Beyond the Credit Score: The Role of Social Capital in Microfinance Lending Decisions

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ABSTRACT

This study explores the extent to which social capital – a form of soft information – influences loan approval decisions across different credit score categories at a Dutch microfinance institution. The reliance on standardized hard information – such as credit scores – has reduced access to financing for those who lack a record of successfully repaying loans, particularly impacting SMEs. Using a dataset of over 14,000 loan applications from 2018 to 2022, we developed a dictionary-based pattern recognition model to detect indicators of social capital within unstructured loan officer reports.

The findings reveal that social capital consistently increases the likelihood of loan approval across all credit score categories. However, the overall effect of social capital did not significantly differ between credit score categories. Additionally, gender did not have an influence on the relationship between social capital and loan approval.

Remarkably, credit scores alone did not significantly predict loan approval outcomes. This indicates that loan officers at this microfinance consistently rely more heavily on social capital than on credit scores when assessing the applicant's creditworthiness. Therefore, this study highlights the impact of human judgement in microfinance lending.

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Keywords
Soft information, social capital, credit scores, relationship lending, textual analysis, financial inclusion

"*During the preparation of this work, the author used ChatGPT to help rephrase and correct grammar and spelling at the sentence level. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.*"

1. INTRODUCTION

1.1 Situation and complication

Traditional banks have increasingly relied on standardized credit scoring and hard information, particularly in the aftermath of the financial crisis (Barboni & Rossi, 2019; Becker, Bos, & Roszbach, 2020). However, this shift has limited access to financing for many, especially those who lack a record of successfully repaying loans. (Kirschenmann, 2016). Hard information refers to information that is quantitative, easy to share and understand without knowing how it is collected, while soft information is qualitative, subjective and context dependant (Liberti & Petersen, 2019). The more resource-intensive and less scalable evaluation of soft information has largely been delegated to cooperative institutions and alternative financial intermediaries, such as European microfinance institutions (Baklouti & Bouri, 2014; Flögel, 2018). However, recent advances in AI technologies have revived interest in integrating soft information into lending decisions (Glaser, Pollock, & D'Adderio, 2021; Raisch & Krakowski, 2021). These technologies offer the potential to 'harden' soft information – being able to translate the qualitative data into quantitative data, enabling more efficient screening processes and improved predictions of entrepreneurial success (Yan, 2025). Additionally, it can reduce bias in the screening process. This has been shown to positively influence financial access and fairer screening processes, especially for women and first-time borrowers (Bose, Filomeni, & Tabacco, 2024).

Although the literature highlights the potential of integrating soft information into the screening process—particularly by finding ways to measure them—significant gaps remain. Specifically, there is limited understanding of what soft information comprises and under what conditions they add value to the screening process. Soft information depends heavily on the context in which it is collected and the ability of decision-makers to interpret it, making it difficult to transfer and standardize it (Liberti & Petersen, 2019). Understanding this gap is important not only for improving decision-making processes within financial institutions, but also for expanding access to finance for entrepreneurs who may not meet traditional loan standards. These entrepreneurs are often classified as high-risk by traditional loan officers due to their lack of formal financial records and limited access to finance, which can result in an underestimation of their true creditworthiness (Bravo, Maldonado, & Weber, 2013).

1.2 Academic and practical relevance

This research provides new insight into the relationship between soft information and hard information in loan approval decisions (Liberti & Petersen, 2019) by researching the role of social capital. Social capital is defined as the resources – such as information, trust, and support – that can be obtained through relationships between people to help them achieve goals that would not be easily reached alone (Coleman, 1988). It represents an important form of soft information, especially important in the screening and evaluation of small-medium sized enterprises (SMEs) (Duong, Nguyen, & Vu, 2024). Finance literature on soft information lacks a better understanding of which types of soft information and under what circumstances they influence loan decisions (Campbell, Loumioti, & Wittenberg-Moerman, 2019; Liberti & Petersen, 2019). Therefore, we argue that in the context of microfinance and SME lending, social capital plays a crucial role. This segment of borrowers often have a limited scale and scope of hard information and thus lenders have to rely more on soft information in loan approval decisions (Baklouti & Bouri, 2014; Del Gaudio, Griffiths, & Sampagnaro, 2020; Grunert & Norden, 2012). Therefore, academic relevance lies in its contribution to the area of microfinance by combining theoretical insights with quantitative data analysis to provide a better understanding of subjective loan evaluations and their impact on financial inclusion.

This contribution is important because financial inclusion can help underprivileged people and businesses to access financial services, which enhances social and environmental development (Corrado & Corrado, 2017). This practical relevance is reinforced by the fact that, in 2025, SMEs account for 99.8% of the total enterprises in the Netherlands (CBS, 2025a). Additionally, according to the most recent data available on these subjects, they contribute 62% of the added value and 71.6% of the total employment in the Netherlands (CBS, 2025a). Furthermore, 51% of the SMEs that express a need for external financing are unable to obtain the funds they need (CBS, 2025b). Hence, improving access to finance for these enterprises is important to strengthen economic, social, and environmental development.

1.3 Research Objective

This study aims to explore the relationship between credit scores and soft information – particularly social capital - in the loan approval process. "Credit scoring is the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit" (Thomas, Edelman, & Crook, 2002). Credit scoring models can rate applicants as "low", "medium" and "high" risk classes. An applicant's credit score serves as a risk signal. A high credit score signals lower risk and favourable loan terms, while a low credit score indicates higher risk and less favourable loan terms (Miljkovic & Wang, 2025). Thus, a higher credit score is positively related to the likelihood of repayment (Chatterjee, Corbae, Dempsey, & Ríos-Rull, 2023). While credit scores capture quantitative risk, soft information can offer qualitative context of the borrower (Liberti & Petersen, 2019). We aim to identify and assess the value that this soft information can bring to entrepreneurial finance. Therefore, the following research question can be formulated:

To what extent does the use of social capital on loan approval decisions in the screening process of small-medium sized enterprises vary in influence per risk level by credit scoring model in the context of a Dutch microfinance institution?

Moreover, this study investigates how gender impacts the role of soft information in loan approval decisions. Research suggests that gender can influence how soft information is being perceived (Bose et al., 2024). This can affect how social capital is used in loan evaluations. Hence, the following sub-question emerges:

To what extent does gender influence the use of social capital in loan approval decisions during the screening process of small-medium sized enterprises across varying risk levels by credit scoring model in the context of a Dutch microfinance institution?

2. LITERATURE RESEARCH

2.1 Soft information as a key role factor in microfinance

SMEs often face problems when applying for a loan, since they usually lack financial history and capability to receive a high credit score in comparison to large enterprises (Flögel, 2018). Therefore, soft information plays a key role in the loan application, as it gives the owner of a SME the opportunity to improve its creditworthiness by their entrepreneurial skills

(Grunert & Norden, 2012; Liberti & Petersen, 2019). These type of loan applications are categorized as relationship lending, a form of lending where lenders depend on constant contacts with SMEs to have a better understanding of their financial behaviour and capabilities (Berger & Udell, 1995). In comparison to larger financial institutions, which typically prefer standardized and hard information evaluations, research indicates that SMEs are more likely to include soft information in lending evaluations. The inclusion of soft information enhances the loan approval process for these SME's, especially when these enterprises don't have complete financial records. (Del Gaudio et al., 2020; Flögel, 2018; Grunert & Norden, 2012).

The incorporation of soft information is especially helpful during a recession, as loan officers were able to identify companies which did not meet quantitative lending requirements but could still receive a loan based on the strength of the relationship between the borrower and loan officer. (Barboni & Rossi, 2019; Becker et al., 2020) Nevertheless, there have been concerns regarding the subjectivity and inconsistency of the usage of soft information. Loan officers may have varied interpretations of the qualifications of the borrower, which could result in unreliable lending decisions (Baklouti & Bouri, 2014; Campbell et al., 2019; Del Gaudio et al., 2020), This highlights the crucial role that the judgement of loan officers plays in microfinance credit assessments.

2.2 Emerging fintech models and the role of AI

Recent changes in the role of soft information in credit evaluations may mitigate unreliable lending decisions. Traditionally, banks gathered soft information directly through the borrower's contact, e.g. friends and family. Nowadays, soft information can be gathered through digital footprints and online transaction. These fintech credit models can improve forecast efficiency when incorporating both hard and soft information (Kowalewski & Pisany, 2022), while alternative lending platforms use this digital behavioural data to develop non-traditional credit scoring models that assesses borrower's creditworthiness (Yan, 2025). Thus, these new data sources expand financial information about SMEs.

Nevertheless, there does not appear to be consensus regarding the role of AI in the mitigation or enhancement of biases. Studies have argued that the recent advancements in AI-driven assessments have contributed to standardizing soft information collection, which therefore reduced subjective biases while maintaining the relationship between the borrower and the loan officer. Nevertheless, these same studies raised concerns about the privacy, data protection, and overall ethical use of fin-tech driven lending (Filomeni, Udell, & Zazzaro, 2020; Kowalewski & Pisany, 2022; Yan, 2025). Additionally, there is concern that these AI-driven models could reinforce historical biases as these models are based on past lending data (Even-Tov, Li, Wang, & Williams, 2024; Tran & Winters, 2024).

2.3 Finding the right balance

The integration of soft information into loan assessment models is an important issue in SME lending, thus financial institutions are trying to reduce biases to enhance optimal lending allocations to these enterprises. Some institutions adapted standardized frameworks to ensure uniformity in assessing the quality of the entrepreneur, but if these standardized frameworks become too rigid it can discourage the flexibility that makes soft information valuable in the first place, which is essential for SME's (Del Gaudio et al., 2020). Next to that, these AI models lack the ability to capture the borrowers body language and other indirect signals (Tran & Winters, 2024).

Hence, recent research suggests that a hybrid lending model, the combination of structured AI-driven assessments with human judgement, is the most effective balance (Chen & Wang, 2024; Even-Tov et al., 2024; Filomeni et al., 2020; Tran & Winters, 2024). In this model, loan officers can have the option to overrule automated choices on the borrower's data based on the soft information that was provided to the loan officer. This ensures that soft information remains valuable, while minimizing the subjectivity of the loan officer in the lending decision (Chen & Wang, 2024). The model should not replace relationship between the loan officer and the borrowers, but it should enhance its relationship.

2.4 The role of gender

In evaluating loan applications, subjective evaluations by the loan officer can unintentionally reflect gender-based biases, as women-led business face stricter conditions, even when their financial performance is equal to a male-led businesses (Bose et al., 2024). Nevertheless, microfinance institutions with a higher proportion of female clients have lower default rates, indicating that women are more reliable borrowers than men, partially due to risk aversion (D'Espallier, Guérin, & Mersland, 2011). This bias is also visible in the pairing between loan officer and borrower, as male loan officers tend to favour male borrowers, which increases the risk of the loan. In contrast, female officers do not show the same leniency toward female borrowers, possibly because they are more risk averse (Campbell et al., 2019). Additionally, women generally receive smaller loans than men. Some argue this is due to the types of industry women enter – typically smaller-scale sectors with lower profit margins, which may justify the smaller loan amounts (D'Espallier, Guerin, & Mersland, 2013). However, others suggest that even when industry is accounted for, gender differences persist, indicating that gender bias may still play a significant role. (Agier & Szafarz, 2013; Wilson, 2016).

All these limitations strengthen the current gap between male and female entrepreneurs. To mitigate this, financial institutions should adopt standardized frameworks combined with human judgement to minimize the subjectivity of a loan officer (Bose et al., 2024; Campbell et al., 2019) while also incorporating transparency by formalizing lending criteria, training loan officers to emphasize consistent decisions making and monitor loan decisions outcomes by gender (Wilson, 2016). As discussed in section 2.3, AI could be a helpful tool in this standardization process, but it should be very carefully designed to exclude historical biases.

2.5 Theoretical framework

This study explores how loan officers make decisions by balancing automated data – credit scores - with their own judgement. This judgement can be influenced by soft information. To describe the usage of soft information in this balancing process, this study relies in particular on the social capital theory. Social capital refers to the resources – such as information, trust, and support – that can be obtained through relationships between people to help them achieve goals that would not be easily reached alone (Coleman, 1988). In the microfinance context, this relates to the financial information, trust and support that entrepreneurs can obtain from family and community. The value of these relationships can function as a criterion that signals financial reliability to the loan officer, which would make the borrower appear less risky and therefore increase their chance of loan approval.

H1: The presence of social capital has a significant effect on the probability of loan approval.

In microfinance and SME lending, such close ties – particularly familial ones – have been shown to act as informal safety nets, helping borrowers meet financial access and stability when formal financial access is limited or non-existent. Kinship networks facilitate financial stability by enabling borrowers to utilize family-based support during periods of distress, effectively substituting for collateral or saving (Kinnan & Townsend, 2012; Nguyen & Canh, 2021). Similarly, immigrant entrepreneurs often depend on family financing to launch and sustain their businesses when formal credit markets are not available to them (Malki, Uman, & Pittino, 2022). Therefore, these family connections can play a significant factor in determining a borrower's capacity to repay a loan since they can provide vital assistance in times of financial difficulty, making it a valuable indicator for loan officers when assessing a borrower's overall creditworthiness.

Studies have shown that decision-makers tend to rely more on human judgement when uncertainty increases (Glaser et al., 2021; Raisch & Krakowski, 2021). Within microfinance lending, this means that loan officers tend to use soft information - social capital - when hard information – credit scores - do not provide a clear outcome. This suggests that when credit scores are high or low, the loan officers are inclined to follow the hard information as this results in a clear outcome, respectively reject or accept the loan. However, when credit scores have a medium score, loan officers are more inclined to use social capital as credit scores do not provide a clear outcome. To better understand this tension, this study relies on the paradox lens. This lens discusses that paradoxes are situations in which elements seem to conflict but exist together and must be managed rather than resolved (Smith & Lewis, 2011). Using the paradox lens, this study argues that loan officers must constantly manage the tension between risk minimization and entrepreneurial support. Microfinance institutions should not choose between standardization and flexibility, but it should rather be well-managed as it leads to the best loan approval outcomes (Canales, 2014).

We hypothesize that in low-risk and high-risk cases, i.e. in cases where the credit score is respectively high and low, loan officers operate under conditions of high certainty, allowing them to focus solely on determining the applicant's repayment capacity. In these cases, the decision-making process of the loan officer tends to be straightforward, as the emphasize is placed on hard information, while soft information can act as a confirmation rather than a decisive factor. When applicants fall within the mid-risk cases, i.e. in cases where the credit score is in the medium range, the paradox becomes more significant. The loan approval outcome is more ambiguous as the credit score alone may not give enough guidance for the decision-making.

H2: The influence of social capital has a significant effect on loan approval within credit score category.

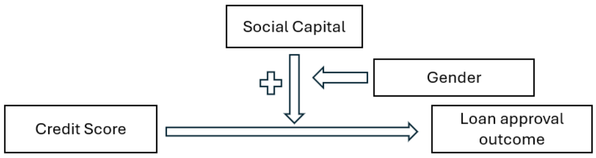
H3: There is a significant difference in the influence of social capital between any credit score category.

Although gender bias is not the primary focus of this study, it being discussed in the literature review acknowledges the relevance in loan assessment outcomes. Previous research has shown that women entrepreneurs may be evaluated stricter, even if their financial performance is similar to a male business (Bose et al., 2024) and that gender dynamics between the applicant and evaluator can influence how soft information is interpreted by the loan officer (Campbell et al., 2019). These findings indicate that the way soft information is used could depend on the gender of the applicant. For example, a male applicant who says "my father supports me" might be seen as reliable, while a female borrower who says the same thing might be judged as less independent or less committed. Therefore, gender may influence how loan officers manage the paradox, as gender might affect how much weight they give to soft information. Thus, gender will be included logistic regression model.

H4: The effect of social capital on loan approval does differ by gender

Figure 1

Conceptual framework



3. METHODOLOGY, DATA AND ANALYSIS

3.1 Dataset

To investigate the relationship between soft information and hard information in loan approval processes, this study makes use of a dataset that is provided by a Dutch microfinance institution. This institution disbursed micro and small and medium sized loans between 1.000- 250.000 Euro, and the dataset captures over 14.000 loan applications which have been submitted between 2018 and 2022. This extensive range in applications and loan amount represents a varying client base that includes applicants who may have no prior lending history as well as those with more a more developed lending history. Thus, the microfinance institution emphasizes the personal aspect of entrepreneurship; applicants who may not meet the standardized lending standards – hard information - can still receive funding based on soft information.

The dataset contains several factors which were considered during the loan evaluation: credit scores on a scale from 1 to 10, gender, loan amount and a loan officer evaluation report. A loan evaluation report contains information that the loan officer collected during the application process. This includes a description of the borrower, their business activities, the conclusion of the risk manager on the borrower and an explanation of the personal as well as the financial situation. Although their evaluation report is unstructured, it provides a qualitative rich basis for analysing soft information.

Before analysing the data, the dataset was cleaned from duplicates. Additionally, applicants who did not contain a loan officer report or applicants who returned while their personal and business circumstances did not change were also deleted. These applicants did not have any value for this study. This reduced the total number of cases from 14,166 to 12,903.

3.2 Research design

This study uses a quantitative research design that combines textual based analysis with statistical modelling, as the research question contains several numeric variables and in this way these interactions can be identified. This is important to measure, as the purpose of this study is to examine how soft information interacts with credit scoring in determining loan approval outcomes.

To identify the presence of social capital in the unstructured loan reports, a custom dictionary-based pattern recognition model was developed in R. This model uses four categories of social capital indicators: *SocialCapitalBorg, SocialCapitalFallback, SocialCapitalFinancialPresence* and *SocialCapitalKeywords*. Justification of these categories are explained in section 3.5. To evaluate the accuracy of the detection method, two rounds of manual validation will be performed on a random sample of one hundred cases. Validating the model is important, as the dictionary-based method can produce systematic errors if not compared to human judgement (Grimmer & Stewart, 2013). Each case will be manually reviewed to determine whether social capital is correctly, or incorrectly, identified.

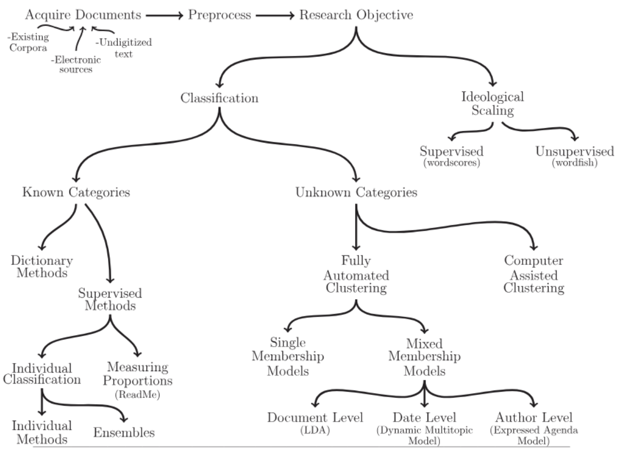
Literature argues that F1 scores above 0.7 are considered as a good benchmark for automated text classification (Nelson, Burk, Knudsen, & McCall, 2021), so this will be the minimum requirement for our model. After the validation, a logistic regression model will be used to estimate the relationship between social capital and loan approval (**H1**). To observe if the influence of social capital differs across credit categories, three separate models were run to see the effect of social capital on low, medium, and high credit score (**H2**). To see whether the influence of social capital differs between credit score categories, the usage of interaction terms will be introduced into the model (**H3**). Following, predicted probabilities will be calculated to visualize the results. Lastly, we will test whether the effect of social capital on loan approval differs between gender (**H4**).

3.3 Justification of methods

3.3.1 Dictionary-based classification

Figure 2

Decision tree of the automated content analysis methods (Grimmer & Stewart, 2013)



To identify the presence of social capital in loan officer reports, several approaches were considered. Figure 2 presents a decision tree of the available automated content analysis methods. As the research objective is to identify whether loan applications contain indicators of social capital, this is a classification. The next distinction in the framework is between known categories and unknown categories. Given the research objective, unknown categories – such as LDA or Dynamic Multitopic Model – are not appropriate. These methods are useful when underlying themes must be discovered and are most useful when no predefined categories are available (Grimmer & Stewart, 2013), but this study does not aim to explore unknown topics in loan applications. Instead, it tries to detect whether loan applications contain a theoretically grounded concept: social capital. Although social capital lacks a single, universally accepted definition, it can be operationalized through recognizable textual patterns and words such as "ouders staan borg" or "partner tekent mee." Thus, methods designed for known-category classification are the most appropriate for this study.

Within the known-category branch, two approaches were considered: supervised learning and dictionary-based classification. Supervised methods require a large training set that has already been labelled by hand, so it can be used to train a predictive algorithmic model (Grimmer & Stewart, 2013). In this case, no such training dataset existed and constructing one would be resource-intensive, as well as conceptually difficult. The concept of social capital is broad and context dependant, making it difficult to define a clear label across each case. In addition, if the algorithm happens to flag social capital, it would be difficult to see its internal decision making, as this is based on the training data, making it difficult to interpret why a specific sentence or word is classified as social capital.

In contrast, when using the dictionary-based classification, a sentence or word is only flagged if it meets specified conditions, which can be traced back to the linguistic rules. In this case, this means that a case is flagged if it contains a borg, fallback, financial or keyword term while co-occurring with a social relationship. Because the terms are based literature (see table 2, section 3.5), the reasoning behind each of the classification can be fully traced back. This transparency is important to not only detect patterns, but also to explain why a case was classified as social capital or not. Due to this reasoning, the dictionary-based classification was selected as the most appropriate approach, as it provided a high degree of transparency and interpretability. (Grimmer & Stewart, 2013).

Nevertheless, there are some downsides with the usage of this method. The dictionaries should not be used outside the context in which they were developed, as words can carry different meanings depending on the context. However, the dictionary in this study will be specifically based on the available dataset. Additionally, dictionary methods have a risk of misalignment between words and context, i.e. it assumes that the emotional meaning of the word is stable across each text. In reality, the meaning of a word is context dependant. In the case of a loan evaluation report, the sentence "the father will support him financially" has a different meaning than "the applicant hopes that his father will support him." Furthermore, dictionary-based methods are rarely validated. To counter this, the method will be manually validated, although this process is practically difficult. (Grimmer & Stewart, 2013)

3.3.2 Logistic regression

Logistic regression is seen as the appropriate method of analysis as the outcome variable of this study – loan approval outcome – is a binary variable, which distinguishes the logistic regression from the linear regression (Hosmer, Lemeshow, & Sturdivant, 2013). Logistic regression is applied for testing **H1**, **H2**, **H3** and **H4**, with the inclusion of an interaction term in **H3** and **H4**. This inclusion of an interaction term is helpful in this research because it makes it possible to assess if the presence of social capital on loan approval outcomes depends on the credit score of the applicant, i.e. it checks the possible interaction among the explanatory variables. The interaction term is applied between the credit category and social capital, as the purpose of testing **H3** is to research whether the effect of social capital differs between credit score categories. Additionally, the purpose of testing **H4** is to research whether gender influences the effect of social capital on loan outcome.

To make the interpretation of these values easier, predicted probabilities of an approved loan - with and without social capital - will be calculated and then visualized. This approach makes it possible to directly compare between different applicant profiles to see whether these variables affect loan approval outcomes. Predicted probabilities are helpful in models with interaction terms, because it can help to clarify the interpretation of the model (Hosmer et al., 2013). The conversion of log-odds coefficients into predicted probabilities makes it easier to understand, and by including them in a visual format helps to makes it more understandable as it allows for direct comparison between the different profiles. Lastly, confidence intervals are added, as they provide more information than p-values alone and give some insight in the uncertainty of the result (Greenland et al., 2016).

3.4 Keyword selection

The identification of social capital in the loan officer reports were based on four conceptual categories: Borg (formal guarantees), fallback (informal guarantees), financial presence (income from partner / relatives), wealth indicators (gifts, inheritance, or family capital). Each of these categories was operationalized though keyword patterns with words and later improved through manual inspection of the flagged and unflagged cases. This had to be done as - while many of these terms could be found in the official Dutch "Van Dale Dictionary" (2022) – the informal and subjective language of loan officers could not be found in the in the dictionary. Thus, the final list of keywords was developed through combining the dictionary words and careful reading on how loan officers write their reports, and which words are used, ensuring that both formal and informal ways of describing social capital were captured. The final keyword list can be found in Appendix A.

Regular expressions are used to detect different versions of the same word, meaning that fallback, fall-back or fall back could all be detected. Furthermore, word boundaries will be used to avoid false matches like detecting the word "man" inside "management." To improve accuracy, the loan reports will be split into individual sentences, in this way the terms would only count if they appeared in the same sentence as the social term. For example, the phrase "tekent mee" will only be flagged as social capital if a social term, like father, is present in the same sentence. However, in the way it is designed right now, it would also detect the sentence "tekent niet mee," thus negative patterns should be added to avoid false positives. Therefore, for every term a negative counterpart will be created. To test whether the model works well, a random generated sample of one hundred reports will be manually checked to see whether the logged phrases were flagged correctly or not. An example of logged phrases can be found in appendix B.

3.5 Operationalization of data

Table 1

Descriptive table for the variables loan approval, social capital, gender and credit score categories

Variable	Type	*M*	*SD*	Min	Max	*n*	%
Loan Approval	Binary	0.88	0.33	0	1	-	
Social Capital	Binary	0.40	0.49	0	1	-	
Gender	Binary	0.30	0.46	0	1	-	
Credit Score (Low)	Categorical	-	-	1	4	1,131	8.77
Credit Score (Medium)	Categorical	-	-	5	7	8,493	65.80
Credit Score (High)	Categorical	-	-	8	10	3,279	25.40

Binary variables are coded as 0 = no and 1 = yes, except Gender (0 = male, 1 = female).

Table 2

Categories of social capital with justification by literature

Social capital	Description	Social tie	Why social capital	Literature
Borg	Partner or family signing as a deposit	Relational trust and formal financial support	Partner of family financially committed to the borrower.	(Karlan, Mobius, Rosenblat, & Szeidl, 2009)
Fallback	Applicant could rely on relatives for help in case of financial distress	Relational trust and informal financial support	Family or friends can act as a safety net, providing informal financial support	(Lee & Persson, 2016)
Financial Presence	Partner having an income.	Financial resources within social relationships	This signals a stable financial resource accessible to the borrower	(Sangwan, Nayak, & Samanta, 2020)
Keywords	keyword matches indicating family wealth	Availability of financial support through social ties	Indicates the presence of financial support possibilities without explicit formal help	(Lee & Persson, 2016)

4. RESULTS

First, the dictionary-based classification method was validated. The goal was to achieve an F1 score of at least 0.7, as this considered as a good benchmark in academic research (see section 3.2). The first sample achieved a F1-score of 0.90, and after refining the model even more, the second sample achieved a F1-score of 0.95, as can be seen in table 3. This indicated that the model is reliable enough to detect social capital indicators.

Following, the amount of social capital indicators was counted in the loan officer reports. Table 4 shows that financial presence was the most common indicator (4,155), followed by borg (2,106), fallback (419) and keywords (216). The total amount of cases that contained at least one social capital indicator were 5,179 cases.

To assess the main effects of the variables credit score and social capital on loan approval, a logistic regression model was performed. Gender was included as a control variable. As shown in table 5, social capital had a significant, positive effect on loan approval (β = 0.28, $p < .001$), supporting **H1**. The low credit score category was used as the reference group. The medium and high credit score category were not significant relative to the low credit score group. Gender was not significant ($p > .05$).

Next, three separate logistic regression models were estimated to investigate the effect of social capital across different credit score categories. Gender was included as a control variable. The results can be seen in table 6. Social capital had a significant effect on loan approval across each group: low credit score (β = 0.52, p = .014), medium credit score (β = 0.26, $p < .001$) and high credit score (β = 0.29, p = .007). These findings support **H2**. Gender was not significant in any of the models ($p > .05$). For a visualisation of the probabilities of loan approval with and without social capital, based on the values presented in table 6, see appendix C.

Succeeding, the strength of the effect of social capital on loan approval across different credit score categories was examined. This was done by estimating three logistic regression models with interaction terms. Gender was included as a control variable. None of the differences of the effect of social capital on loan approval between credit score categories were significant ($p > .05$), as displayed in table 7. Therefore, **H3** was not supported. Gender was not significant in any of the comparisons ($p > .05$).

Lastly, it was tested whether the effect of social capital on loan approval differs by gender by estimating logistic regression models with an interaction term between social capital and gender. Gender was used as a control variable, while also being tested with the interaction term. None of the interaction effects between social capital and gender were significant across any of the credit score categories ($p > .05$), as shown in table 8. Thus, **H4** was not supported. The main effect of gender was not significant in any credit score category ($p > .05$).

Table 3

Model validation results for two samples

Sample	TP	TN	FP	FN	Accuracy	Precision	F1-score
1	38	54	3	5	0.92	0.927	0.904
2	46	49	1	4	0.95	0.979	0.948

Table 4

Counts of social capital indicators in loan officer reports

Category	*n*
Borg	2,106
Fallback	419
Financial Presence	4,155
Keywords	216
Cases that contain social capital (≥1 category)	**5,179**

Table 5

Main effects of the model without interaction

Predictor	β	SE	*z*	*p*	*95% CI*
Intercept	1.84	0.09	19.90	< .001	[1.66, 2.03]
Credit Score (Medium)	0.05	0.10	0.49	.627	[-0.15, 0.23]
Credit Score (High)	-0.08	0.10	-0.77	.441	[-0.29, 0.12]
Social Capital	0.28	0.06	4.99	< .001 ***	[0.17, 0.40]
Gender	0.10	0.06	1.69	.095	[-0.02, 0.22]

***, **, * *coefficients are statistically significant at 0.001, 0.01 and 0.05, respectively.*

Table 6

Separate models for low, medium, and high credit categories

Credit category	Predictor	β	SE	*z*	*p*	*95% CI*
Low	Intercept	1.72	0.11	15.11	< .001	[1.50, 1.95]
	Social Capital	0.52	0.21	2.47	.014 *	[0.12, 0.95]
	Gender	0.34	0.22	1.56	.119	[-0.08, 0.79]
Medium	Intercept	1.91	0.05	41.06	< .001	[1.82, 2.01]
	Social Capital	0.26	0.07	3.58	< .001 ***	[0.12, 0.40]
	Gender	0.04	0.07	0.58	.559	[-0.10, 0.19]
High	Intercept	1.73	0.07	23.52	< .001	[1.59, 1.88]
	Social Capital	0.29	0.11	2.72	.007 **	[0.08, 0.50]
	Gender	0.18	0.12	1.54	.123	[-0.05, 0.41]

****, **, * coefficients are statistically significant at 0.001, 0.01 and 0.05, respectively.*

Table 7

Comparison of social capital effects between credit score categories

Comparison	Δ in β	SE	*z*	*p*	*95% CI*
Low vs Medium	0.27	0.22	1.20	.229	[-0.16, 0.72]
Low vs High	0.23	0.24	0.95	.342	[-0.23, 0.70]
Medium vs High	0.04	0.13	0.34	.734	[-0.30, 0.21]
Gender	0.10	0.06	1.72	.086	[-0.01, 0.22]

****, **, * coefficients are statistically significant at 0.001, 0.01 and 0.05, respectively*

Table 8

Interaction between social capital and gender across credit score categories

Credit Score	Predictor	β	SE	*z*	*p*	*95% CI*
Low	Intercept	1.73	0.12	14.74	< .001	[1.49, 1.98]
	Social Capital	0.51	0.24	2.17	.030 *	[0.04, 0.97]
	Gender	0.33	0.25	1.33	.185	[-0.17, 0.83]
	Social Capital x Gender	0.06	0.53	0.11	.916	[-0.98, 1.09]
Medium	Intercept	1.93	0.05	38.93	< .001	[1.83, 2.03]
	Social Capital	0.22	0.09	2.52	.012 *	[0.05, 0.39]
	Gender	0.00	0.09	0.00	.999	[-0.17, 0.83]
	Social Capital x Gender	0.12	0.15	0.77	.443	[-0.18, 0.42]
High	Intercept	1.75	0.08	22.27	< .001	[1.60, 1.90]
	Social Capital	0.25	0.13	1.98	.048 *	[0.00, 0.49]
	Gender	0.12	0.15	0.76	.447	[-0.17, 0.40]
	Social Capital x Gender	0.15	0.24	0.62	.536	[-0.32, 0.61]

****, **, * coefficients are statistically significant at 0.001, 0.01 and 0.05, respectively.*

5. DISCUSSION

This study investigated the influence of social capital on loan approval decisions in microfinance. To achieve this, the main research question and a sub-question was formulated. In addition, four hypotheses were formulated to answer these questions.

The first hypothesis **H1** was supported. This means that applicants who have the presence of social capital are more likely to receive loan approval, regardless their credit score. This finding is in line with the literature (Del Gaudio et al., 2020; Flögel, 2018; Grunert & Norden, 2012; Liberti & Petersen, 2019), which emphasize the importance of soft information in SME lending as it can compensate for the limited hard financial data. Additionally, this finding supports literature that highlights how financial family support can act as a form of informal financial support when access to finance is difficult (Kinnan & Townsend, 2012; Malki et al., 2022; Nguyen & Canh, 2021).

The second hypothesis **H2** was also supported, but the third hypothesis **H3** was not supported. Thus, the influence of social capital was consistent across low, medium, and high credit score groups, but did not differ between these credit score categories. While prior research has shown that decision-makers tend to rely more on human judgement when uncertainty increases (Glaser et al., 2021; Raisch & Krakowski, 2021), this was not observed here. Loan officers did not rely more heavily on social capital in medium-risk cases, where uncertainty is theoretically the highest.

On the contrary, loan officers relied consistently on social capital to assess an applicant's creditworthiness, regardless of their credit score. This aligns more with Canales (2014), who argues that loan officers should not choose between using standardized rules and personal judgement, but use them both. Even when credit score suggests approving or denying a loan, loan officers still consider social capital in their decision-making process

The fourth hypothesis **H4** was not supported. The effect of social capital on loan approval does not differ by gender across low, medium and high credit scores. Loan officers did not favour one gender over the other in their use of social capital when making loan approval decisions. This finding contradicts previous research that highlighted the gender bias in lending decisions, especially in how soft information is interpreted by loan officers (Bose et al., 2024; Campbell et al., 2019).

In the model, the main effect of gender is the effect of gender when social capital is zero. This main effect of gender was not statistically significant across each credit category, suggesting that male and female applicants had similar chances of loan approval when no form of social capital was present. This does not align with earlier studies which suggested that women are often evaluated more critically than men, even when industry is accounted for (Agier & Szafarz, 2013; Wilson, 2016).

6. CONCLUSION

This study found that social capital significantly increases the likelihood of loan approval consistently across all credit score categories, although there is no difference in the strength of this effect between credit score categories. In addition, gender does not have an influence on this relationship. The findings highlight the role of social capital in SME lending at this Dutch microfinance institution, suggesting that loan officers value financial relational support as an indicator of creditworthiness, surpassing credit scores.

6.1 Theoretical implications

In terms of theoretical implications, the existing literature talks about the role of soft information in helping SMEs to obtain a loan when standardized financial information is missing or incomplete (Del Gaudio et al., 2020; Flögel, 2018; Grunert & Norden, 2012; Liberti & Petersen, 2019). This study contributes to that literature by showing that social capital plays a consistent role across each credit score level. This suggest that social capital is not only relevant when standardized financial information is weak, but also when it is strong. This implies that loan officers treat social capital as a consistent variable in their decision-making process. This contradicts previous literature (Glaser et al., 2021; Raisch & Krakowski, 2021), which argue that soft information only matters in uncertain and ambiguous situations.

Existing literature has measured soft information in the lending environment using different methods. Campbell et al. (2019) and Even-Tov et al. (2024) both measure soft information indirectly. Campbell et al. infer soft information using loan outcomes and the decision patterns of a loan officer, while Even-tov et al. use the duration of meetings between the borrower and loan officer as a proxy for soft information. Both approaches suggest the presence of soft information without directly analysing the text or analysis written by a loan officer. Our approach is more similar to Del Gaudio et al. (2020), in that we both aim to measure soft information in qualitative data. However, Del Gaudio et al. analyse structured qualitative borrower characteristics, while we focus on unstructured loan officer reports. We contribute by using a dictionary-based classification method, which can be used for unstructured data. This allowed for transparency and interpretability, as it can be traced back why a specific case is flagged as social capital (see Appendix B for an example). Thus, this method offers a theory-driven way to identify soft information directly in unstructured loan officer reports.

Several studies have recognised gender bias and investigated how the interpretation of soft information leads to women being disadvantaged in the lending process (Agier & Szafarz, 2013; Bose et al., 2024; Campbell et al., 2019). In contrast, this study contributes to that literature by showing that gender does not significantly affect the role of social capital in loan approval decisions at this Dutch microfinance institution. Thus, we nuance the existing findings of these studies and suggest that gender bias depends on the specific context in which it occurs.

Lastly, this study addresses the theoretical gap on the lack of clarity on what soft information comprises and when it adds value to loan evaluations (Liberti & Petersen, 2019). By focussing on transparently measuring forms of social capital, based on theory and literature, we show that soft information can be identified and quantified.

6.2 Practical implications

Financial institutions can improve financial access for a broader group of entrepreneurs if they structurally integrate soft information in the loan evaluation process. Although credit scores serve as a risk signal, this study shows that loan officers at the Dutch microfinance institution consistently weighted soft information into their decision-making regardless of the borrower's credit score. Even when standardized financial indicators are available – like the credit score – social capital is viewed by loan officers as a reliable signal of repayment potential. Additionally, these findings suggest that financial institutions who put too much reliance on hard information can lead to the rejection of applicants whom loan officers consider as creditworthy, based on the presence of social capital. This suggests that soft information should be recognized as a valuable input in loan assessments and not as substitute or confirmation of hard information.

The loan evaluation process would become more consistent and transparent when soft information is systematically collected and assessed using criteria based on theory and literature. Currently, social capital is assessed on a subjective basis by the loan officers. A standardized approach would lead to more predictable loan outcome decisions because it reduces the personal bias of a loan officer. Using the same criteria for evaluating social capital ensures that each borrower is judged consistently, creating a more transparent loan evaluation process. This can be potentially achieved through the usage of AI models or hybrid lending models.

While social capital can improve access to finance, it also raises important ethical considerations. Access to social capital is not equally divided among borrowers. Entrepreneurs from wealthier families or strong-financial networks are more likely to benefit from the incorporation of social capital in the decision-making process. So, while these entrepreneurs have a higher chance of loan approval, they may exclude those without such networks. If financial institutions have a limited budget to allocate, relying on social capital would prioritize the network-favoured borrowers. This can contribute to greater inequality in access to finance.

Overall, social capital can enhance financial access for SMEs, which are essential for economic, social and environmental growth. However, not all the 99.8% of SMEs in the Netherlands will benefit equally from social capital. The benefits depend on the SME owner and the financial strength of their social network. Instead of using this financial strength as a criterion for loan approval, financial institutions should use it to identify borrowers who may need additional support to manage their repayments. This shifts the focus from repayment risk to other signals that can also demonstrate an entrepreneur’s potential for success and finally leads to loan disbursement after all.

6.3 Limitations

The dictionary-based pattern recognition relies on specific keywords and certain expressions, and while it did show promising results in the sampling test, it may not capture all the cases in which social capital is available. One could say that this can be solved by simply including this in the keywords, but it is not that simple. If the keyword lists were expanded by adding more words or sayings, it could potentially detect more cases of social capital. However, it would also increase the risk of detecting false positives, especially with words who could appear in a different context. This would reduce the precision of the model. Then again, keeping the keyword list too short will result in a lot of mixed cases. The final set was built through a lot of testing, manually checking and validation, which also results in the following limitation: bias.

The list of keywords and the categories were developed by me, using concepts from literature and theory. As there is not a standardised word set available to use - especially not in the Dutch language – this inevitably leads to a form of personal bias. However, basing the keywords and categories on literature and theory limits the influence of personal bias. Moreover, the manual validation of the model has a risk of confirmation bias, as it will favour myself if the model works appropriately. To mitigate this, I kept the documents on which I carried out the manual validation so other people could check it themselves.

Additionally, the lack of control variables is a limitation of this study. Originally, I wanted to use gender and loan amount as control variables. Gender is a control variable to test for **H1**, **H2** and **H3**, but not for **H4** as “Gender” is tested as an independent variable. However, loan amount could not be used as a control variable. For each rejected loan, the loan amount in the dataset is zero instead of the original requested amount. Therefore, this disbalanced the logistic regression and it would not be used as a control variable. This occurred after I cleaned the whole dataset of duplicates and unusable loan officer reports, meaning that it was not possible to include other control variables in the dataset.

6.4 Future research

Future research is needed to establish whether loan officers made the correct decision, i.e. that the loan is repaid and the company exists. This study shows that social capital positively influences the probability of loan approval, but it does not show whether that decision is correct. Investigating company survival rates and/or repayment behaviour would verify whether the reliance on social capital improves or worsens the actual outcome of an approved loan. By actual outcome, it is meant whether the SMEs remain in business, pay their repayments on time and the default rate.

Future research could also explore the possibility to develop an AI model which could flag social capital that builds on the dictionary-based classification model. If AI can identify and expand on the cues that were used in the model, it could help to identify social capital systematically. This would enhance the consistency of decision-making and exclude biases, resulting in fairer screening outcomes. However, AI models may unintentionally reinforce previous biases, such as the bias that occurred during this study as can be found in the limitations. Thus, the AI models should be reviewed by multiple independent persons to identify inconsistencies and minimize individual biases.

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9. APPENDIX

9.1 Appendix A

9.1.1 Borg

Term	Definition (translated)	Synonyms	Relevance
Borg	someone who holds himself liable for another in the event that the latter fails to fulfil his obligations (nowadays mainly with regard to financial obligations)	Borgstelling, borgtocht, waarborgsom, borg NP, verbonden als borg, garant staan	Formal financial backing by a relative
Meeondertekenen	regarding a document signed together with others	Tekent mee, meetekenen	If a relative co-signs the loan, they become jointly liable for it. This also indicates formal financial backing by a relative.

9.1.2 Fallback

Term	Definition (translated)	Synonyms	Relevance
Fallback	reserve, something one has on hand/can fall back on, fallback position, emergency provision	Fall[-]back(scenario), financieel terugvallen op, vangnet, financieel ondersteunen	Non-formal financial backing by a relative

9.1.3 Financial presence

Term	Definition (translated)	Synonyms	Relevance
Inkomen	the entire sum that someone receives in money or monetary value as the proceeds of assets, business, or labour	Salaris, loondienst, loonlijst, structureel inkomen, hoofdinkomen	Income from a partner or relative, possibility to help applicant in case of financial instability
Dienstverband	employment relationship or agreement	Loondienst, vaste baan	Steady employment of a partner or relative, indicating financial stability

9.1.4 Keywords

Term	Definition (translated)	Synonyms	Relevance
Familiekapitaal	common capital of the members of a family	Vermogende ouders / familie, financiele hulp van ouders, financieel ondersteund door ouders / partner	Familial financial capacity, indicating possibility for help in case of financial instability
Schenking	The donation, especially because of a free agreement, whereby one party (the donor) enriches the other party (the recipient) at the expense of assets (cf. Articles 175 and 177, Book 7 of the Dutch Civil Code)	Gift, erfenis	Wealth transfer through family relationships, indicating possibility for help in case of financial instability

Appendix B

Figure B1

Logged sentences of loan officer reports that contain a form of social capital

LogBorgSentences	LogFallbackSentences	LogFinancialSentences
NA	NA	NA
NA	NA	NA
✓ partner is borg np | positive: borg | social: partner	NA	✓ partner met inkomen welke grotendeels privé lasten dekt...
NA	NA	NA
NA	NA	NA
NA	NA	NA
✓ [redacted] baart (1993, kredietnemer) is geregistreerd par...	✓ fall back scenario is terugbetalen uit loondienst of vanuit i...	✓ fall back scenario is terugbetalen uit loondienst of vanuit i...
✓ partner met goed inkomen tekent mee | positive: tekent ...	NA	✓ partner met goed inkomen tekent mee | financial: inkome...
NA	NA	✓ partner inkomen, bestendig (wajong) | financial: inkomen ...
NA	NA	NA
✓ partner heeft vast inkomen en zal meettekenen als borg | ...	NA	✓ partner heeft vast inkomen en zal meettekenen als borg | ...
✓ 1 kredietnemer en partner borg np vanwege inkomen | p...	NA	✓ 1 kredietnemer en partner borg np vanwege inkomen | fi...
NA	NA	NA
NA	NA	NA
NA	NA	✓ [redacted] runt samen met partner, die klein aanvullend i...
NA	NA	NA
NA	NA	NA
✓ of hij zelf voldoende succesvol wordt is de vraag, maar pa...	NA	✓ partner met prima inkomen ad 42/k, zelf een wia ad 10/k ...

Figure B2

Example of a sentence that is flagged as a fallback scenario

✓ fall back scenario is terugbetalen uit loondienst of vanuit inkomsten partner (daarnaast staan beide ouders erachter die in nood kunnen bijspringen) | positive: fall back, bijspringen | social: partner, ouders

Appendix C

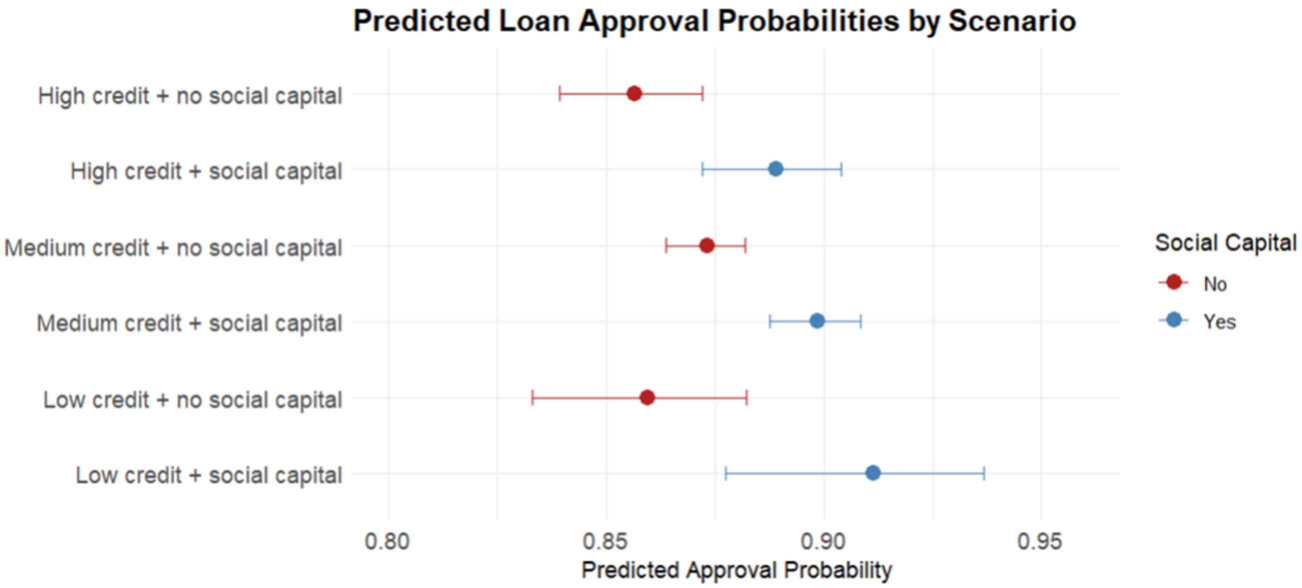
Table C1

Loan approval probabilities by credit score and presence of social capital.

Scenario	Predicted probability	Lower_95CI	Higher_95CI
High credit score + no social capital	0.856	0.839	0.872
High credit score + social capital	0.889	0.873	0.904
Medium credit score + no social capital	0.873	0.864	0.882
Medium credit score + social capital	0.898	0.888	0.908
Low credit score + no social capital	0.859	0.833	0.882
Low credit score + social capital	0.911	0.877	0.937

Table C2

Predicted loan approval probabilities per scenario



Although it might look that there is a difference between credit score categories, these results are not statistically significant as can be seen in table 7.