Enhancement of a credit rating tool for Company X

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Abstract

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The main goal of this thesis is to enhance an existing credit rating model in order to prevent fraud and decrease the number of non-paying loans. This thesis is issued by a new non-bank lending company that is seeking to improve its processes and become more profitable.

The theory framework introduces and explains the concepts of small and medium business, financial market and various credit risk analysis techniques. Methods already utilised at the commissioning company were researched to understand if they can be improved further. Bankruptcy prediction models were chosen as an additional method for a more accurate analysis of the financial data. The chosen model was tested by analysing a group of Finnish companies.

This thesis also considers options on how the commissioning company can detect and eliminate fraud. A framework for fraud detection was created, as well as a model for the analysis of qualitative data, such as the digital activity of the company. Every factor was given a "weight" according to the importance of it to the founder of Company X. The created model rates the company based on the non-financial information available online by converting it into quantitative data. This helps the employees at Company X to better understand the company's position and in turn make accurate lending decisions.

The qualitative and quantitative parts of the tool were combined to create a new credit rating model. The results of the testing of the tool show if the additional factors improve the credit risk analysis compared to the previously used framework. Company X representative has found the model to be valuable and has given his feedback.

Keywords
Credit risk analysis, bankruptcy prediction model, fraud detection, financial ratios, credit scoring

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1 Introduction

In this chapter I will introduce my topic and the research question that I will be answering. The origin of my research question will be defined and the investigative questions that will help me formulate the answer for my main question are going to be described. It will also include the demarcation of my research and the description of the case company.

1.1 Background

Nowadays Finland is attracting a lot of capital from the outside and more businesses are opening up. Most of those businesses need capital in order to grow, but they cannot get it due to banks taking too much time to process the application or having strict requirements. Small and medium sized businesses overcome this obstacle by applying for loans from lending firms. Lending firms have lighter requirements and a simpler process for getting a loan. This situation is good for lenders as they get more customers, however one issue arises. The issue is that lending companies need to manage their risk better than ever if they want to stay profitable. Companies use specific risk assessment models (RAM) to measure the credit risk. There are many approaches to assessing risk, but most of them are based on the analysis of numerical data. Numerical data gives a good estimate if the company is going to pay the loan back, but it does not take into account the behaviour of the owner and the qualitative information about the firm. It is crucial for companies to keep updating their approaches to risk assessment and implementing various ways of analysing any data that is available.

1.2 Project objective

The aim of this thesis is to improve the credit rating tool used by Company X. At the moment, the company has its' own credit risk assessment model and they use credit ratings provided by different agencies. A risk assessment model is used for analysing the credit risk of a loan application and identifying fraud. Some companies change the payback rate if there is a higher risk involved. This thesis will include a review of the models based on 'hard' data that are used to assess credit risk and an evaluation of the model that Company X is using. The models which grade businesses based on their financial results are becoming less efficient as in some cases they are unable to detect fraud. There will be an overview of the risk assessment models used by lending companies that make use of the qualitative data, and then a proposed criterion for identifying fraudulent loan applications. The main purpose of this thesis is to enhance an existing risk assessment model by implementing methods that analyse quantitative and qualitative data.

The project objective is the enhancement of the credit rating model used to measure credit risk for company X. The project will be implemented with the project tasks that are listed in the overlay matrix below. Table 1 presents the theoretical framework, project management methods and results chapters for each project task.

Table 1. Overlay matrix

Investigative question	Theoretical Framework	Project Management Methods	Outcomes
PT 1. Theory Framework	Financial and Managerial Accounting. Banking industry. Position and status of SME's in the business world. Risk assessment models	Primary Research: -Interview Secondary Research: -Academic literature -Databases	Chapter 2
PT 2. Evaluation of the quantitative risk assessment models	RAMs' based on numerical data	Analysis of the metrics used to assess companies. Working in Excel.	Chapter 3
PT 3. Creation of the qualitative approach to assess credit risk	RAMs' based on qualitative data	Analysis of the criteria that are used by other lending companies. Creation of custom criteria for fraud detection in Excel	Chapter 3
PT 4. Reconstructing the risk assessment tool	Combination of the outcomes of previous tasks	Combining the qualitative and quantitative models in Excel	Chapter 3
PT 5. Testing of the model	The outcome of previous tasks	Working with Company X	Chapter 4
PT 6. Assessment of the project	The outcome of previous tasks	Project and outcome analysis	Chapter 5

1.3 Demarcation

In my thesis I want to study different risk assessment models that are used by banks and other financial institutions to measure the credit risk and make decisions regarding loan applications. The project scope consists of improving an existing risk assessment tool by adding various financial metrics that measure the likeliness of the borrower to pay his loan back, and a clear criterion which identifies if the loan application is fraudulent or not.

Risk management has always been a crucial part of any business, especially in banks and other financial institutions. The economic environment has been becoming riskier year after year. "Interest rates have fluctuated wildly, stock markets have crashed, and speculative crises have occurred in the foreign exchange markets" (Mishkin 2016, 50). In order for financial institutions, such as banks and lending companies to survive in this environment, they need to master the ability to cope with an increased risk. One of the methods that helps them is the implementation of the risk assessment model. There will be a chapter dedicated to analysis of various risk assessment models and the main reasons for using specific models.

The quantitative approaches of which the main ones are, financial statement lending and small business credit scoring, are going to be described and explained. Analysis of the risk assessment model that is used by Company X will be performed and suggestions on how to improve it are going to be made.

The qualitative approach to assess credit risk is usually a checklist with five to ten criteria that the potential borrower must comply with. The models that make use of the "soft" data are going to be researched and a checklist with the criteria that is specific to Finland's market is going to be made.

The expected end result of my thesis will be a tool consisting of a checklist and a modified quantitative approach to assessing credit risk that will make the process of screening potential borrowers simpler. Testing of the created model will be carried out with the assistance from company X.

1.4 International aspect

The international aspect is going to be fulfilled by researching and analysing risk assessment models that are used in different countries. As well as that, the company is planning to expand and attract customers from all over the Nordic countries.

1.5 Benefits

One of the biggest stakeholders for my thesis is going to be my commissioning company. The main benefit that they receive by working with me is their own credit rating model that analyses both the qualitative and quantitative data. This tool will potentially improve the evaluation of companies that apply for loans.

My field of specialisation is finance and accounting and I think this topic will allow me to research many concepts that will deepen my knowledge in this specific field. Risk management is a vital part of any business and expanding my knowledge in this sphere will add value to me as a professional. Investment management is another sphere which I am interested in and by studying different risk assessment models I can become better at identifying profitable opportunities.

1.6 Key concepts

- Credit risk- “the potential for financial loss if a borrower or a counterparty in a transaction fails to meet its obligation” (Leesambo 2013, 328)
- Risk Management- “process by which managers identify, assess, monitor and control risks associated with financial institution’s activities” (Koch & MacDonald 2010, 849).
- Credit Scoring- “the use of a statistical model based on applicant attributes to assess whether a loan automatically meets minimum credit requirements” (Koch & MacDonald 2010, 821).
- Adverse selection -“the problem created by asymmetric information before a transaction occurs: the people who are the most undesirable from the other party’s point of view are the ones who are most likely to want to engage in the financial transaction”(Mishkin & Eakins 2016, G-1).
- Moral hazard- “the risk that one party to a transaction will engage in a behavior that is undesirable from the other party’s point of view” (Mishkin & Eakins 2016, G-11).
- SME- “Small to medium-sized enterprise, a company with no more than 500 employees” (Lexico 2019).
- Non-bank financial institution- a financial institution that doesn’t have a banking license and cannot accept deposits from the public but facilitates financial services such as financial consulting and investment (The World Bank 2020.)
- Financial distress- "a condition in which the operating cash flow in the company cannot repay its current liabilities such as accounts payable or interest expense. A disruption of the company's liquidity" (Husein & Pambekti 2014, 408).
- Discriminant analysis - "a statistical technique that identifies some financial ratios that are considered the most important in influencing the value of an event, and then it develops it into a model with a view of making it easier to draw conclusions from an event" (Husein & Pambekti 2014, 409).

1.7 Case company

The case company is a non-bank financial institution and can be labelled as a lending firm. They focus on giving loans to Finnish small-and-medium sized companies. The loan size and the payment period cannot be disclosed as the company wants to stay anonymous. The process of getting a loan is fast and businesses can apply straight from the Company X's website. The company specialises in helping businesses when they have a shortage of cash or need more money to expand (Company X 2019.) The company was founded in 2019 and it currently holds a position in the top five lending companies in Finland.

The company has asked me to keep their name out of the public version of the thesis. Lending companies compete on the basis of making the best risk assessment tools and pricing their loans accordingly, so mentioning the name of the company in this thesis will eliminate their competitive advantage. The loan size and the payment period are specific to every non-bank lending company on the market and if I mention this information in the thesis, there is a chance that people will be able to figure out the company. This is the reason for why the company name and terms are not going to be mentioned in the thesis.

2 Theoretical framework

2.1 SME's in Europe

The markets all around the world are growing and more businesses are opening up. At the start any company could be put into a category of small and medium sized enterprises. In Finland, the definition for SMEs is "enterprises which have fewer than 250 employees and have either an annual turnover not exceeding EUR 50 million or an annual balance-sheet total not exceeding EUR 43 million and which conform to the criterion of independence" (Tilastokeskus 2019). The graph below shows the number of enterprise openings in Finland. It can be clearly seen that since 2015 the amount of businesses that were founded has been increasing on a yearly basis.

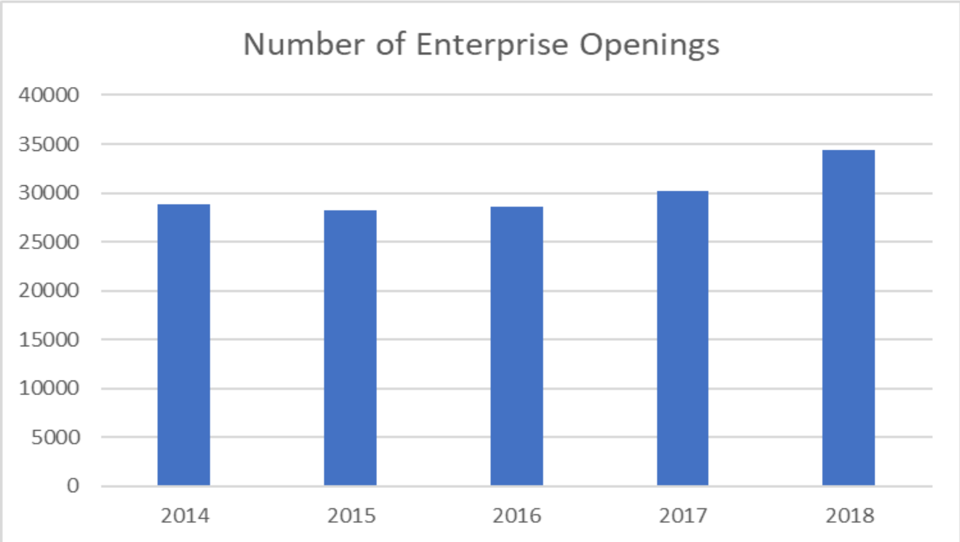

Figure 1. Enterprise openings from 2014 to 2018 in Finland (Statistics Finland 2019.)

Small and medium sized enterprises play a crucial part in every existing economy. Those enterprises provide a large share of global employment and contribute to the development of the countries by paying their taxes (International Labour Organization 2019.) Europe's economy is dependent on SMEs as they represent 99% of all businesses in EU (European Commission 2019.)

SME's need capital in order to grow and expand. Entrepreneurs need to choose which capital structure they want to utilise, either equity or debt financing. The capital structure needs to be set in a way to maximize the value of a firm (Artikis 2007, 321.) Owners of SME's often use their personal funds in order to start the business. Many entrepreneurs finance their business at the start by borrowing money from their friends and family as it is difficult for them to get financing elsewhere. After the business has been operating on the market for a year or more, it will have enough data to be able to apply for debt financing. The most common source of external financing that entrepreneurs choose is bank lending. Those individuals rely on straight debt in order to fulfill their cash flow, start-up and investment needs (OECD 2016.)

SMEs have certain difficulties and face a few obstacles when they are trying to access capital from the bank in the form of a loan. There a few reasons for this phenomenon. One of the most significant reasons is that the whole SME sector is described as having low survival rates and a large diversity of entities which makes it hard for lenders to analyse the risk. Some SMEs are not suited for debt financing due to the irregular cash flows, lack of collateral or the long maturities to finance capital expenditure (Nassr & Wehinger 2016, 50.) In addition to that, SMEs can be described as having a bigger variance in profit and growth than the larger firms, which leads to uncertainty regarding their future (OECD 2006, 18.)

In addition to that, asymmetric information is a more serious problem in SMEs than in larger firms. SMEs produce financial statements to keep track of their financial position, however, it is often the case that those reports do not yield any credible financial information (AccountingTools 2019; OECD 2015, 15). Furthermore, in smaller firms the finances of the owner and the business are mixed, and it is difficult to distinguish them (OECD 2015, 15.) Debt financing appears to be ill-suited for newer, innovative and fast-growing companies which have a high-risk profile. The problem lies within the considerable start-up capital that is needed to finance projects with high growth prospects. It is difficult to forecast the profit patterns for such projects, so the potential lenders are reluctant to finance them (OECD 2015, 11.) A lot of money is spent to start a company, so many SMEs can’t offer adequate collaterals to the bank. The banks are not able to identify if the borrower possesses technical, managerial and marketing skills to generate sufficient cash flows and pay back the loan, so they are reluctant to give out the loan (Bădulescu 2010, 27.)

Banks require a lot of documentation from their potential borrowers and some entrepreneurs do not have enough time to gather all of it, as they have a business which they need to run (Green 2014.)

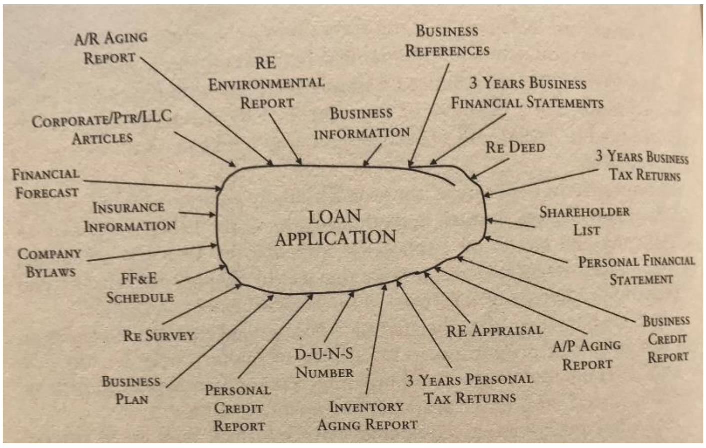

Figure 2. Common Loan Application Requirements (Green 2014)

Due to the fact that SMEs are so important for the national economy and financial stability of the country, many governments have been implementing policies that support entrepreneurship. The "Small Business Act" has been implemented in Europe in 2008 that utilises the "think small first" principle and promotes entrepreneurial spirit among EU citizens (European Commission 2019.) The “think small first” principle is about considering the needs and interests of SMEs at the early stages of policy making. The "Small Business Act" (SBA) support SMEs by lessening the regulatory burden, facilitating better access to finance and making it easy to internationalise (European Commission 2020b.) In Finland, the impact of those policies can be clearly seen due to more enterprises opening. Finland has a strong SBA profile and the country addresses all of the SBA principles (European Commission 2018, 1.) Finland has improved access to finance for SMEs and performs above the EU average in this category. However, the amount of rejected loan applications has doubled between 2016 and 2017, from 3.8% to 6.5% (European Commission 2018, 10.)

The Finnish government continues to support entrepreneurship by financing and implementing policies. Finnish people are recognizing more opportunities for entrepreneurship as the “perceived opportunities” figure has increased by 7% from 2014 to 2015 (Global Entrepreneurship Monitor 2015, 16.) The latest report on Finland's economy shows that the number of bankruptcies filed by SMEs have decreased for the fourth year in a row (OECD 2019b, 2.) The access to finance is better both due to the government support, but also because more financing options are becoming available on the market (OECD 2015,104.) The financial market and the various options of financing are going to be described in the next chapter.

2.2 Financial sector

The financial sector can be defined as "the set of institutions, instruments, and the regulatory framework that permits transactions to be made by incurring and settling debts; that is, by extending credit" (OECD 2013). As the economy develops the financial sector grows and the economy of the country becomes dependent upon the state of that sector. There are about 15,000 companies in the European Union and the United States that access capital markets through issuing of the shares or bonds (Boldeanu 2016, 60.) More companies finance their activities by other means, approximately 25 million in the EU and about 5.7 million in the United States (Boldeanu 2016, 60.) Major assets of the financial sector are represented by currency, loans and deposits including inter-bank loans and deposits (Boldeanu 2016, 65.)

Access to affordable credit and other financial services is recognized as a pre-condition for boosting growth and reducing income disparities (Mahajan & Kalel 2013, 7.) The financial sector is important for any economy as it enables a more efficient transfer of resources from savers to investors as well as promotes the use of funds by households, businesses, traders and governments. An efficient financial sector is vital to economic progress. (Reserve Bank of Australia 2014.)

“Financial intermediaries collect savings from individuals or organisations, issue in return claims against themselves, and use the funds thus acquired to purchase ownership or debt claims” (Desai 2009, 364). The differentiation of financial assets leads to the development of the financial structure (Desai 2009, 364.) The increasing number of financial assets on the market which are suited to the needs of particular customer segments leads to the creation of more financial intermediaries. Financial intermediaries could be classified into several groups:

- The banking system
- Other depository organisations such as mutual funds or credit unions
- Insurance organisations
- Development banks
- Non-banking finance companies
- Financial markets
- Other financial intermediaries

The two groups that are important for this thesis are the groups where there is a practice of issuing commercial loans, and those are the banking system and non-banking finance companies.

The banking system can be split into two groups: commercial banking and central bank. A commercial bank is a profit-seeking business firm, dealing in money and credit. One of the primary functions of commercial banks is the advancement of loans. Banks give out both personal and commercial loans. A commercial loan is granted to a borrower in order to meet a short-term requirement of capital, for example working capital (Somashekar 2009, 245). Loans are given for a certain period of time with a specified interest rate. The main revenue stream of a bank is the interest on given loans. One of the main purposes of a commercial bank is “to borrow money for the purpose of lending at a higher rate of interest” (Somashekar 2009, 9).

The banks are able to give out loans with the money that they receive as deposits. Most of the deposits that the bank has are payable on demand, so it is crucial for banks to manage their risk. Banks face a variety of risks, but the one that is related to loans is the single largest risk that banks face and it is called the credit risk. Credit risk is the potential loss that a bank would endure if a borrower, otherwise called the counterparty fails to meet its obligations in accordance with agreed terms (Apostolik, Donohue, GARP & Went 2009, 14.) According to Fraser, Gup and Kolari, (2001) credit risk is considered to be the reason for the majority of bank failures. Due to this, banks have come up with various ways to measure credit risk. As commercial banks invest capital and effort into developing different strategies for managing credit risk, they aim to earn profit from every loan they issue. This means they are less willing to give out loans to small-medium sizes enterprises as the risk is higher and the profit is smaller. Based on the data on loan maturities it can be seen that over the last decade banks have given more long-term than short-term loans to SMEs (OECD 2019b, 3.) This has led to non-banking financial institutions such as loan companies to appear on the market and serve SMEs who need short-term loans.

Alternative lending choices have become available, especially online, it has become much easier for small business owners to obtain short-term financing elsewhere to cover their working capital and liquidity needs."Uptake of alternative financing instruments by SMEs is growing like never before, while bank lending to SMEs is growing less strongly" (OECD 2019).

The alternative lending options are usually provided by non-banking financial companies (NBFC). One type of NBFC is non-banking loan companies. Commercial banks have a complicated procedure for their commercial loan application and have a minimum amount that a company must request, so SMEs turn to loan companies that specialise in giving out loans. Those companies are able to give both short-term and long-term loans without requiring a lot of documentation. Lending companies have a competitive advantage over the banks as they are able to serve many business sectors and do it all distantly. Another name for this type of companies is finance companies. Finance companies are less regulated than banks, as they do not take deposits from the public, so no government deposit insurance is involved (Kidwell, Blackwell, Whidbee & Sias 2011.) Some sources (Deloitte 2019) classify SME lending companies into three different types: eCommerce lenders, peer-to-peer lenders and non-bank direct lenders. Company X would be put into the category of non-bank direct lenders, as the company offers easy-to-access loan products for SMEs and assumes "the balance sheet risk in order to make a profit in the margin between the rates they take on their own debt, and the loan rates they offer to businesses" (Deloitte 2019).

As mentioned above, all financial institutions that deal with loans need to thoroughly analyse the credit risk in order to stay profitable. Firstly, companies need to diversify their portfolios, then conduct credit analysis of the borrower to measure default risk exposure and monitor the borrower over the life of the loan to detect any changes in the financial health (Kidwell, & al. 2011.) The average interest rate that the banks have charged SMEs on the loan of up to 1 million euros was 2.8% in 2016-17 (OECD 2019b, 5.) Finance companies generally charge higher interest rates than do depository institutions such as savings banks and credit unions. Company X prices its loans individually depending on the credit risk of the loan, but their average interest rate is 2%. The interest rate is chosen based on the credit risk, so for companies to price their loans correctly they need to develop various methods of calculating credit risk. Those methods are going to be discussed in the next chapter.

2.3 Credit risk assessment models

In financial markets, there is often a case when one party does not know enough information about the other party in order to make a definite decision. This phenomenon is called asymmetric information and it causes two problems: moral hazard and adverse selection (Mishkin 2013.) Those concepts highlight the reasons for the analysis of the risk. Moral hazard is a risk that a party to a transaction did not enter the transaction in good faith and has given misleading information about its financial health or has an incentive to take a risk in order to earn an unfair gain against the counterparty (Mwangi 2018, 9-10.) The other problem that is caused by the asymmetric information phenomenon is adverse selection. This problem occurs when the potential borrowers who are most likely to produce an unsatisfactory outcome are the ones who most actively seek out a loan and thus are more likely to be selected (Mishkin 2013.) This means that borrowers with bad credit risk get a higher chance to get chosen. This can lead to financial institutions such as loan companies to price all the loans at the same rate, as they cannot evaluate risk accurately.

That is why companies invest time and capital into creating credit risk evaluation tools that could lessen the asymmetry of information.

Every financial institution has its own approach to processing loan applications, but they all follow the same outline. Koch and Macdonald (2010) mention that there are 8 steps and they are application, credit analysis, decision making, document preparation, closing, recording, servicing and administration and collection. The application step consists of a potential borrower filling a form and providing the requested information to the lender. After the lender receives all of the necessary information, he is able to focus on credit analysis. The credit risk analysis for commercial customers consists of an evaluation of the company's financial position and its future prospects. "Credit risk analysis consists of estimating the probability that a borrower fails to return credit in accordance with the terms agreed (probability of default) and the expected loss that the bank would incur in case of default (loss given default)" (Guimón 2005, 34).

Lending techniques can be classified into two main categories. Both methods require screening and monitoring processes that are similar in nature and intensity. One of them is called transactional lending and it depends on the analysis of the “hard” information, which is quantitative. Transactional lending includes many methods and the most popular ones are financial statement lending, asset-based lending and credit scoring (Berger & Udell 2002, F33.) The other lending technique is called relationship lending and it is based on the evaluation of the “soft” information, such as the "perceptions of the personal characteristics or other information that cannot be retrieved from the borrower’s formal financial information" (Trönnberg & Hemlin 2012, 1033).

The choice of the lending technique that is applied to a potential borrower depends on the size of the company that is asking for the loan. It is said that bigger banks depend on transactional lending, meaning that they focus on serving large and transparent companies that have a long history of financial information. The big banks have automated many processes and transactional lending is suitable for them as it does not require time to have a continuous dialogue with the potential borrower. The small banks depend on relationship lending, meaning that they focus on small enterprises (Mkhaiber & Werner 2018, 8.) The small banks or lending firms can collect "soft" information and easily transmit it through the communication channels of their organization.

Financial institutions can assess the credit risk and be satisfied with the result, but they still need to have measures in place to control that risk. There a few methods in which banks and loan companies can secure themselves from experiencing a loss in case the borrower defaults. One of the methods is asking for a collateral. A collateral can be defined as the specific assets pledged by the borrower. The assets that the borrower often uses as a collateral are cash and property (Apostolik & al. 2009, 95.) Some companies require a personal guarantee when giving out a loan. A personal guarantee can be defined as "a pledge of the stock, deposits, or other personal assets held by owners of the company in order to secure a business loan. In case of default, the lender will be able to take those personal assets to cover the loss" (Atrill, McLaney & Harvey 2014, 474). Company X requires a personal guarantee from a borrower when giving out a loan.

A method that is associated with the collateral and does not require a thorough analysis of the performance of the company is asset-based lending. The focus is on the quality of the available collateral. It requires the lender to monitor the assets pledged by the company. The assets that the company has to pledge are typically accounts receivable or inventory. Many SME cannot access capital via this type of lending as their assets are not of the appropriate quality (Berger & Udell 2002, F-37.) Company X does not utilise this type of lending, and therefore it will not be mentioned in this Thesis.

Loan officers or managers that make decisions on loan applications pay attention to different characteristics when evaluating a client. A study done by Bruns and Fletcher (2008) researched how banks in Sweden evaluated the credit risk of SME's. They found that profitability was the most important factor. Profitability can be calculated from the past financial performance of a company. Past performance provides a tangible measure of success and shows the competence of a firm (Bruns & Fletcher 2008.) The data which is required to calculate profitability can be taken from external accounting software. The data can be used to compute quantitative measures such as ratios. Financial ratios are based on the company's financial statements which are the income statement, balance sheet and cash flow statement. The second most important factor is the financial position of the firm (Bruns & Fletcher 2008.) The financial position is partly dependent on past performance, but it is treated in a different way by the loan officers. It is an indicator of whether or not the borrower has enough capital to repay the loan if the project that the money is given for fails. The third most important factor for loan officers was the borrower's competence within the business project (Bruns & Fletcher 2008.)

2.3.1 Financial statement lending

Technology is developing, and more credit risk assessment methods are being created with the use of formulas and algorithms. In this section the methods that make use of the qualitative data are going to be mentioned and explained.

Financial institutes that mostly deal with large public firms prefer to use the financial statement lending as the information is easily accessible, structured correctly and the data is accurate. The financial statement lending places focus on evaluating the information from the firm's financial statements such as balance sheet and income statement. The decision to give out a loan or not is based on the strength of the financial statements (Berger & Udell 2002, F-37.) Some small firms that have been operating on the market for a long time and have strong audited financial statements are also suitable for this type of lending.

The financial statements could be reorganized in many ways to show a specific characteristic of the chosen firm. There are several analyses which financial institutions apply to their potential borrowers in order to make a decision on their loan applications. Ratio analysis is widely used as it is a simple method and can give a valuable insight into the company's operations (Mwangi 2018, 16.) Ratios express one quantity in relation to another.

Comparison techniques provide a simple method of analysis by considering the difference from the prior period to the current period (Yallapragada 1989, 33.) Common-size analysis involves expressing financial data, including entire financial statements, in relation to a single financial statement item, or base. This analysis can be performed both on the balance sheet and the income statement. The vertical analysis is done using one reporting period, whereas horizontal analysis refers to an analysis comparing a specific financial statement with prior or future time periods, or to a cross-sectional analysis of one company with another (Robinson, Henry & Pirie 2015.) The horizontal analysis can be used as a trend- or time- analysis. This type of analysis enables managers to see the changes in performance over time and help the analysts to understand the reasons for the change.

Cross-sectional analysis compares a specific metric for one company with the same metric for another company, allowing comparison disregarding the size of the company (Robinson & al. 2015). This could also be done with the use of financial ratios. In order to compare different-sized firms the manager will use ratios and see how their potential borrower performs in comparison with the market leaders. This method of analysis enables an assessment of relative performance (Mwangi 2018, 16.)

Financial statements allow the capital providers to assess a firm's use of capital. Nowadays, as the financial statements become more complicated, banks find it more difficult to process them (Chakraborty, Leone, Phillips & Minutti-Meza 2018, 6.) This means that managers at financial institutions need to choose carefully which ratios they pay attention to. Financial ratios that are derived from the balance sheet and the income statement shed light on issues like: "the ability to control expenses, operating efficiency in using resources to generate sales, marketability of the product line, coverage that earnings provide over financing cost, liquidity position (indicating the availability of ready cash, track record of profitability, financial leverage, contingent liabilities)" (Rose & Hudgins 2010). Four main areas that bank evaluate when deciding on a loan are liquidity, operating efficiency, profitability and leverage positions of the company.

The profitability ratios show if the company is able to generate a profit on the invested capital. One of the simplest and most crucial ratios is the **gross profit** (gross margin) which is calculated by "reducing purchases of supplies adjusted by change in inventories of consumables from net sales" (Korhonen & Corporate Analysis & Committee for Corporate Analysis. 2013). This ratio must not be overlooked as it represents the amount of capital that the company has for covering costs and expenses that are not related to the making of the product or provision of the service. The other two ratios which are mentioned in the literature are the return on total assets and the return on equity. **Return on assets** (ROA) shows "the overall rate of return on the business's assets and is calculated by dividing net income after taxes by total assets" (Yallapragada 1989, 35). The higher the ratio, the more income is generated by a company on its assets. The second ratio which is **return on equity** (ROE) calculates the return earned by a company on its equity capital. This ratio can be calculated by dividing net income after taxes by the firm's amount of equity. It is said that people responsible for assessing risk do not utilise those ratios often, as they should find out about the profitability of the firm by conducting the common sizing of the income statement (Yallapragada 1989, 35)

The liquidity ratios measure the borrowing’s firm liquidity position. Those ratios show if the current assets of the company are sufficient enough to meet organizations current liabilities (Yallapragada 1989, 34). The liquidity measures which are reviewed by the majority of the lenders are current ratio, quick-ratio and net-working capital calculations. The **current ratio** that is calculated by dividing current assets by current liabilities is a gross measure of liquidity. Historically, analysts have viewed a current ratio of about 2.0 to be consistent with adequate liquidity. However, the current ratio should be compared to that of the other firms within the same industry in order to understand if there are any problems. The **quick ratio** which is calculated by adding cash to accounts receivables and dividing the sum by current liabilities provides a more conservative measure of aggregate liquidity. The quick ratio takes into account that some current assets cannot be converted into cash and that inventory can take time to be sold (Robinson & al. 2015) Both the current and quick ratios are static liquidity figures, so they measure the situation at the balance sheet date. The ratios can fluctuate during the financial year.

Operating efficiency ratios, otherwise called activity ratios measure how well firms manage and utilize their assets. The ratio that is always looked at is the **inventory turnover** ratio, as it reflects how well the company produces, markets and sells its products. This ratio is calculated by taking the cost of goods sold and dividing it by the average inventory. It indicates the resources tied up in inventory and can, therefore, be used to indicate inventory management effectiveness. A higher inventory turnover ratio means a shorter time that inventory is kept, and thus a lower DOH (Days of Inventory on Hand). In general, inventory turnover and DOH should be benchmarked against the industry norms. If the inventory turnover ratio is higher than industry norms it can mean two things, either that the company manages its inventory effectively or that the company does not keep enough inventory, so there are shortages which damage the revenue of the firm. A high inventory turnover ratio relative to industry norms might indicate highly effective inventory management. Again, comparing the company's sales growth with the industry can offer insight. The lenders should look at the growth of the revenue of the firm and compare it to the inventory turnover (Robinson & al. 2015.)

Another ratio is the **receivables turnover**, which is calculated by dividing revenue by average receivables, and along with it the days of sales outstanding (DSO) can be calculated. The DSO represents the time between a sale and cash collection, reflecting how fast the company manages to collect cash from the customers to whom it offers credit. If the ratio is high, it can be perceived both from the positive and the negative points of view. High DSO can mean that the company has an efficient credit and collection system, but it could also mean that the credit terms that the company offers to its clients are too strict, meaning that the company might lose customers to competitors with more flexible credit system (Robinson & al. 2015.)

The last category that lenders look at is the leverage ratios. The financial leverage that a company can employ depends on the nature of the business and its assets. Two important ratios are **times interest earned**, which measures the number of times the company can pay interest on its outstanding debt and **fixed charge coverage ratio** that shows how many times a firm can pay for the interest and other fixed charges with its current earnings. Total debt to total assets and net fixed assets to tangible net worth are ratios that show the managers the amount of debt compared to the size of the firm. Net fixed assets to tangible is an indicator of the proportion of the firm’s fewer liquid assets financed by net worth. The greater the ratio, the greater the level of debt financing fixed assets and the more likely it is that liquidation proceeds will fall short of net worth in the event of failure (Koch & MacDonald 2010.)

A vital part of the financial statement lending is the analysis of the cash flow statements. The cash flow statements show the lender if there is a sufficient flow of funds to the business to cover the interest payments in the future. Two main questions that need to be answered related to the cash flow analysis are:

- Are anticipated cash receipts of a commercial customer going to fulfill all of the customer’s cash payment obligations?
- Does the customer have the ability to remain a going concern if the anticipated cash flows do not materialize?

There are a few drawbacks to this lending technique. One of them is that there is no single correct value for financial ratios. The lender will determine if the ratio is too high, too low or just right based on his/her knowledge of the market and previous experience. In the past research it has been found that the capability of humans to make a judgement whether the loan is profitable or not is quite poor (Glorfeld & Hardgrave 1996, 933.) Humans are prone to bias, so the emotional or physical state can affect the decision (Handzic, Tjandrawibawa & Yeo 2003, 97.) In order to understand how the company is performing, its financial ratios need to be compared to other companies that operate on the same market. There can be a problem as different companies may use different accounting methods and techniques, such as those used in inventory valuation, depreciation, revenue and expense recognition, that can complicate the comparison procedure. Some companies prefer to use leased equipment and those assets do not appear on the balance sheet, which completely changes the financial ratios (Gadoiu 2014, 93.) Also, many companies resort to practices that allow them to veil artificially their situation, making the ratios look better than they really are (Brigham & Houston 2008, 106.)

There is knowledge which is hidden in the past application data which is hard for humans to decode (Handzic & Aurum 2001, 971.) There is too much data to analyse and the relationship between certain data cannot be recognized by humans. This is the main reason for developing other lending techniques that use technology to help humans see all of the patterns and correlations.

2.3.2 Credit scoring lending

Credit scoring is another method which is used to evaluate the credit risk of loan applications. Credit scoring models use statistical modeling techniques to transform quantifiable information sometimes referred to as “hard” information about a small business (business credit reports, company financial ratios, sales figures, corporate structure, and industry identity) into a numerical “credit score” that ranks individual borrowers based on their likelihood of defaulting on a loan. The method produces a score that a bank can use to rank its loan applicants or borrowers in terms of risk.

A growing number of banks are using credit scoring models in their small-business lending operations, most often for loans under $100,000, although scoring is by no means universally used. Credit scoring models were adopted slowly as business loans are distinctly different to consumer loans and credit card loans. This means that there was not much information available to build the models. The first banks to use scoring for small-business loans were larger banks that had enough historical loan data to build a reliable model.

The reason for the increased use of the scoring methods is that the methods are relatively cheap and simple compared to the modern approaches. Some research (Mester 1997, 6) revealed the widespread use of credit scoring models showing that 97 percent of the banks use credit scoring to approve credit card applications, whereas 70 percent of the banks use credit scoring in their small business lending. There are a few benefits that are associated with the use of credit scoring. Firstly, it reduces the time and the cost of making a loan, which in turn allows lenders to make more loans to SMEs. Credit scoring allows to control the risk more effectively and removes the human bias from the lending process. Credit scoring automates the analysis of credit risk, giving more time to lenders for review of questionable loan applications (Asch 2000, 2.)

Credit scoring systems are based on discriminant models or related techniques, such as logit or probit analysis or neural networks, in which several variables are used jointly to establish a numerical score for each credit applicant. Neural networks are used for credit scoring in commercial, consumer and mortgage loans. An important feature of neural networks is that they are able to learn. The study that was carried out by Handzic & al. (2003) found out that neural networks can be helpful in the decision-making concerning loan application, but there are still limitations related to this method. The method which has been adopted by many financial institutions and has shown to be effective is bankruptcy prediction models.

2.3.3 Bankruptcy prediction models

There is no general definition for the term bankruptcy. In Finland, bankruptcy is defined as "insolvency proceeding covering all the liabilities of the debtor, where the assets of the debtor are used in payment of the claims in bankruptcy" (Tilastokeskus 2019a). Altman stated that firms which are facing bankruptcy are "those firms that are legally bankrupt and either place in receivership or have been granted the right to reorganize under the provisions of the National Bankruptcy Act" (Altman 1968). Some research studies mention the term "financial distress" when talking about bankruptcy. Bankruptcy can be seen as financial distress in the sense that companies are not able to meet their payment obligations (Fejer-Kiraly 2015, 99.) Financial distress is one of the first indications of the bankruptcy of a firm, therefore many bankruptcy prediction models estimate if the company is experiencing any financial difficulties or not. The bankruptcy prediction model could be defined as "the anticipation and early warning system against financial distress" because the model is used to analyse the condition of the firm prior to the crisis (Husein & Pambekti 2014, 408).

One of the most widely used credit scoring techniques is bankruptcy prediction model. Each model has its own set of financial ratios, otherwise called variables, and a coefficient for every variable that depends on the importance of a particular variable. The variables that are chosen for the bankruptcy prediction model determine the effectiveness of the model. The model predicts if the company would go into bankruptcy or not and therefore is called a bankruptcy prediction model. These models predict the bankruptcy of a firm in one or two years. Altman and Zmijewski models predict the probability of a firm going bankrupt within two years (Archana 2018, 63-66.)

In 1968, E. Altman has created a multiple discriminant analysis model (MDA) known as the Z-Score (Horváthová & Mokrišová 2018, 3.) The model was based on the data of the companies from the manufacturing sector (Archana 2018, 61.) Altman used 22 financial ratios, from which multiple discriminant analysis showed only 5 to be significant bankruptcy indicators. (Archana 2018, 61.) The formula is as following:

$Z= 0.012\ X1+0.014X2+0.033X3+0.006X4+0.999X5$
X1 = Working Capital / Total Assets
X2 = Retained Earnings / Total Assets
X3 = Earnings Before Interest and Taxes / Total Assets
X4 = Market Value of Equity / Total Liabilities
X5 = Sales / Total Assets

The Z-score model calculated the chance of bankruptcy of a firm within a specified time period. The model was accurate 95% of the time when the companies one year prior to bankruptcy were tested, but when the companies five years to bankruptcy were tested, the accuracy was 36% (Archana 2018, 61.) Since 1968, Altman had revised the Z-score model to analyse different industries. There was a model for private firms and a model for non-manufacturing firms (WallStreetMojo 2019.) The model that was made to analyse non-manufacturing firms includes four variables. The fifth variable used in the original formula is taken out from the revised version "in order to minimize the potential industry effect which is more likely to take place when such an industry sensitive variable as asset turnover is included" (Altman 2000). Also, the revised model is suitable for "industries where the type of financing of assets differs greatly among firms" (Altman 2000). If the model is used to analyse the “companies in the emerging markets, a constant term of +3.25 is added as to standardize the scores with a score of zero (0) equated to a D (default) rated bond” (Altman 2000).

Z = 3.25 + 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4
X1 = (Current Assets - Current Liabilities) / Total Assets
X2 = Retained Earnings / Total Assets
X3 = Earnings Before Interest and Taxes / Total Assets
X4 = Book Value of Equity / Total Liabilities

For the revised model, the final Z score can be divided into three categories. If the result is more than 2.6, then the firm is in the "safe zone" and is unlikely to file for bankruptcy. If the result is between 2.6 and 1.1, then the company is in the "grey zone" and has a moderate probability of defaulting. If the Z value is below 1.1, then the company is in the "distress zone" and has a high chance of reaching the stage of bankruptcy (WallStreetMojo 2019.)

Several bankruptcy prediction models were introduced by different researchers since Altman has created the Z-score model. One of those models was introduced by Mark E. Zmijewski in 1984 and was called the Zmijewski model (Gusni, Wiludjeng & Silviana 2019, 189.) It was based on the financial ratio analysis that "measured the performance of debt or leverage and liquidity of a company" (Husein & Pambekti 2014, 409). This model emphasizes the magnitude of the debt in predicting financial distress condition of the company. The model contains three variables and two of them represent leverage. “The bigger the amount of debt is, the more accurate predictions of the model to the possibility of companies experiencing financial distress” (Husein & Pambekti 2014, 414). The model is as follows:

X = -4.3 – 4.5X1 + 5.7X2 – 0.004X3
X1 = After Tax Earnings / Total Assets
X2 = Total Debt / Total Assets
X3 = Current Assets / Current Liabilities

The results are classified into two groups, companies that are potentially bankrupt and not. If the result is greater than 0.5 then the company is classified as bankrupt. If the result is less than 0.5, then the company is classified as non-bankrupt (Archana 2018, 68.)

Another model was introduced in 2001 and it emphasized the profitability of the firm. The model was created by Jeffrey S. Grover, and it was a reassessment of the Altman Z-score model (Gusni & al. 2019, 189.) The model has three variables, two of them are taken from the Altman model, and the third variable is a profitability ratio. The model is as follows:

$G = 1.650X1 + 3.404X2 – 0.016\ X3 + 0.057$
X1 = (Current Assets - Current Liabilities) / Total Assets
X2 = Earnings Before Interest and Taxes / Total Assets
X3 = Net Income / Total Assets

The result of this model is labeled as G score. Grover model categorized companies as bankrupt that had the G score less than or equal to – 0.02. While the score for companies categorized as non-bankrupt is 0.01 or more (Prihathini & Sari 2013.)

The Zmijewski model and the Altman model do not have any common financial indicators, so they give different results. The Altman and the Grover model are not significantly different from one another therefore their results can be similar.

There are a couple of drawbacks to this lending method. One of them is that there are economic differences between the time when the model was developed and the present, so the relationship between the dependent and independent variables might change. (Grice & Dugan 2001, 153.) The factors that are likely to change over time include inflation, interest rates, credit availability and technology. Another drawback is that some of the models were developed by using a small sample of companies and a short window of time, meaning they might not be as reliable (Grice & Dugan 2001, 153.)

2.3.4 Relationship lending

Relationship lending is based on the analysis of the "soft" information about the owner and the company. The lenders base their decision on the proprietary data that they collect through a variety of contacts over time. Some of the information is gathered by the provision of the loans, deposits and other financial products. Additional information can be obtained by contacting the local community, such as suppliers and customers, who may be willing to give certain information about the firm and the owner or the business environment in general (Berger & Udell 2002, F-37.) A lot of research focuses on the relationship lending being about only the relationship itself, meaning that the interest rate on the loan, availability of the credit, the collateral requirement and other aspects of the loan that are decided by the lender are going to be influenced by the strength of the relationship.

Company X has recently commenced its operations, so the analysis of the relationship between the company and the client in terms of time are useless. In this thesis, relationship lending can be viewed as the lending that utilises "soft" information with little regard to the relationship between the borrower and the lender.

Technological advancements can allow lenders to harden soft information and make it easier for lenders to analyse the firms. Big data can help identify fraudulent activities and improve the evaluation of the credit risk. As there are not many studies done on the topic of analysing big data in the context of lending, the framework for 5C's will be used to identify useful information.

The five C’s

Character- there must be a purpose for the customer to request to take out a loan. The lending officer needs to make sure that a borrower has a responsible attitude. The credit risk manager should determine the quality of management's relationship with both the employees and its customers (Apostolik & al. 2009, 123-124.) As the technology is developing, we have many sources from where we can obtain data about the character of the borrower. Social media can be helpful in understanding the behavior of the borrower and his intentions. There are websites that can tell us how the employees are treated and if they are satisfied with their jobs (Careerbliss 2020.) Also, customer reviews all over the internet can help the credit risk manager understand if the firm's offer is fulfilling the customer's needs.

Conditions- recent trades in the industry. The main question that needs to be answered when analysing conditions, is what are the economic conditions of the country and the industry in which the company operates (Apostolik & al. 2009, 123-128.) The credit risk manager needs to evaluate the external risk that might affect the performance of the potential borrower. This type of information can be collected from internet sources. There are updates on the changes in the market, reports on the stability of industries and live figures of the financial markets (stock market).

Capital- the credit risk manager needs to find out the capital structure of the company, meaning he/she needs to determine if the firm is financed by debt or equity. This information can be obtained from the financial statements of the company.

Capacity- the borrower must have the authority to request a loan and the legal standing to sign a binding loan agreement. Company X enables customers to make a loan application through their website, which checks the banking credentials of a potential consumer (Rose & Hudgins 2010, 528). Also, capacity can mean the ability of the company to generate sufficient cash flows and the ability of the management to operate efficiently and effectively (Apostolik & al. 2009, 123-128.) Cash flow statements and financial ratios can provide information to cover this aspect of the 5C's.

Collateral- can the borrower provide potential support for the loan. Company X requires a personal guarantee, meaning that they do not need to pay too much attention to the assets that the firm can pledge as a collateral.

Sometimes there is also **control**, which looks at a chance that there are changes in the law and regulation that could adversely affect the borrower (Rose & Hudgins 2010, 528)

Social media is used by most people in the developed countries and a lot of personal information can be obtained from the social pages of individuals. Banks and lenders are starting to make use of that. There is a technology that allows banks to check the credit ratings of the people that you have as "friends" on Facebook and see if the credit score is acceptable. This concept assumes that a person surrounds himself with like-minded people and therefore will have similar behaviour patterns to those of his friends (Horizon Community Bank 2016.) LinkedIn can be used to see the job stability and income potential (Horizon Community Bank 2016.) LinkedIn profile shows information such as the frequency of changing the jobs, and it can also provide proof for the expertise that people have in the company. The company's social media page is vital, as it can show the online strategy that the business utilises.

Fraud detection is a major sphere where the analysis of qualitative data is essential. Some people apply for a loan in bad faith, meaning that they do not want to use the given money for the purpose that they have stated in their loan application. Analysis of the qualitative data can help detect fraud at the beginning of the loan application. The lending and insurance industries have a few similarities. One of them is that in both industries, the company representatives receive applications and have to make decisions which are based on the information in the application. Companies in both industries face a problem of fraud in the early stage of their sales process, which is the application. The insurance industry has a long history dealing with fraudulent applications and therefore there is more academic material. In order to detect fraud, the company representative would need to analyse personal information which is publicly available. In the insurance industry, the company needs to know that the person's claim about the damage is real, and in the lending industry the company needs to know if the business and future plans of the business are real and possible.

The same techniques which are used by insurance investigators, people who find out if the insurance claim is real or not, could be used by the credit risk analyst. The process of information gathering is done according to a certain framework, which every company customises according to their needs. Typically, this process includes searching the web by focusing on the name, the phone number, the email, the address and other personal areas of the individual being analysed (Association of Certified Fraud Examiners 2019.) All of the obtained information gives a summary of the lifestyle of the potential client, his history and his future plans. The same type of data can be used by lending officers in order to understand if the person has a history of being involved in fraudulent activities, his intentions for the business and the lifestyle that he has. This will help the lending officer to determine if the application is fraudulent or not.

Credit managers can find out about the state of the business and the future plans of the potential borrower from the internet. There is information on the web about any sale promotions that the business hosts and if the owner of the firm has been accused of fraud before. The most precise search engine for a single word and double work queries is Google (Bute, Hussaini & Inuwa 2017, 149.)

3 Development of the custom approaches

This chapter will include the empirical study of the thesis. I have conducted an interview with the founder of Company X (Appendix 1) and collected information that will be mentioned in this chapter. I had an initial interview where most of the questions were asked and any questions which came after that were answered in the follow-up discussions. Currently, non-bank financial institutions' average percentage of non-paying loans is approximately 30% and all the companies on this market aim to decrease that figure. The objective of this chapter is to develop two approaches, one which will analyse quantitative data and another one which will analyse qualitative data.

3.1 Approach utilising financial data

Company X is processing approximately five loan applications every day and they need to have an effective risk analysis model in order to be able to rate the potential borrowers. Company X works solely online and does not conduct any face-to-face meeting with their customers. This means that any data about the company that is available online or through the financial statements should be analysed as it is the only source of information for making the decision on whether to give out a loan or not. The financial information is given a considerable attention at Company X. Company X has a "cold" approach, as they mainly judge the company based on its financial performance. Company X provides its potential borrower with a loan offer within 2 hours after the loan application is submitted. The process of risk analysis includes elements of financial statement lending and credit scoring lending.

Company X takes various approaches to analysing the performance of the company. Employees check the most relevant financial metrics. Financial ratios that Company X sees as the essential ones are "profit margin", "liquidity ratios" and "return on assets". If those ratios are satisfactory, then the Company X decides to review the application further. This indicates that the company primarily considers profitability and liquidity for its analysis. The "profit margin" and the "return on assets" are profitability ratios that show how well the company manages to generate profit with the available resources. The liquidity ratios show the capability of the company to cover their current liabilities with their current assets and as mentioned in the theory framework, there is "quick ratio" and "current ratio". The founder of Company X could not share the whole framework that they use for analysing quantitative data, so I had an objective of finding a method that they have not utilised.

During the interview, we have discussed different techniques that are used worldwide to analyse the financial information of the companies and determine the credit risk. The owner highlighted that currently they have a good model for credit risk analysis for loans with a time period of one year and less. Company X needed a technique that would allow to see the credit risk for one-year and two-year loans. One technique which fit that criteria and was not used by Company X was "bankruptcy prediction models". My aim was to find a model that included the financial ratios that were highlighted as important by the owner of the company X.

The four bankruptcy prediction models that I researched were presented to the company owner. We discussed strengths and weaknesses of every model and chose the ones that satisfy the company's needs at best. The original Altman Z-score model was rejected as it is the oldest model and it is mainly made for analysing manufacturers. Company X does not deal with many manufacturers as they usually request loans higher than the company’s limit. Grover model and the revised Altman Z-score model focus on liquidity and profitability ratios which are considered to be important by the company's representative. The Grover model has a very narrow range for classifying the company as bankrupt and the non-bankrupt, so therefore the revised Z-score model was chosen due to a wider classification of the results. The Zmijewski model was chosen as it has fundamentally different variables to both the Grover model and the revised Altman Z-score model. Both, the Zmijewski and the revised Altman model predict a firm's bankruptcy in two years (Archana 2018.)

An excel with the chosen models was created. The employee of Company X would need to fill in the financial metrics and then the score of a particular model would be automatically calculated via the formulas and indicate if the company is in financial distress or not.

Zmijewski model

Insert the figures for financial metrics and check your result

The ratio	**No**	Result	Coefficient
Profit after tax / Total assets	X1	0.03423237	4.50
Total debt / Total assets	X2	0.6659751	5.70
Current assets / Current liabilities	X3	1.65668663	0.004
The Formula			
-4.3-4.5*X1+5.7*X2-0.004*X3		-0.6646143	

If greater than 0.5, then the company can be classified as bankrupt.
If the result is less than 0.5, then the company is classified as non-bankrupt.
This formula predicts the chance of the company to go bankrupt in **2 years.**

Financial metrics	
Profit after tax	33
Total assets	964
Total debt	642
Current assets	830
Current liabilities	501

Figure 3. Zmijewski model

Revised Altman Z-score model			
Insert the figures for financial metrics and check your result			
The ratio	**No**	**Result**	Coefficient
(Current Assets - Current Liabilities) / Total Assets	X1	0.34128631	6.56
Retained Earnings / Total Assets	X2	0.25103734	3.26
Earnings Before Interest and Taxes / Total Assets	X3	0.04356846	6.72
Book Value of Equity / Total Liabilities	X4	0.5046729	1.05
The Formula			
6,56*X1+3.26*X2+6.72*X3+1.05*X4		3.87990654	

If the result is greater than 2.6, then the company is in the "safe zone".
If the result is between 2.6 and 1.1, then the company is in the "grey zone", and has a moderate probability of defaulting.
If the result is less than 1.1, then the company is in the "distress zone" and has a high chance of reaching the stage of bankruptcy **within 2 years**.

Financial metrics	
Retained Earnings	242
Total assets	964
Current assets	830
Total liabilities	642
Current liabilities	501
Book value of Equity	324
EBIT	42

Figure 4. Altman revised Z-score model

Additionally, I decided to create a visual representation of turnover growth. In the interview, the founder of the company has mentioned that besides the financial ratios, they emphasize the importance of "sales growth". Every company values the most up-to-date data and considers the data of today to be the most important. Company X considers three years of the past financial data to be significant for analysis. This part of the tool can be used to check if the company has consistent sales and profit figures and if there is any growth from year to year. I have created an excel sheet that can be filled in to see the growth of turnover and profit over the last four years.

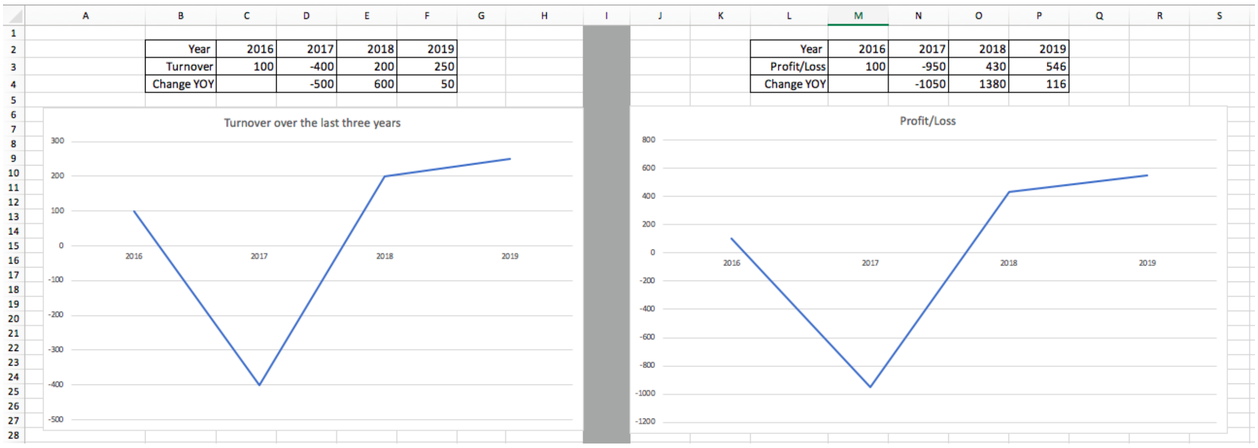

Figure 5. Tool for visual representation of turnover and profit growth

Also, company X engages in credit scoring lending. The company has its own credit scoring model that includes factors such as financial metrics and payment behaviour. They utilise the results from other credit scoring agencies. Their main partner at the moment is "Asiakastieto".

3.2 Approach utilising non-financial data

Reasons

Company X does not have a model to analyse the qualitative information of a company. The most important reason for why company X needs this model is to detect fraud. The financial statements can be manipulated in such a way that it looks like the company is performing well and has a prosperous future. In reality, the owner might be already selling all of the business equipment and organizing promotions in order to sell out the last products. In order to detect fraud, the company needs to have a tool for fraud detection. Fraud is defined as "using deception to make a personal gain for oneself dishonestly and/or create a loss for another" (Chartered Institute of Management Accountants 2009, 3). In the lending business, a fraudulent loan application is an application that contains false data about the company, the owner or the future plans for the business. In the non-bank lending industry, fraud occurs quite often as the industry is relatively new and does not have many regulations. The key to detecting fraud in the lending industry is a thorough review of the loan application and analysis of the "soft" information about the company and the owner. In some aspects, insurance fraud is similar to the fraud that lending companies encounter.

One of the main purposes of my tool is an in-depth analysis of the person's history that can guarantee to the lender that the person is not inclined to conduct fraud. “Asiakastieto” provides you with a credit rating of the person, but it does not specify if the person has been engaged in any fraudulent activities in the past. The person might only have a clean record in Finland, but his actions outside Finland are not shown in “Asiakastieto”. (Appendix 2) The search for information on the web by name, email, phone number can uncover useful information that can help with the loan decision. Also, “Asiakastieto” does not provide the lender with information about the situation of the business at the time of the application for the loan. The service does not monitor if the business has any promotions or big sales, which could indicate that the business is closing, so the lender needs to check that by himself.

Another reason for making a tool for the analysis of the qualitative data is getting additional information about the company and its operations. It enables lenders to check the digital activity of the potential borrower and understand what customers think about its products or services. This information improves decision making and should result in a decrease of non-paying loans.

Fraud Detection Check

The first part of my tool for analysing qualitative information is concentrated on fraud detection. There are not any free frameworks that are publicly available that can be used by lending companies to analyse "soft" information of the potential borrower. I have based my framework on the methods that insurance companies use to detect fraudulent applications (Association of Certified Fraud Examiners 2019.) The owner of the business should be considered first. If the person has any history of fraud in the past, then the company should not consider giving him a loan. The basic check is performed through search engines. It is better to use more than one search engine in order to get the best results. Each search engine indexes its information differently. (Association of Certified Fraud Examiners 2019, 83.) This means that you will get different results in every search engine that you use. This increases the effectiveness of the analysis as you are able to find more data. I have suggested using three search engines for every factor that is going to be mentioned below. I have tested several search engines and chose the three ones with the biggest variety in their results.

The first search engine which should be used is "Google" as it is the most popular one and shows the result based on your location and other factors. It shows the most popular pages for the given search. The person conducting fraud can create websites and promote them, so when someone "Googles" information related to that person, they will only see positive info. The second search engine is "duckduckgo". This search engine does not have tracking, so it shows results which are not affected by location, search history or other personal factors (Kissiah 2019.) This enables the lender to see if the person has been accused of something in other countries as any forums or blogs with his name will show up. The third search engine is "WebCrawler". This search engine combines results from "Yahoo", "Google", "Windows Live", "Ask" and other popular search engines (Kissiah 2019.) I chose it as it had the greatest difference in results compared to Google with other search engines that I have tested. The "WebCrawler" also shows little summaries of the main information on the website, so the employees of Company X can save time while conducting the fraud detection process (Kissiah 2019.)

Company X eliminates chances of fraud at the beginning of its loan application by requesting the bank credentials of the owner of the business. This factor eliminates identity theft, as in Finland you cannot get online bank credentials without identifying yourself to the governmental authorities.

In the beginning of the fraud detection process the employee of Company X would need to input the mobile phone number of the owner of the business into the three search engines and check the results. The results of the search should correspond to the information that the business owner has provided in his application. When businesses are closing down, the owner tries to sell as many assets as he can, in order to get back his investment. The owner could sell those assets online and include his personal phone number as the one to contact. The employee of Company X needs to check if there are any business assets that are on sale that mention the personal phone number of the applicant. If he is selling a few items related to his business, that might imply that he is planning to close the business. The employee of Company X should also check if there any articles that mention this phone number in a negative context, which could mean that the application is fraudulent. The next step is to check the email address of the potential borrower. This search can help you find if the email has been mentioned in any sale of items, news articles or blogs discussing fraudulent activities. Then, the employees should check the name of the person and scan through the results to see if there are any red flags. If the employee is still unsure whether the person is a fraud or not, he can check the social circle of the potential borrower. He can do that by finding the names of close relatives or friends and seeing what information is available about them. After the employees have identified that the person does not have history conducting fraud, they should start checking the company.

The address of the company should be input into the search engine to check if the business is truly located there and see pictures that show the condition of the building located at that address. The employees should find where that address has been mentioned and check that this address is not available for rent in the near future. I have found a database of companies including Finnish ones, that shows the general information about the business, such as the length of operation, number of employees and the revenue (Zeckit 2020). The employee should check if the company is present in the database and see if the facts about the company correspond to the ones in the loan application. If the employee of Company X does not find any suspicious or misleading information about the potential borrower, then he moves onto the second part of the tool. The check for misleading information based on the phone can be seen in Figure 6. The same framework is implemented for every other factor such as name, address, email and social circle.

Phone Check	Comments	
Input the phone number into the search engine and check if anything is being sold or is there any deceptive/wrong information.If the items that are sold related to the business, then put a red flag.		
Link to the search engine		Description of the website
https://www.google.com/		The most popular search engine in the world
https://duckduckgo.com/		This search engine doesn't track you, so the results are not location-based, nor they are affected by your previous search history.
https://www.webcrawler.com/		This search engine gathers the results from the Yahoo, Google, Windows Live, Ask and other popular search engines.

Figure 6. Phone number check

Assessment of the company

The second part of the tool has a purpose of rating a company based on the qualitative information that is available online. This is needed as the financial information is not enough to see how the owner operates the business. Nowadays, it is very important to establish a good online presence for your business for it to be successful. The digital activity of the business can determine how customers find out about it and how the information about new products or promotions is being delivered to them. I have made a model that includes factors for analysing the digital activity of the business and have given them a "weight" according to the importance that they have for Company X. There are two variations of this part of the tool, one is made for organizations that sell to final customers, and the other one is made for organizations that deal with other businesses. Business-to-consumer (B2C) organizations need to keep their social media pages active so their customers are constantly informed about their products/services and promotions. In the first variation of the tool, social media pages are considered and are assigned an appropriate “weight”. In business-to-business (B2B) sphere the importance of the social media pages is less, but the customer reviews and the website are more significant. Therefore, in the second variation of the tool, the social media pages are not considered, and bigger “weights” are assigned to factors such as customer reviews and the website. After rating each factor, the employee at Company X will have a grade for the company from 0 to 100.

Public awareness rating

In the beginning of the second part, the employee needs to check the public awareness of the borrower's company. In order to do that, he should use five search engines mentioned in the tool and check if there are any news articles that mention the company or any additional information about the company itself. One of the websites that is mentioned is “millionshort” and it allows you to filter your results in various ways (Kissiah 2019a.) This helps the employee to take out unnecessary information and see if there are any websites that give extra information about the potential borrower. There could be articles about the working conditions of the business written by the past or present employees. In B2C variation, the weight which is given to this factor is “3”, and in B2B it is “5”. The general outline of the rating is seen in Figure 7.

Company Credit Risk Analysis
The fields which are marked with red outline need to be filled in*
Public Awareness

Put the name of the company in the search engine in the basic and the news section and then add "---" fo Google to search specifically for that name		This website gives you an option to remove a certain amount of popular results from your searches, allowing you to dig deeper for your information.		Searches the web and gives you results which are not affected by your location, search history, or any other personal information.		Searches multiple search engines at once		Searches multiple search engines at once	
https://news.google.com/?hl=en-US&gl=US&ceid=US:en		https://millionshort.com/		https://duckduckgo.com/		https://www.dogpile.com/		https://www.webcrawler.com/	
Are there any news articles about the company or the owner?	no	Are there any news articles about the company or the owner?	yes	Are there any news articles about the company or the owner?	no	Are there any news articles about the company or the owner?	no	Are there any news articles about the company or the owner?	no
Any additional information about the company?	yes	Any additional information about the company?	yes	Any additional information about the company?	no	Any additional information about the company?	yes	Any additional information about the company?	yes

Criteria	Rating
A lot of information about the company	5
Moderate amount of information	4
Some basic information about the company	3
A few websites about the firm	2
No information about the firm	1
Company's rating*	3
Rating with the Given Weight-(3)	9

Figure 7. The public awareness rating

Social media rating

Then, the next factor is social media. Businesses can update their customers on new offers and promotions through social media. People find businesses on Facebook and Instagram, leave reviews and have discussions about how the offering of the business could be improved. It is not enough for a business to just have the social media page, it needs to be active. The activity could be classified into various groups and rated based on the amount and quality of the posts. In my model, the employee first gives a rating to the social media page overall, considering the basic info about the business and the appearance of it. Then, the employee needs to rate four more factors about the posts on a scale of one to five based on the given criteria. The factors are "when was the last post", "the frequency of the posts", "how many posts per month" and "the quality of the post". There are descriptions alongside some of those factors in order to assist the employee in the rating process. Businesses can have social media pages on several platforms, but I assume that SMEs would focus solely on one platform and have another one in order to reach more customers. Due to this fact, I have given a "weight" of “5” to the primary social media page, and “2” to the secondary social media page if the business has it. In the B2B variation of the tool, there is no rating given to social media pages. Figure 8 shows the whole social media section of the model and figure 9 details every criteria for the social media analysis.

Main social media page (Facebook/Instagram)									
Social media page overview		**How many posts per month?**		**The frequency of the posts**		**When was the last post?**		**The quality of the posts (content)**	
Criteria	Rating	Criteria	Rating	Criteria	Rating	Criteria	Rating	Criteria	Rating
Detailed description of the business. Excellent appearance.	5	10 or more	5	One post every three days	5	Less than 1 week	5	Check the grammar, the relevance of the post, comments. Is there info about the services/products.	5
A sufficient description of the business. Good appearance.	4	From 10 to 8	4	One post every week	4	Less than 1 month	4		4
Some details about the business. Satisfactory appearance.	3	From 8 to 5	3	One post every month	3	Less than 3 month	3		3
Hardly any description of the business. Bad appearance.	2	From 5 to 3	2	One post every three month	2	Less than 6 month	2		2
No description of the business. Messy looking.	1	From 0 to 3	1	One post every year	1	Less than 1 year	1		1
Company's rating*	5	**Company's rating***	5	**Company's rating***	5	**Company's rating***	5	**Company's rating***	5
Total Rating									5
Rating with the Given Weight-(5)									25

Main social media page (Facebook/Instagram)									
Social media page overview		**How many posts per month?**		**The frequency of the posts**		**When was the last post?**		**The quality of the posts (content)**	
Criteria	Rating	Criteria	Rating	Criteria	Rating	Criteria	Rating	Criteria	Rating
Detailed description of the business.	5	10 or more	5	One post every three days	5	Less than 1 week	5	Check the grammar, the relevance of the post, comments. Is there info about the services/products.	5
A sufficient description of the business. Good appearance.	4	From 10 to 8	4	One post every week	4	Less than 1 month	4		4
Some details about the business. Satisfactory appearance.	3	From 8 to 5	3	One post every month	3	Less than 3 month	3		3
Hardly any description of the business. Bad appearance.	2	From 5 to 3	2	One post every three month	2	Less than 6 month	2		2
No description of the business. Messy looking.	1	From 0 to 3	1	One post every year	1	Less than 1 year	1		1
Company's rating*	5	**Company's rating***	5	**Company's rating***	5	**Company's rating***	5	**Company's rating***	5
Total Rating									5
Rating with the Given Weight-(2)									10

Figure 8. Social media analysis

Social media page overview	
Criteria	Rating
Detailed description of the business. Excellent appearance.	5
A sufficient description of the business. Good appearance.	4
Some details about the business. Satisfactory appearance.	3
Hardly any description of the business. Bad appearance.	2
No description of the business. Messy looking.	1
Company's rating*	5

How many posts per month?	
Criteria	Rating
10 or more	5
From 10 to 8	4
From 8 to 5	3
From 5 to 3	2
From 0 to 3	1
Company's rating*	5

The quality of the posts (content)		**The frequency of the posts**		**When was the last post?**	
Criteria	Rating	Criteria	Rating	Criteria	Rating
Check the grammar, the relevance of the post, comments. Is there info about the services/products.	5	One post every three days	5	Less than 1 week	5
	4	One post every week	4	Less than 1 month	4
	3	One post every month	3	Less than 3 month	3
	2	One post every three month	2	Less than 6 month	2
	1	One post every year	1	Less than 1 year	1
Company's rating*	5	**Company's rating***	5	**Company's rating***	5

Figure 9. Factors and rating criteria for social media analysis

Website rating

The next area which the employee should analyse is the website of the firm. This element was considered to be important for Company X both when dealing with B2C and B2B organizations, so it was given a "weight" of “6” and “7” relatively. If the B2B company does not have a social media page, then the only way they are able to communicate with their potential customers online is through their website. The employee should analyse the website of the firm, check if it is user-friendly and easy to navigate. The appearance and features of the website should be evaluated. The employee should check if the website is being updated, it should contain up-to-date information about the location of the business, the products or services that it provides and a general description of the business. As employees at Company X review many websites daily, I have not included an extensive criterion, as I believe that employees are going to be able to assess the website by themselves and give an accurate rating. After they have rated the website, they need to rate if the information on the website is updated. This means that they need to check if the address is correct, the price of the products is the same as the one on social media, and if any important changes in business are mentioned. The next step is to check the domain of the website to make sure that it is on safe servers and the date when it was acquired. The last criteria is the development of the website. There is a website which takes screenshots of most of the websites on the Internet, and an employee will be able to check how the website has been developing (Internet Archive 2020.) If the website is not found, then the employee should give a five and move onto the next part.

Website			
How professional does the website look?		**Is the website updated?**	
Criteria	Rating	**Company's rating* (1-5)**	5
Professional appearance. Contains extensive info about the business and its offering.	5	**The website statistics**	
Good appearance. Contains general info about the business and its offering.	4	http://whois.domaintools.com/	
Satisfactory appearance. Contains sufficent amount info about the business and its offering.	3	**Company's rating* (1-5)**	5
Poor appearance. Contains necessary info about the business. Product information is missing.	2	The development of the website	
Inadequate appearance. Little info about the business. No product information.	1	https://archive.org/web/	
Company's rating*	5	**Company's rating* (1-5)**	5
Total Rating	5		
Rating with the Given Weight-(6)	30		

Figure 10. Factors and criteria for website analysis

Customer reviews rating

The last element in my model for assessing the company is customer reviews. The employee searches for reviews online and checks what are the customer’s opinions on the offerings of the company. Every company has reviews on various websites depending on the industry in which it operates. The employee should check those websites and then see "Google reviews" as most companies have ratings there. The employee should see most of the ratings and calculate what is the average rating that the customers give to the business. In the B2C variation the "weight" of this factor is “4”, as company X considers is to be less important than the website, but more important than the public awareness. The “weight” of this factor in the B2B variation of the tool is “8” as customer reviews are considered to be a vital source of information in this sphere.

Customer reviews	
What is the customer's rating of the company	
Criteria	Rating
Professional/Excellent/Positive	5
Good	4
Satisfactory	3
Poor	2
Very poor/Negative	1
Company's rating*	5
Rating with the Given Weight-(4)	20

Figure 11. The criteria for customer reviews

The employee needs to input the company's rating in each factor. After the fields that are marked with an asterisk are filled in, then the final grade will be calculated automatically. The companies with rating of more than 60 are in the "green" zone, meaning that the company invests effort, capital and time to be present online and get to their customers. The companies with the rating 40-60 are in the "yellow" zone, meaning their digital activity is at a satisfactory level, but could be improved. The companies with the rating below 40 are in the "red zone", meaning that they lack digital presence and need to consider investing into that matter.

4 Testing of the tool

In this chapter I will explain how the testing of the tool was carried out. The process of testing and the classification of results is going to be described.

4.1 Preparation

The testing of the tool was done remotely. The representatives of Company X have suggested that I should test the created tool by analysing a certain number of companies and deciding whether or not they are eligible for the loan. The effectiveness of the quantitative would be determined by comparing the results derived from it with the results of the tool that is used by Company X. The qualitative part would be utilized to see the digital activity of the company and would aid the final loan decision. The tool would be counted as effective if 72% (18) of the potential loan decisions from the created tool and the tool used by Company X is the same.

The founder of Company X has given me access to a database with financial information of different private companies. He also provided me with a list of 25 companies that I should analyse with my tool. All of the companies were SMEs. I am unable to share the list of the companies that I was given for analysis as some of them are potential customers of Company X.

4.2 Quantitative approach

For the quantitative part I have created an Excel with a list of all of the chosen companies. The testing was simple due to the automation of the processes, but I needed to be careful with inputting the right figures into the corresponding fields. I started by searching for the company in “Asiakastieto” and getting its latest financial statements. After that I found all of the necessary figures for the bankruptcy prediction models and filled them in. The created tool automatically calculated the key performance indicators and the final result. The results gotten from Zmijewski model and the revised Atman Z-score model were recorded. Then I added the turnover and profit data to visualize the growth rate over the past three years. If both bankruptcy prediction models showed that the company is going to be bankrupt and the profit and turnover growth was “downward”, then the loan decision was “no”. If both bankruptcy prediction models showed that the company is going to be non-bankrupt and the profit and turnover growth was “upward”, then the loan decision was “yes”. If the bankruptcy prediction models showed different results, then the loan decision was not derived.

Company	Y-tunnus	Company Name	Zmijewski	Altman	Turnover Growth	Profit Growth	Loan decision	Year
1			0.8612	-1.8640	Downward	Stable	No	2018
2			-2.7734	9.9556	Downward	Stable	Yes	2018
3			0.8597	1.4304	Downward	Stable	Yes/No	2018
4			1.8745	-0.8131	Downward	Slightly Downward	No	2018
5			1.2654	1.0697	Downward	Slightly Upward	No	2018
6			-1.9524	7.8120	Stable	Upward	Yes	2019
7					No financial statements available, so no opportunity for quantitative analysis. In this case I perform qualitative analysis. 78/100 for qualitative analysis.		Yes	2019
8			-2.0057	5.3545	Stable	Slightly Upward	Yes	2018
9			0.1865	-0.2055	Upward	Downward	Yes/No	2017
10			0.1386	1.5494	The café is still operating so the model works		Yes	2017
11			-3.2112	10.4298	Upward	Upward	Yes	2018
12			2.4047	0.3872	Downward	Downward	No	2018
13			1.8009	1.6940	Stable/Upward	Downward	No	2019
14			-0.3625	3.1966	Upward	Upward	Yes	2019
15			2.6503	-2.3495	Stable	Slightly Downward	No	2019
16			0.6988	-1.9501	Upward	Upward	Yes/No	2019
17								
18			1.7626	-1.5039	Downward	Downward	No	2019
19			0.9555	-0.5672	Upward	Stable/Downward	No	2018
20			0.4334	0.7840	Upward	Upward	Yes	2019
21			2.2548	1.0040	Stable	Downward	No	2019
22			-0.4517	2.9741	One year available		Yes	2018
23			-3.9711	10.8893	Stable	Upward	Yes	2018
24			1.7120	2.6932	Slightly Upward	Downward	Yes/No	2018
25			1.5566	-0.8890	Stable/Downward	Downward	No	2018

Figure 12. Snapshot of quantitative testing sheet

4.3 Qualitative approach

The main purpose of the qualitative part was to verify the loan decision made in the quantitative part. I skipped the testing of the “fraud detection” part as Company X did not see the need to test it as they were already happy with it. I created another Excel sheet that included the name of the company, qualitative rating and any additional comments. I have analysed all of the 25 companies by using the qualitative model created. I filled in the tool by checking the information on the internet such as the company’s website, social media pages and customer reviews. The tool automatically calculated the rating and I filled it into the testing sheet. The rating classified companies into three categories which were “green”, “yellow” and “red”. I also added comments about the various factors which were analysed.

Name of the company	Qualitative Rating(x/100)	Comments	Quantitative Result
	56	The company has a moderate website with enough info. There is barely any customer reviews, only from 2012. There is no social media pages.	No
	35	The company has little info on the website. No customer reviews. Financially it's stable and shows good results. It's a firm that operates locally and depends on the local clients.	Yes
	20	The company doesn't have a webiste. There is no online presence at all. And no customer reviews as well	Yes/No
	45	They have a nice website with a lot of info and a blog. However the last blog post was done in 2018, the same as last Facebook post. The website has the contact info and the location of the business.	No
	42	The company doesn't have a working website, but there are reviews and quite a lot of info about it on the web. No scoial media as well.	No
	54	No working website. One review on Google, which was 5 months ago. A lot of websites that state some facts about the firm.	Yes
	78	Pleasant website. Lots of info on the website about the services.	Yes
	82.5	There is news about this company since 2013. The facebook page is kept up to date with a few posts being posted every month. The website is moderate, but it has all the necessary info.	Yes
	25	No website. No reviews. Closer towards "no" as the performance is poor from the financial side.	Yes/No

Figure 13. Snapshot of the qualitative testing sheet

5 Results, conclusions and feedback

In this chapter I will analyse the results and the conclusions that I have gotten from the testing. I will describe the outcome of the testing. The conclusions which are drawn from the results are mentioned and any further work that can be done with the tool is suggested. The reliability of the tool is discussed, and evaluation of learning is provided.

5.1 Results

Company X's tool analyses quantitative information and has a high chance of rating the company correctly. Company X has created its tool using five years of historical data from Finnish companies which makes the model more reliable for the Finnish market. Also, this tool has been implemented for a year at Company X which means that the tool is useful for arriving at the final loan decision. The new model which I created was assessed by comparing the results from it with the ones from Company X's tool. The final loan decision based on my tool was determined by combining results from both qualitative and quantitative testing. Company X was happy with the qualitative tool that I proposed, and the company representatives wanted to see the effectiveness of the quantitative part. Due to this reason a "weight" was assigned, the quantitative testing had a weight of 80% and the qualitative testing had a weight of 20%. This ratio would make a better comparison of my model to the Company's X model.

There were 24 companies which I needed to analyse as one of the company's codes did not show any result. The results of the quantitative testing were balanced as I have gotten 9 "approved", 10 "rejected" and 4 "unsure" potential decisions for loan applications. There was one company that did not have any financial data, so the decision was solely based on the result of qualitative testing.

In my tool, there were six companies which did not have the same result in both quantitative and qualitative testing. The companies had either very good financial performance, but their digital activity was poor, or the company had excellent digital activity, but poor financial performance. In the testing, the quantitative results were given more importance, but when the result of quantitative testing was not definite, the results of the qualitative part assisted with the final loan decision. When the testing was completed, the results were: 12 approved loan decisions and 12 rejected ones.

Company	My Final Loan Decision	Company's decision	Aligned Or Not
1	No	No	+
2	Yes	Yes	+
3	No	Yes	-
4	No	No	+
5	No	Yes	-
6	Yes	Yes	+
7	Yes	Yes	+
8	Yes	Yes	+
9	No	No	+
10	Yes	Yes	+
11	Yes	Yes	+
12	No	No	+
13	No	Yes	-
14	Yes	Yes	+
15	No	No	+
16	No	No	+
17			
18	No	No	+
19	No	No	+
20	Yes	Yes	+
21	No	Yes	-
22	Yes	Yes	+
23	Yes	Yes	+
24	No	No	+
25	No	No	+

Results	
Aligned	20
Not Aligned	4

Figure 14. The results of testing

The effectiveness of the tool was assessed by checking how many of the results were the same as the ones that Company X has gotten with their tool. 20 out of 24 decisions were the same, which means that the tool was 83% aligned. The company's tool at the moment does not consider the digital activity of the company and therefore is based on financial data and payment behavior. The results which did not align are discussed below.

The 3rd company was classified as bankrupt by Zmijewski model and given a moderate chance of defaulting by Altman model. The quantitative result was supported by the qualitative one. The company did not have a working website, no customer reviews and had barely any information on the internet. Company X could check this company as their tool had a positive loan decision.

The 5th company was classified as bankrupt by both bankruptcy prediction models. The qualitative result was completely opposite, the company had a rating of 67/100. Company X's result was a positive loan decision, and so my quantitative result was not accurate.

The 13th company was classified as bankrupt by Zmijewski model and given a moderate chance of defaulting by Altman model. The qualitative result was 63/100 which meant that the loan should be approved if we only take into account the analysis of "soft" information.

Company X's decision was positive, which was the second time when bankruptcy prediction models were not accurate.

The 21st company had poor results both from quantitative and qualitative testing, but was given a positive loan decision by Company X.

5.2 Conclusions

The results show that the bankruptcy prediction models should be used with caution and be backed up with another method of analysis. The qualitative results were helpful and made it clear to which companies the loan should be given. After the company representatives checked the results, they highlighted the effectiveness of the qualitative part of the tool. The qualitative part provided Company X with additional information that could help them with their decision regarding loan applications. Company X founder mentioned the 3rd and the 21st company and said that those cases help to see the importance of the digital side of the business and to understand that solely depending on numbers might lead to the wrong decision.

The fraud detection framework is used by the representatives of company X in case they need to check if the applicant has any history of fraud outside of Finland.

Bankruptcy prediction models were not as accurate at analysing the credit risk of the companies compared to Company X's tool. The variables that are chosen for the bankruptcy prediction model determine the effectiveness of the model. The bankruptcy prediction models could be not as accurate because they are based on data from the United States. Finnish economy has its own special characteristics meaning that there are other indicators of potential bankruptcy or financial distress. This technique can be used to analyze the companies that apply for two-year loans; however, their result should be backed up by either another method of quantitative testing or qualitative analysis. The goal that was set in the beginning was partly met as the owner wanted to have a tool that would allow him to check the credit risk of companies that apply for one- and two-year loans.

The qualitative part was done correctly, and the founder of Company X was happy with it. As mentioned in the theory framework, there are disadvantages of transactional lending and one of them is that the companies are able to manipulate financial statements to look good. The qualitative part of my instrument enabled the representatives of Company X to see what was representing all of the financial information that they analyse. They got a deeper insight into how the company operates and how it is seen from the customer's point of view.

5.3 Reliability

The reliability of the created tool is high due to a few reasons. One of them is that the tool is created based on the information gotten from the research of peer-reviewed and academic sources such as journals and books. The financial information for the testing comes from an official and trustworthy source. Company X's model results determine the effectiveness of my tool and it can be said that the results of the company's model are accurate.

The reliability of the created model can be improved. In two years, Company X can check if the tested companies have gone bankrupt or not and then compare that information with the results of the quantitative part of my tool. Company representatives will be able to see which bankruptcy prediction model is better suited for the Finnish market and for which industries it works best.

5.4 Further work

Now the company has a tool for analysing the qualitative side of the companies that apply for loans. The qualitative part of the tool should be implemented in order for the credit officers to start analysing company's websites, social media pages and other information available on the web in more detail and with a purpose of decreasing the default rate. The company has mentioned that they will be using the qualitative model that I made as a framework for building an automated web-based tool to analyse "soft" information.

The quantitative part should be reviewed later on, as the bankruptcy prediction models are ideal for predicting the bankruptcy within 2 years. If by the end of two years, Company X sees that bankruptcy prediction models work, then they should implement them as an addition to the tool which they are using now.

5.5 Evaluation of learning

The author has gained valuable knowledge and developed several skills throughout the whole process of writing this thesis. When writing and researching material for the theory framework, the author has learned about SMEs and the ways that they are financed, the importance of the financial sector for any economy, credit risk and various techniques on how to calculate it. All of this knowledge contributes to the author becoming a better specialist in the finance sphere and makes him more valuable as a candidate for the jobs in that sphere. The author has gained more experience working in Excel while making the instrument. He has improved his research skills as he needed to research and choose certain factors for qualitative testing that would estimate the credit risk most accurately.

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Appendices

Appendix 1: The interview outline

The Company

1. What kind of a firm are you?
- Commercial Loan Company
- Private Debt Company
- eCommerce lender
- Finance Company
- Loan Company

2. How many employees do you have?

3. Could you classify your loan into one of those categories?
- Working Capital Loans
- Self-liquidating inventory loans
- Term business loans

4. Why do you give out loans ranging from 1,000eu to 100,000eu?

5. I have noticed that you use Google Advertisement as I have seen your adverts on several websites while browsing the web. What other marketing channels you utilise to reach SME's?

6. Do you offer any assistance to the borrower after he takes out a loan?

7. Do you have a lot of competition on the Finnish market? What is your competitive advantage?

8. What is the process of loan application at your company?

9. What is the default rate of your loans or how many non-paying loans do you have as a percentage?

10. Do you have face-to-face meetings with your potential borrowers or is it all done online?

Credit Risk Analysis

1. How successful is your current credit risk analysis tool?

2. What aspects of a firm would you give the biggest "weight" when deciding to lend money or not? (Profitability, Liquidity, Operating efficiency, Leverage/Cash flows)

3. How important is the position of the company in the industry on the Finnish market?

4. Do you engage in financial statement lending?

5. Do you make use of the common-size or cross-sectional analysis?

6. If so, what category of ratios do you consider to be the most important?
7. Do you feel that enough information can be obtained from financial statements of SME's in order to make a decision on a loan application?
8. Do you utilise credit scoring lending?
9. Do you have a custom credit scoring model? If so, which factors do you include in your scorecard?
10. Do Finnish banks have a credit scoring system for businesses, and they share the results with lending companies on request?
11. Which credit scoring agencies you use?
12. Have you tried the Altman's Z-score model or any of the other methods based on discriminant models?
13. Do you analyse any of the "soft" information that is available for a borrower?
14. If so, is there a framework or a checklist that you have for evaluating the qualitative information of a potential client?
15. Which information do you feel you is missing when evaluating credit risk of a borrower?
16. Do you consider intangible assets such as patents and trademarks when evaluating a potential borrower?
17. Which databases do you have access to that general population doesn't? Can that information help you in making a decision on a loan?
18. Do you check the legal status of the borrower? Some people who live outside Finland have access to the financial banking services, but their residence permits might be temporary
19. Can you check the criminal record of the potential borrower?
20. Could you explain the reasoning behind the pricing of the loans? Do you have a certain criterion for a certain price? Range?

Appendix 2: Chat with the representative of “Asiakastieto".