the additional and valuable qualitative data was gathered as a complementary to the quantitative survey. These elaborations have been summarized and with the respondent's permission presented in chapter 4.11.

3.3.2 Secondary data

Secondary data of relevance for this thesis was collected from previous studies and research in the area of AI and ML solutions in the financial services industry. It was influenced by sources such as the World Bank and from the UK, where they looked at a larger sample of data and made conclusions about potential applications for AI and ML (Biallas & O'Neill 2020; Bank of England 2019). There are some clear benefits of using secondary data. One of these clearly defined aspects are time-limited projects; for example, this thesis. Secondary data also saves time because the data has already been collected and is easily accessible in library databases in forms of surveys, publications, and previous research papers performed by other researchers. The thesis is based on when and where the sources have come to existence and question why the sources exist in the first place.

3.4 Research Ethics

All the survey participants were informed about this research and its purpose (Eliasson 2006). Furthermore, another aspect in research ethics was that the respondents of the survey were offered anonymity, and in accordance to the research theory this could also generate more survey answers (Patel & Davidson 2019, p. 66). The existing research theory mentions that if a survey offers anonymity, the survey candidates tend to be more inclined to participate in the survey, thereby increasing the overall response rate (Patel & Davidson, 2019). If there is a lack of anonymity, the potential respondents can choose not to participate because they perceive that their response could be linked to themselves and their organization. The information-gathering around AI and ML in organizational use-cases can be perceived as sensitive information. Because of this reason, anonymity plays a critical role in incentivizing to respond to the survey because it can indicate the use-case of AI and ML in credit scoring models. In our survey, the respondents were informed that their survey answers would be treated anonymously and that there was no risk of detailed sensitive information coming to public knowledge.

3.5 Data analysis

The received answers were compiled in stacked bar charts that show the percentage of each answer alternative as a part of the total per question and company size. The analysis categorized measurement variables where the category of the respondent's stance was "Yes", "No" or "I don't know". The questions were categorized into variables in a nominal scale given in percentage rate, detailing the use case of AI and ML as a percentage response to the surveyed questions.

3.6 Source Criticism

To qualify the use of sources used in this thesis and the respondent firms' experience, the approach maintained a critical view in the research process. In order to be critical, the sources were evaluated by considering questions such as: what was the purpose of the scientific article? Is it from a marketing perspective, and is there a need to question the document's author? Moreover, to what extent is the author a trusted source? Does the author have a professional background with regards to the topic of research? Moreover, it should be a critical discussion about the research itself (Patel & Davidson 2019).

The thesis covered a wide range of sources and questioned the fundamentals of the research publications as well as the authors behind them, thereby intending to come as close to reality as possible.

When it comes to the survey, the responses were evaluated on available information about the surveyed companies as well as the respondent's position and professional background.

3.7 Validity

There are some, more or less advanced ways to ensure the validity of an instrument. Two of the more easily accessible approaches are to assure content validity and current validity (Bryman & Bell 2018). Content validity can be achieved by a logical analysis of the content in the instrument. The analysis is connected to the theoretical framework for the research. Finding literature studies closely aligned with the proposed research area is later translated from the literature to variables studying AI and ML. These variables are later formalized into specific questions. Moreover, these instruments are used to conduct actual measurement thereby gaining desirable information (Patel & Davidson 2019). Validity is given when the data has relevance to the given problem it tries to address, meaning to what extent it measures the things that the researchers try to measure (Bryman & Bell 2018). To be able to reach a solid degree of validity this thesis regularly examined its questions and the purpose of the research, to ensure that the research purpose is closely aligned with the results of the thesis. For any research it is important that the validity is high in demand, to ensure that the research measures the objectives that were meant to be researched (Bryman and Bell 2018).

3.8 Reliability

Discussing the reliability is to what extent the instrument resists random influence. The descriptions ascertained by individuals are stated as “observed value”. The information gathered includes both the individual's actual value and margin of error. The margin of error can depend on the instrument's lack of reliability (Patel & Davidson 2019). Reliability can depend on many factors but it is not comprehensible which specific factors determine reliability. For example, the research can repeat the same individual’s measurement and get the same value, but this can also be confirmed by an independent factor. Whenever an instrument is reliable, the margin of error decreases and the thesis strives to be as close to the measured companies’ correct value (Patel & Davidson 2019, p. 103). This thesis is based on the concept of reliability, but as stated, the thesis is mainly based on a survey which achieves reliability after the survey has been conducted. A thesis can be assured reliability in other ways such as observations that can determine the reliability of the results, depending on the authors of the thesis (Patel & Davidson 2019).

The problem with regards to surveys is that surveys do not reach reliability before testing (Bryman & Bell 2018). The assumption is that authors can only assure individuals answering the survey to interpret the survey as the authors intended the survey to be interpreted (Patel & Davidson 2019). The authors of this thesis attempted to be specific and detailed regarding the layout of the questions in order to make it simple for the respondents to answer the questions.

In the final stage, the authors sent the survey to professionals at micro, small, medium, and large Swedish financial institutions who are responsible for credit risk management, particularly credit risk managers and head of credit risk officers.

Lastly, to determine the survey's reliability, a discussion and conclusions drawn after the survey were evaluated (Patel & Davidson 2019).

The following type of questions were used for the evaluation:

1. Were there questions that may have been skipped?
2. Did the survey include every alternative possible or should more alternatives exist?
3. Did the questions cover the research area that was meant to be covered?
4. Did the questions reflect the examined research questions?

By studying the results of these questions closely, we could determine if the survey was reliable (Patel & Davidson 2019).

4. Empiric results

In this chapter, the results and findings of the conducted survey are presented. The survey consisted of 10 close-ended questions regarding the usage of AI and ML in credit risk management. The results are based on 25 unique responses from professionals working with credit risk management and/or AI in the Swedish financial services industry.

In the following sections, responses to each question are summarized in stacked bar charts expressed in percentage for each respective company size. Each chart is also summarized in words which serves as a basis for further analysis and discussion in chapter 5. Section 4.11 contains the additional comments submitted by some of the survey respondents.

4.1 Question 1

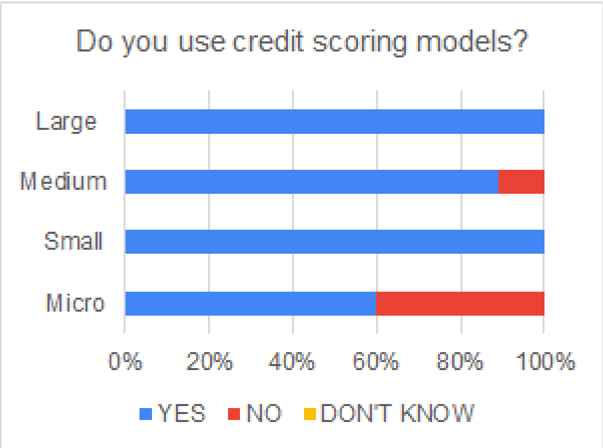

Chart 1. Responses from the survey participants on the question "Do you use credit scoring models?"

In chart 1, we can observe that all respondents from the large companies answered that they use credit scoring models. This is followed by medium-sized companies, where 89% of respondents answered that they use credit scoring models. All of the small companies' respondents answered that they use credit scoring models, and among the micro-companies, only 60% answered that they use credit scoring models.

4.2 Question 2

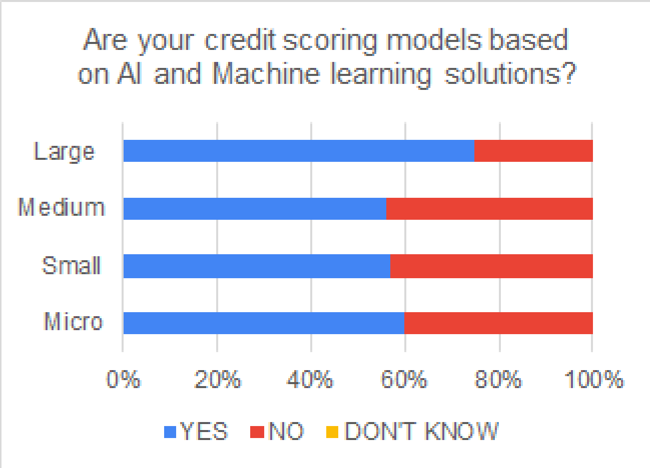

Chart 2. Responses from the survey participants on the question "Are your credit scoring models based on AI and Machine learning solutions?"

When asked the respondents if their credit scoring models are based on AI and ML solutions, 75% of the large companies answered "yes" (chart 2). Among the medium-sized companies, 56% answered "yes". 57% of the respondents in the small companies answered "yes", and in the micro-companies, 60% answered "yes".

4.3 Question 3

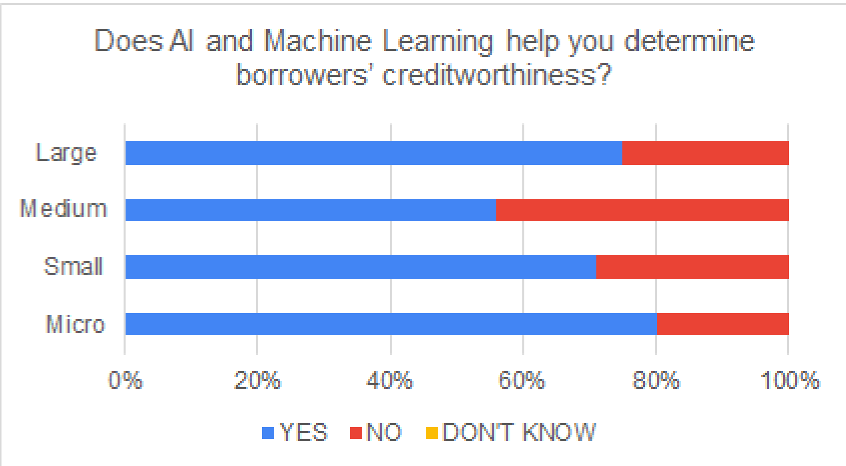

Chart 3. Responses from the survey participants on the question "Does AI and Machine Learning help you determine borrowers' creditworthiness?"

When it comes to the usage of AI and ML solutions to determine borrowers' creditworthiness, the majority of interviewed companies answered "yes", 75% amongst the large companies, 56%

amongst the medium companies, 71% amongst the small companies, and 80% amongst the micro-companies (chart 3).

4.4 Question 4

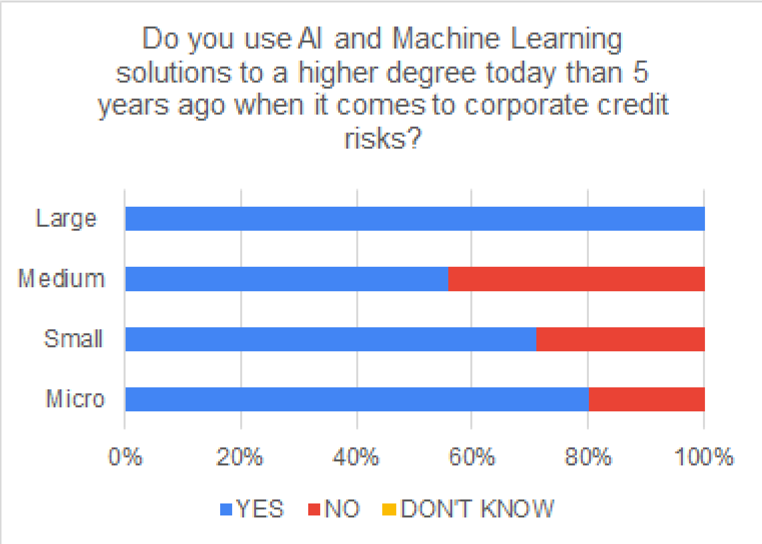

Chart 4. Responses from the survey participants on the question "Do you use AI and Machine Learning solutions to a higher degree today than five years ago when it comes to corporate credit risks?"

100% of the large companies' respondents answered that they use AI and ML solutions to a higher degree today than five years ago (chart 4). Among the medium-sized companies, 56% answered "yes", and amongst the small companies, 71% answered "yes". 80% of the micro-companies answered "yes".

4.5 Question 5

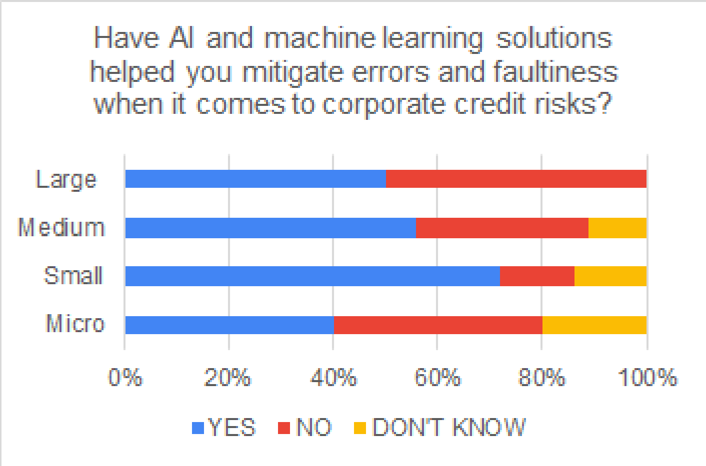

Chart 5. Responses from the survey participants on the question "Have AI and ML solutions helped you mitigate errors and faultiness when it comes to corporate credit risks?"

Among the large companies, half of the respondents answered "yes" (chart 5) to the question whether AI and ML solutions helped them to mitigate errors and faultiness when it comes to corporate credit risks. In the medium-sized companies, 56% of the respondents answered "yes", 33% answered "no", and 11% answered they did not know. In the smaller companies we can observe that the majority (71,4%) answered "yes", 14,3% answered "no", and 14,3% answered that they do not know. Among the micro-companies, 40% of the respondents answered "yes", another 40% answered "no", and 20% answered that they do not know.

4.6 Question 6

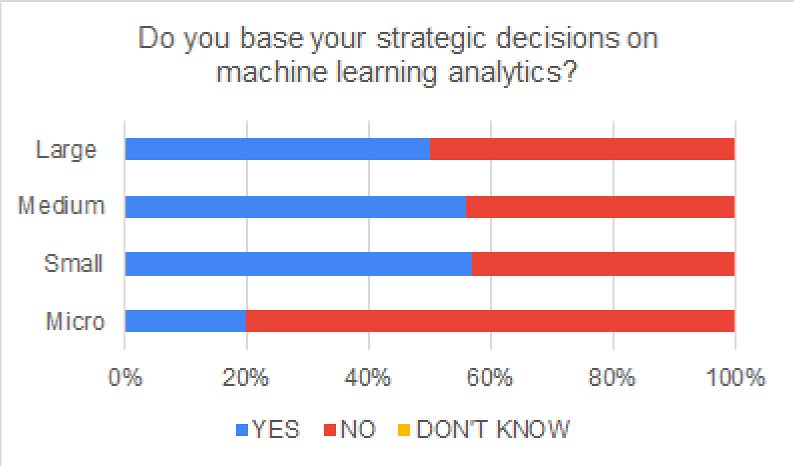

Chart 6. Responses from the survey participants on the question "Do you base your strategic decisions on machine learning analytics?"

In regard to strategic decisions being based on machine learning analytics, most companies had similar answers. Half of the respondents in the large companies answered "yes" (chart 6). 56% in the medium-sized companies and 57% in the small companies answered "yes". The micro-companies had the least amount of "yes" answers (20%).

4.7 Question 7

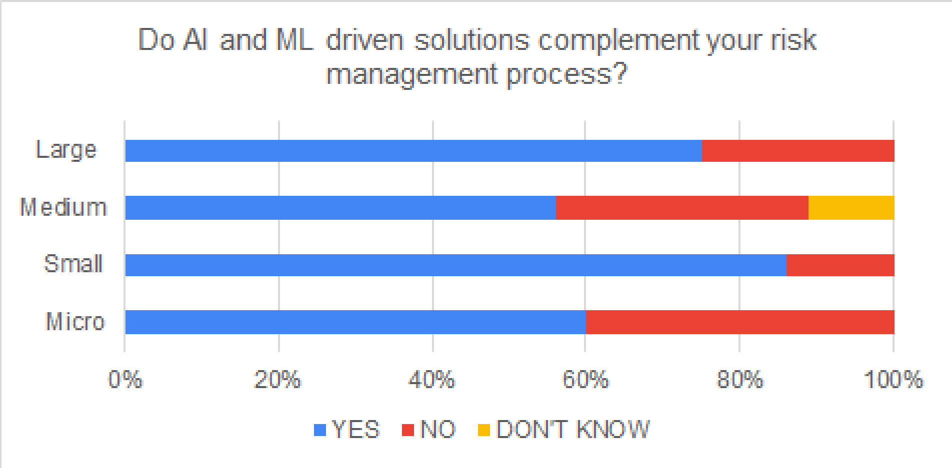

Chart 7. Responses from the survey participants on the question "Do AI and ML-driven solutions complement your risk management process?"

Among the large companies, 75% answered that they use AI and ML solutions to complement their risk management process (chart 7). 56% answered "yes" in the medium companies, 33% answered "no", and 11% answered that they do not know. 85,7% of the respondents in the small companies answered "yes", while in the micro-companies 60% answered "yes".

4.8 Question 8

Chart 8. Responses from the survey participants on the question "Do you have an established credit scoring model for predicting and identifying credit risks among corporate clients?"

100% of the respondents in the large companies answered that they do have an established credit scoring model for predicting and identifying risks among corporate clients. In the medium-sized companies, 78% answered "yes", 11% answered "no", and 11% answered that they don't know. In the small companies, 57% of the respondents answered "yes", 29% answered "no", and 14% answered that they don't know. 60% of the respondents in the micro-companies answered "yes".

4.9 Question 9

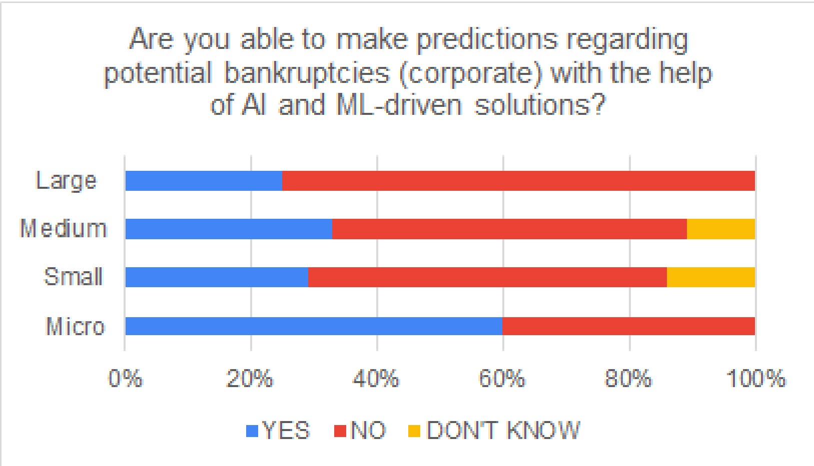

Chart 9. Responses from the survey participants on the question "Are you able to make predictions regarding potential bankruptcies (corporate) with the help of AI and ML-driven solutions?"

When it comes to making predictions regarding potential bankruptcies among corporate borrowers with the help of AI and ML-driven solutions, the vast majority of all the respondents answered "no" (chart 9). Among the large companies, 75% answered "no". In medium-sized companies, 56% answered "no", 33% "yes", and 11% answered that they do not know. The small companies' respondents had similar answers where 57% answered "no", 29% "yes", and 14% answered that they do not know. Among the micro-companies, 60% answered "yes".

4.10 Question 10

Chart 10. Responses from the survey participants on the question "Is it a goal for your organization to further develop your AI and ML solutions within risk management?"

In our last question, we asked the respondents if further development of AI and ML solutions within risk management was a goal for their organization. The majority of the respondents answered "yes" (chart 10). In large companies, 75% answered "yes" and 25% "no". In the medium companies, 67% answered "yes" while 33% answered "no". Among the small companies, all of the interviewed companies answered "yes", and in the micro-sized companies, 80% answered "yes" while 20% responded that they don't know.

4.11 Additional comments from the survey respondents

In a couple of cases, the survey respondents have submitted additional comments.

A respondent working for a large Swedish financial institution answered that they do not use AI and ML in credit risk management and that they still rely on traditional statistical credit models. The respondent mentioned, however, that they do use AI and ML in some other operations. Another respondent from a large Swedish financial institution motivated that financial institutions such as Finansinspektionen (Sweden's financial supervisory authority) requires that the Swedish financial companies report their credit scoring models in a way that is not adapted for AI algorithms. The first respondent partially confirmed this, explaining that transparency is crucial when it comes to risk judgement. The same respondent further explained that AI and ML often provide “yes” or “no” answers without any detailed explanations, and therefore there are moral and ethical aspects to be taken into account.

A third respondent with the experience from several large Swedish financial institutions explained that many of these institutions have relatively unmodern IT infrastructures with many different systems. This would make an AI implementation more problematic as it would require considerable IT modernization and investments to be done. Such IT projects are generally considered risky and time/resource consuming, and the return on investment is not easy to estimate. In addition, there is a certain amount of concern regarding how much of the credit risk analysis should be handed over to machines (AI and ML).

A fourth respondent from a large Swedish financial institution gave a similar explanation pointing out difficulties in justifying large IT investments such as AI while the financial service industry is under pressure to lower its costs. There is still a lot of human interaction within credit risk management, and this sector does not have the same liquidity as the stock market where AI and ML are widely used. This respondent also confirms a general lack of knowledge about AI and ML technology in the financial sector, making it difficult to estimate future areas of usage for this kind of technology.

5. Analysis

This chapter presents the analysis of the empirical data in chapter 4 with a reference to the literature review in chapter 2 and the methodology in chapter 3.

The traditional credit scoring methods for risk management that are based on a set of quantified customers' characteristics and analysed with traditional statistical methods (chapter 2.3.1) are established and used by the vast majority of the surveyed financial institutions. In the few cases where the survey respondents answered that they do not use credit scoring methods, the question that arises is how a financial institution can manage their risks without any credit scoring methods. It is possible that a misunderstanding could have occurred when answering this question.

A pattern that can be observed is that most of the surveyed financial institutions, regardless of their size, have either started or plan to start implementing AI and ML as support in their credit risk management process. However, it is unclear whether it will be used in combination with the traditional credit scoring methods to gain the benefits from both (chapter 2.3.3), or as a complete replacement.

When it comes to the credit scoring models being modelled as algorithms for AI and ML solutions, the results show that it is not the case in approximately 40% of the surveyed financial institutions. An explanation could be that the AI and ML technology benefits are not considered large enough compared to the traditional credit scoring methods. Moreover, the laws and regulations asking for transparency and understanding of AI algorithms do not seem to be entirely in place for this type of technology yet (chapter 2.4 and chapter 4.11). Another explanation could be that the AI-based credit scoring lacks the level of detail and understanding provided by the traditional credit scoring models (chapter 2.3.2). Increased use of AI and ML would also require including many additional loan applicant variables that would lead to a fast volume expansion of complex data (chapter 2.1) as well as building and maintaining complex algorithms (chapter 2.3.2).

Simultaneously, the survey shows that in more than 50% of cases, financial institutions use AI and ML to evaluate their creditworthiness. The question is to what degree such methods are truly AI and ML-based or just perceived as such. For example, small companies show the highest score of AI and ML usage. Keeping in mind the complexity of AI and ML development as well as the implementation and the amount of data it requires (chapter 2.1), it could be the case that some of the respondents may have confused AI and ML with the traditional credit scoring methods that are automated to a high degree. However, we can see a clear tendency of perceived increased use of AI and ML during the past five years across all company sizes.

When it comes to detecting errors and faultiness among corporate clients with the help of AI and ML, the figures are lower than for private loan takers. An explanation for this could be that it is much more complex to analyze corporate loan takers than private persons. Corporate loans are usually of a higher magnitude and include higher risks for the financial institutions (i.e. banks). Thereby it probably requires human judgement supported by AI and ML, especially in estimated bankruptcies among corporate clients (chapter 2.3.3).

Strategic decision making in financial institutions shows a high degree of human-based judgement which could be perceived as a lack of trust in AI and ML algorithms when it comes to long term strategic corporate decisions. Strategic decisions are primarily based on a vision of the future and intuition that can be difficult to translate into concrete variable values that AI and ML algorithms require to provide accurate results. Strategic decisions are not based on purely historical data that AI and ML algorithms use as a source for learning. As mentioned in chapter 2.3.2, AI and ML algorithms are a simplification of reality which could make these unsuitable to use in strategic decision making. However, as mentioned in chapter 2.3.3, the decision-making process could benefit from the combination of human intuition and AI analytics.

The majority of the interviewed companies foresee increased use of AI and ML technologies in the future of financial business. One could interpret the negative answers as mistrust in AI and ML algorithms for the reasons discussed earlier in chapter 2.3.2 and 4.11. The respondents may not yet see the business case when comparing AI and ML with the traditional credit scoring models (chapter 4.11). It could also be the case that the financial institutions' ambitions to increase AI and ML usage are not clearly communicated or understood by all employees and thereby, our survey respondents.

6. Conclusions and future research

The purpose of this thesis was to examine to what extent Artificial Intelligence and Machine Learning is implemented in the Swedish financial services industry (specifically when it comes to credit risk management) and to what degree it is in accordance with the existing research in the area.

In its essence the thesis concludes that the use of Artificial Intelligence and Machine Learning solutions for credit risk management in the Swedish financial service industry is present and increasing. Still some questions and concerns remain which need to be addressed in future research and by financial institutions and policy makers in order to fully adopt the Artificial Intelligence and Machine Learning solutions for credit risk management. We have also provided reasons for not using Artificial Intelligence and Machine Learning in credit risk management.

The conclusions from this thesis could potentially provide additional perspectives and input to the Swedish financial industry and policy makers in order to further explore the use of Artificial Intelligence and Machine Learning technologies in credit risk management.

6.1 Conclusions

The literature study provided a context for analysis of the gathered empirical results, thus leading to the following conclusions.

The use of Artificial Intelligence and Machine Learning in credit risk management has been a subject for intensive research and development, especially over the last two decades. A number of different methods for credit scoring have been developed and evaluated towards the traditional statistical credit scoring methodologies. Previous research shows that Artificial Intelligence and Machine Learning provides more accurate results compared to the traditional methods. At the same time, this new technology is associated with a number of concerns such as: understanding the results, legal regulations, ethical dilemmas, and IT investments.

The Swedish financial services industry indicates a moderate increase in use of Artificial Intelligence and Machine Learning over the past five years which is in line with the international trends described by the reviewed research community, authorities, governments, and consultant companies that support the financial services industry. It is also aligned with the trends described in the United States by the World Bank and the United Kingdom indicating an increased use of Artificial Intelligence and Machine Learning technology as a complement to the traditional credit scoring models.

The use of Artificial Intelligence and Machine Learning in credit scoring amongst Swedish financial institutions seems to be larger amongst the private loan applicants compared to the corporate clients.

When it comes to the traditional credit scoring methods, they are still the foundation at the majority of the studied Swedish financial institutions. This is interpreted as a sign of caution as the Artificial Intelligence and Machine Learning technologies are still relatively new and there is a lack of understanding among the broader community in the Swedish financial institutions. Artificial Intelligence and Machine Learning is also based on large amounts of data and complex algorithms which puts demands on the concerned financial institutions to modernize their IT-infrastructure and increase the competence in this area.

When it comes to the legal aspects of usage of Artificial Intelligence and Machine Learning in the credit risk management area, there are activities done by the Swedish authorities and the European Union in order to prepare for the entrance of this new technology. This is in line with the activities done by the European Union legislators. The current regulations communicated by different parties in the thesis, highlights that existing documentation from the financial authorities is not fully adapted to fit Artificial Intelligence and Machine Learning-driven solutions. This can lead to underutilization of these tools on a larger scale. This could lead to inefficiencies caused by the constraints in traditional credit evaluation models.

In order to gather the benefits from both traditional credit scoring methods and Artificial Intelligence and Machine Learning based solutions, the future of credit scoring will most likely utilize a combination of both.

In this thesis we could not find scientifically proven evidence of a correlation between the level of Artificial Intelligence and Machine Learning usage and the size of the surveyed Swedish financial institutions.

6.2 Suggestion for further research

This thesis concludes that Artificial Intelligence and Machine Learning solutions are used in the Swedish financial services industry. However, the survey should be extended to a larger population of Swedish financial institutions in order to be more representative. It should also cover an equal amount of company sizes in order to be able to draw conclusions about the correlation between the company size and the level of Artificial Intelligence and Machine Learning usage.

There is an interesting aspect of Artificial Intelligence and Machine Learning implementations related to ethical dilemmas, i.e. relying on new and complex technology that is partly independent from human intervention and it is used for decision making that has a direct impact on credit evaluation. A question that should be further investigated is: how can Artificial Intelligence and Machine Learning be used in combination with human judgement in order to provide the optimal decisions best for both parties.

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Appendix

Survey questions

1. Do you use credit scoring models?
2. Are your credit scoring models based on AI and Machine learning solutions?
3. Does AI and Machine Learning help you determine borrowers' creditworthiness?
4. Do you use AI and Machine Learning solutions to a higher degree today than 5 years ago when it comes to corporate credit risks?
5. Have AI and machine learning solutions helped you mitigate errors and faultiness when it comes to corporate credit risks?
6. Do you base your strategic decisions on machine learning analytics?
7. Do AI and ML driven solutions complement your risk management process?
8. Do you have an established credit scoring model for predicting and identifying credit risks among corporate clients?
9. Are you able to make predictions regarding potential bankruptcies (corporate) with the help of AI and ML driven solutions?
10. Is it a goal for your organization to further develop your AI and ML solutions within risk management?