Explorative Insights into Soft Information and Gut Feelings in the SME Lending Process

Rosella Bolhoeve
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT
This study examines the role of soft information and the perception of loan officers in the credit evaluation process for small and medium-sized enterprises (SMEs), analyzing loan reports from a Dutch micro-lending foundation. SMEs often struggle with obtaining financing due to insufficient hard information. Through a mixed-method approach using quantitative content analysis with Latent Dirichlet Allocation (LDA) and qualitative analysis of 14,166 loan reports, this research identifies key soft information prioritized by loan officers. The analysis shows that personality traits, especially extraversion and conscientiousness, influence the perception of loan officers, and therefore the lending decision. Additionally, social capital and entrepreneurial passion are important factors in creditworthiness assessments. The study emphasizes the value of soft information in mitigating perceived risks when hard data is scarce. By enhancing our understanding of these elements, the research provides valuable insights into SME financing decision-making.

Graduation Committee members:
F. Koefer, Msc
Dr. M.L. Ehrenhard

Keywords
SME lending, credit evaluation, soft information, perception, Latent Dirichlet Allocation, qualitative content analysis, founder characteristics

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) are crucial to the economies of developed nations. Eurostat data shows that micro and small enterprises with up to forty-nine employees contribute approximately 35.4% of economic value and employ 48.5% of the workforce. Meanwhile, medium enterprises with fifty to two hundred forty-nine employees add 15.7% to the economy and account for 17.1% of employment (Eurostat, 2023). Despite their importance, SMEs and startups face significant challenges in securing the financial resources needed for initiation and growth. This difficulty largely stems from their informational opacity due to the lack of comprehensive financial documentation and limited collateral assets, making it challenging for traditional lending institutions like banks to assess their risk accurately (Chen et al., 2015). Financial opacity significantly complicates SMEs' access to credit from financial institutions, as lenders perceive a higher risk in providing funds to these businesses.

In addition to being informationally opaque, young SMEs tend to rely significantly on banks for financing needs (Grunert and Norden, 2012). Loans from large traditionally risk-averse banks are the main source of external financing for SMEs in the Netherlands, although alternative sources of finance are gaining more importance for SMEs (OECD, 2024). Qredits is a private foundation that offers micro-loans for SMEs and entrepreneurs in the Netherlands. They aim to assist entrepreneurs with a viable business plan who face difficulties securing funding from traditional financial institutions. By issuing 35,000 loans, Qredits has facilitated the creation of 42,500 jobs, resulted in €76,5 million in government savings, and enabled 60% of the entrepreneurs they support to achieve financial independence (Qredits, 2022). The loan application assessment focuses on the individual borrower and their unique circumstances, addressing the needs of a demographic that cannot be accurately evaluated through traditional methods and criteria. Qredits' loan professionals have produced a little over 14,000 loan evaluation reports between the years of 2018 and 2022, which have been compiled into a dataset that is accessible for the purposes of this thesis. This dataset will serve to examine the priorities of loan officers when they lack access to the comprehensive information typically required by traditional lenders.

Information opacity in SMEs creates a marked information asymmetry with potential lenders, who usually base their assessment on hard data. To address this challenge, financial institutions can resort to relying on soft information. According to Campbell et al. (2019), soft information encompasses elements of an entrepreneur's social, educational, and professional background, offering insights into a borrower's creditworthiness and potential that hard information alone may not reveal. Access to a broad spectrum of qualitative data allows lenders to achieve a complete understanding of the borrower's situation, compensating for areas where hard data might be incomplete. Investors believe that a positive review of the business viability metrics, along with a good impression of the entrepreneur cultivates a positive gut feeling about the investment and allows them to make confident investment choices (Huang & Pearce, 2015). This observation highlights how soft information contributes to the formation of gut feelings, thereby affecting the decision-making process in investments. However, despite its significant role, there's a gap in understanding precisely which soft information is relevant in shaping these gut feelings and, subsequently, the final lending decisions.

1.1 Research Objective

This paper's primary objective is to explore and analyze the soft information that loan officers emphasize when evaluating the creditworthiness of SME founders under conditions of informational opacity. It incorporates both quantitative and qualitative content analysis to systematically identify and categorize the key traits of entrepreneurs deemed essential by lending professionals. The study seeks to deepen our understanding of which soft information-driven characteristics of SME founders are central to lending decisions when hard data is scarce. By highlighting the subjective evaluations used to mitigate risks associated with limited hard data, the intention is to enrich our knowledge of decision-making processes in SME financing. This exploration contributes to a more nuanced understanding of how soft data influences financing decisions in the context of SMEs. The research question for this study is:

What perceived traits of SME founders affect creditworthiness evaluations of opaque borrowers?

1.2 Academic and Practical Relevance

The existing body of literature acknowledges that gut feelings significantly influence early-stage investment decisions, yet there is a gap in our understanding of the specific soft criteria that drive these intuitions. The subjective perception of loan officers is widely acknowledged to play a vital role in the decision-making process of loan approvals. Research indicates that using both hard and soft information together enhances the accuracy of predicting loan defaults more effectively than relying solely on hard information (Baklouti & Bouri, 2014). With more opaque borrowers, the predictive power of soft information gains prominence over hard information (Cornée, 2019). Moreover, research has been done on the relationship between soft information and the bargaining power of SMEs during loan evaluation (Grunert & Norden, 2012; Chen et al., 2015). Although there's considerable research on how subjective information affects loan default rates and bargaining power, its impact on the loan approval process has been largely ignored. Ciampi et al. (2021) underscore the critical importance of delving deeper into the non-financial attributes of SMEs to enhance the quality of lending decisions. They note that the concept of relationship lending has been explored to some extent. However, research has not adequately addressed the distinct characteristics of emerging entrepreneurs who have yet to establish any formal relationships with financial institutions. Furthermore, the literature reveals a deficiency in studies examining the behavioral and psychological traits of entrepreneurs, a gap highlighted by Goel and Rastogi (2023). This oversight highlights the need for research exploring the personal and psychological aspects of entrepreneurs. Such research could reveal the complex factors impacting lending choices, offering essential insights into financiers' decision-making processes.

For entrepreneurs and SME founders, understanding the soft criteria that influence investor decisions is crucial. By understanding the role of personal founder characteristics, potential borrowers can emphasize these aspects in their interactions with loan professionals, demonstrating the qualities investors value and increasing their likelihood of securing funding (Lavi & Yaniv, 2023). Furthermore, this understanding can encourage personal growth, inspiring entrepreneurs to deliberately develop these traits. Research has shown that individuals, with or without intervention, can deliberately alter traits such as conscientiousness (Magidson et al., 2014). This strategy is not only a means of financial support but also a way to cultivate skills that could lead to greater success in entrepreneurship.

2. LITERATURE REVIEW

SMEs and early-stage companies often face challenges in providing concrete data, leaving banks and other financial institutions with little to base their decisions on. Consequently, lending to these less transparent entities introduces greater uncertainty in evaluating the company's viability. In uncertain situations, investors are more inclined to use soft information, such as perceptions of the entrepreneur, in lending decisions (Huang & Pearce, 2015). Soft information differs from hard information traditionally used in critical ways: it is often relayed through text instead of numbers, and its context plays a vital role. The context in which soft information is collected, as well as the collector, are considered components of the information, making them inseparable. This type of information depends on personal evaluations, making it subjective and thus more challenging to communicate and transfer (Liberti & Petersen, 2019). This covers the intricate aspects of an individual's profile, such as social and personal background, making soft information a source of insights that hard data cannot provide. Research has demonstrated the impact of soft information on loan terms, showing that positive perceptions of soft information contribute to improved loan terms in the context of SME lending (Grunert & Norden, 2012; Chen et al., 2015). For instance, entrepreneurs viewed as competent leaders may be offered loans at lower interest rates. This emphasizes the significant role of soft information in the credit evaluation process, particularly for businesses with limited hard information.

The belief among investors that positive gut feelings lead to confident investment decisions highlights the significance of perceptions and intuition in evaluating uncertain situations, as noted by Huang & Pearce (2015). Investor gut feeling refers to the intuitive judgments shaped by an investor's experience and knowledge, particularly in the context of starting and growing businesses. This elaborate process combines cognitive and emotional aspects merge analytical thinking with perception. Its purpose is to help investors consider opportunities that might otherwise seem too risky (Huang, 2018), thus becoming crucial in evaluating potential investments. Gut feeling relies heavily on soft information perceived by the loan professional, underscoring the importance of such information in shaping investment decisions, especially with opaque borrowers and limited hard data. The remainder of this theoretical framework will explore and understand the types of soft information relevant to shaping investor gut feelings towards opaque borrowers.

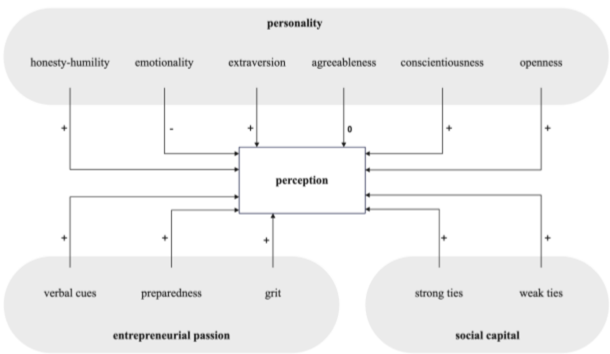

Figure 1. Conceptual Model

2.1 Personality Traits

According to research by Goel and Rastogi (2023), the evaluation of an entrepreneur's character by loan officers plays a crucial role in subjective credit scoring, focusing on personal insights rather than just hard data. They found that personality traits significantly affect an entrepreneur's risk of loan default. Furthermore, meta-analyses concluded that the personalities of entrepreneurs affect business success (Rauch & Frese, 2007; Zhao et al., 2010). Consequently, the findings from these studies suggest that incorporating personality assessments into the loan approval process could enhance the quality of investment decisions. This is particularly relevant for very small companies, where the founder's influence is more pronounced. As loan officers engage with potential borrowers, they will inevitably form views on their personalities and assess their potential as entrepreneurs. The substantial influence of entrepreneurs' personalities on business outcomes and loan assessments highlights the need for a deeper understanding of these traits. Adopting a structured approach to analyze and categorize personality traits could offer deeper insights into how these traits influence loan evaluations.

Since the 1980s, the Five Factor Model, or Big Five, has been widely used to study personalities, including those of entrepreneurs. It categorizes personality into five traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness to new experiences. Though not without its critics, the Five Factor Model is widely seen as the most scientifically rigorous classification of personality (Goldberg, 1993). The model has also been met with criticism and caused discussion among experts in the field, mostly regarding the methodology (Block, 1995). However, other authors praise its empirical robustness (Costa & McCrae, 1995). The most relevant limitations discussed by some are its inability to predict specific behaviors based on traits, its lack of causal explanations for human behavior, and its simple and comparative statements about individuals that reduce their complexity (McAdams, 1992). However, more recent research has frequently been successful in linking certain personality dimensions to behaviors and outcomes, such as leadership and academic performance (Judge et al., 2002; Poropat, 2009). Brandstätter's (2011) meta-analysis connected the Big Five to entrepreneurial success, further highlighting the model's applicability for this paper. Overall, the Big Five is still the most widely accepted and utilized model for categorizing and depicting personality traits. The traits are thought to be necessary and mostly sufficient for explaining the covariation of most personality traits (McCrae, 2020). Evidence from numerous research traditions underscores these factors as essential dimensions of personality that are consistent across different cultures and age groups (McCrae & Costa, 1997; Draguns & Tanaka-Matsumi, 2020). The model's origins lie in natural language analysis, leading to a detailed inventory of words used to depict personality traits. Remarkably, these descriptive scales maintain their effectiveness across multiple languages (McCrae & John, 1992). This makes the model particularly effective for analyzing the dataset and thoroughly interpreting the personalities of entrepreneurs as seen by lenders.

The HEXACO model, considered an extension of the Five Factor Model, integrates an honesty-humility dimension to offer a more comprehensive framework. It retains the five dimensions similar to the Big Five Model and supplements them with honesty-humility (Ashton & Lee, 2007). The additional dimension might be especially relevant for loan application assessments. Goel and Rastogi (2023) indicate that integrity, or a lack thereof, is a significant factor in loan defaults. Borrowers with financial capability may strategically default if they lack integrity, which the honesty-humility dimension addresses. Thus, incorporating this dimension enhances personality assessments in loan approvals, offering deeper insights into borrowers' likelihood to honor or default on loans. Honesty-humility is defined by sincerity, fairness, greed avoidance, and modesty. Conscientiousness is defined by organization, diligence, perfectionism, and prudence. Openness to experience is defined by aesthetic appreciation, inquisitiveness, creativity, and unconventionality. Extraversion is defined by expressiveness, social boldness, sociability, and liveliness (Lee & Ashton, 2004). For instance, a person who is perceived as a well-organized, sociable, and creative person could be seen as a good entrepreneur by some. Brandstätter (2011) conducted research utilizing the Five-Factor Model of personality to explore the link between personality traits and entrepreneurial success. By synthesizing data from five meta-analyses, he concluded that conscientiousness, openness to new experiences, and extraversion are positively associated with entrepreneurial success, indicating a strong link between these personality dimensions and the ability to thrive in entrepreneurial roles. Therefore, the following hypotheses can be formulated:

H1: The perception of high levels of honesty-humility in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H2: The perception of high levels of extraversion in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H3: The perception of high levels of conscientiousness in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H4: The perception of high levels of openness for new experiences in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

Neuroticism or emotionality is defined by fearfulness, anxiety, dependence, and sentimentality. Agreeableness is defined by forgiveness, gentleness, flexibility, and patience (Lee & Ashton, 2004). According to Brandstätter (2011), neuroticism, named emotionality in the HEXACO model, shows a negative correlation with entrepreneurial success. However, the findings regarding agreeableness remain somewhat unclear. A negative correlation between agreeableness and need for autonomy has been found, while need for autonomy seems to be positively correlated with entrepreneurial success. This would suggest that high levels of agreeableness could be negatively correlated with entrepreneurial success (Brandstätter, 2011; Koestner & Losier, 1996; Rauch & Frese, 2007). However, Zhao et al. (2010) did not find a significant correlation between agreeableness and business performance, concluding that a direct relationship between the two factors could not be proven. Therefore, the following hypotheses can be formulated:

H5: The perception of low levels of emotionality in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H6: The perception of high levels of agreeableness in entrepreneurs is not significantly associated with gut feelings in the evaluation of opaque borrowers

2.2 Social Capital

Social capital, "the ability to secure benefits through membership in networks and other social structures" (Portes, 1998, p. 8), enables entrepreneurs to recognize opportunities, access resources, and gain legitimacy. As a result, this factor plays a significant role in predicting entrepreneurial success. Research has shown a positive correlation between the extent of an entrepreneur's personal networks and their small business's performance, with network diversity greatly enhancing company outcomes (Stam et al., 2014).

Both strong and weak ties with key customers are positively related to the economic growth of start-ups (Pirolo & Presutti, 2010). Strong ties are close contacts with frequent interactions, often providing secure and consistent access to resources. Examples include close family and friends who run businesses, and support from a spouse. Weak ties, in contrast, are casual connections that often offer valuable information and extend beyond one's immediate social network (Davidsson & Honig, 2003).

Additionally, strong social skills contribute to expanding social capital, thus increasing the likelihood of business success. Strong social skills are also a facet of the personality dimension of extraversion. These skills are instrumental for entrepreneurs in making favorable impressions on loan officers, accurately understanding others, and persuading effectively, thereby boosting the chances of securing a loan (Baron & Markman, 2000). An entrepreneur's social capital offers valuable soft information to lenders and investors, significantly impacting investment decisions by building trust and lowering perceived risks. Thus, the following hypothesis were formulated:

H7: The perception of high levels of strong ties in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H8: The perception of high levels of weak ties in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

2.3 Entrepreneurial passion

Entrepreneurial passion is defined as "an entrepreneur's intense affective state accompanied by cognitive and behavioral manifestations of high personal value" (Chen et al., 2009, p. 201). Thus, when individuals have a strong inclination toward an activity they enjoy, they will consider it to be important and adjust their behavior accordingly. This can manifest as increased entrepreneurial behavior, creativity, grit, and preparedness, all of which enhance performance (Chen et al., 2009; Mueller et al., 2017; Murnieks et al., 2014; Murnieks et al., 2020). For example, loan officers might observe greater preparedness, a determination to overcome obstacles, and expressions of enthusiasm and passion from the entrepreneur. Notably, some of these displays, such as diligence and liveliness, are related to the personality dimensions of conscientiousness and extraversion (Lee & Ashton, 2004). Additionally, the affective state can enhance an entrepreneur's persuasiveness, facilitating the development of social capital. The passion of resource seekers, despite being intangible and hard to measure, can assist in persuading loan officers and creating a positive gut feeling (Chen et al., 2009). For opaque SME start-ups, loan officers heavily rely on soft information provided by entrepreneurs, such as their passion, when forming opinion. Therefore, manifestations of entrepreneurial passion such as the level of preparedness, enthusiasm, and grit of entrepreneurs are likely to be considered by loan evaluators. Thus, the following hypotheses were formulated:

H9: The perception of high levels of entrepreneurial passion in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H10: The perception of high levels of preparedness in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

H11: The perception of high levels of grit in entrepreneurs is associated with positive gut feelings in the evaluation of opaque borrowers

3. METHODOLOGY

3.1 Dataset

The dataset analyzed contains exactly 14166 loan reports. Of these, 12066 were disbursed, 3745 were applications for new businesses, and 4521 meetings were conducted face-to-face and the remaining per video call. The lowest amount disbursed was €1000, while the highest amount was €250000. Loan officers fill out different boxes in their system, which are displayed as separate columns in the dataset. All columns with non-categorical text in the dataset were analyzed, comprising the loan officer conclusion, the risk manager conclusion, the business activities, the description of the entrepreneur, the description of the market, the explanation of the applicants private situation, and the explanation of the financial analysis. Each column was analyzed since inspection showed they all contained relevant information at various instances within the dataset. The other columns, containing hard information, are less relevant to the research question. The dataset is created by Qredits, a financial institution in the Netherlands that focuses on offering loans to entrepreneurs who have difficulties securing funding from traditional financial institutions. They aim to look at the individual circumstances of each entrepreneur and their business to assist a demographic that cannot be accurately evaluated by the traditional methods that focus on hard information. They aim to give a diverse population of entrepreneurs more chances to make a positive social and economic impact. To support their entrepreneurs, they provide coaching and trainings (Qredits, 2022). The loan process begins with the loan seeker completing an online application, providing personal and business information. Qredits reviews the application for completeness and schedules a meeting with the entrepreneur and one of their loan professionals. During the meeting, the loan professional evaluates the entrepreneur's personal situation and discusses the provided documents. Following the meeting, the loan officer performs a financial background check, such as verifying existing loans and late payments. The gathered information is then used to write loan reports in the dataset, leading to the final decision on loan approval (Qredits, n.d.). The applications took place between 2018 and 2022, encompassing the period of the COVID-19 crisis. As a result, 2699 of the reports concern loans aimed at helping small businesses survive the crisis. The Dutch government provided funds for this initiative (Ministerie van Algemene Zaken, 2020).

3.2 Quantitative Content Analysis

Topic modeling is a content analysis method that uncovers hidden topics within a corpus of documents. As an unsupervised learning technique, it identifies patterns in unlabeled data, aiming to group related words into themes. This method facilitates the understanding of large document collections by revealing underlying themes that might not be obvious at first glance. The lack of a defined framework for assessing the impact of soft information on SMEs renders topic modeling particularly effective for uncovering relevant themes. Latent Dirichlet Allocation (LDA) is one of the commonly used methods for topic modeling (Jelodar et al., 2019). The basic concept behind this approach is that documents are produced from a mixture of topics, where each topic is characterized by a distribution over words. This approach enables documents to share content, allowing for overlaps instead of segregating them into distinct categories, reflecting the natural usage of language (Blei et al., 2003). The result is a model that reveals the significant topics within each document and identifies the most representative words for each topic. The model is used to detect patterns and gain a better overview of the expansive dataset at hand.

Text pre-processing follows Denny and Spirling's (2018) recommendations to refine input data, enhancing the effectiveness of the topic modeling process and resulting in a better LDA model. First, the dataset is filtered to ensure it solely contains the content of loan reports while excluding other textual information. Subsequently, the data is cleansed of punctuation, numerical values, and excess whitespace, while converting all text to lowercase to ensure uniformity. While Denny and Spirling’s article suggests stemming words to their root forms, this approach generated some unclear tokens. To address this issue, lemmatization was employed to convert words into their normalized forms, serving as a more effective vocabulary reduction technique. These steps are conducted using the SpaCy module as it offers extensive lemmatization support for the Dutch language and provides a relatively useful list of Dutch stopwords (Honnibal et al., 2020). In addition to SpaCy's provided list, additional stopwords are removed from the dataset. These include general stopwords not included in the provided list and domain-specific stopwords common within this specific context but do not contribute to gaining meaningful insights. Furthermore, an iterative process is used to remove moderately common but insignificant words such as months, names, and broad descriptors that add little information. Since the analysis of bi-grams and tri-grams did not uncover relevant or meaningful n-grams, none were included. This is most likely because the dataset often lacks grammatically correct full sentences. Additionally, words with three characters or fewer were found to be often meaningless, abbreviations, or typographical errors, and were thus filtered out. Lastly, the text is tokenized, breaking it down into individual words to make analysis and processing easier.

For the Latent Dirichlet Allocation the gensim library, one of the most well-known tools for LDA in Python, was used (Jelodar et al., 2019; Řehůřek & Sojka, 2010). Initially, the tokenized dataset is converted into a dictionary, where extremely frequent and infrequent words are filtered out to avoid hindering the analysis (Jacobi et al., 2016). The number of words filtered out on each end was determined through an iterative process to optimally remove overly specific and common words that do not add value. Consequently, words that appear in fewer than one hundred documents or more than half of the reports are excluded from the analysis. Then, the dictionary is converted into a corpus format suitable for processing. An LDA model is then initialized. Each document is added to the model, which is then trained over multiple iterations to learn the distribution of topics across the reports. Finally, the top words for each topic are printed, providing insights into the themes represented by each topic. Each word in a topic has a probability showing how strongly it is associated with that topic (Řehůřek & Sojka, 2010).

A key limitation of LDA is the necessity to predefine the number of topics, a decision that significantly affects the outcome. Finding the optimal number of topics for a dataset is challenging, as there is no universal strategy that fits every situation. Typically, selecting the most suitable number of topics involves a process of trial and error (Blei et al., 2003). Through a process of trial and error, it was determined that the optimal number of topics is around twenty-five to thirty, and these models were generated and compared in detail. After careful consideration, it was determined that the preferred number of topics is 27. A smaller number can also work but often excludes some coherent and relevant topics. A larger number often produces multiple topics that are very similar to one another. Moreover, LDA assumes topics are independent of each other, which might not always be realistic. In real-world data, topics can be related or hierarchical. This limitation can lead to less meaningful or interpretable topics in certain contexts. Furthermore, LDA assumes that the order of words in a text does not matter. This simplification ignores the context and structure of language, such as syntax and semantics, which can lead to a loss of meaning and nuance (Blei et al., 2003).

During parameter adjustments, the coherence and perplexity scores were closely monitored. Since there are no universal benchmarks for desirable coherence and perplexity scores, the aim is to continuously improve these values during the process (Blei et al., 2003). Lower perplexity indicates the model is better at predicting the sample. The perplexity score is -7.13, which is low compared to initial scores. For the UMass coherence measure, lower scores suggest better topic interpretability by humans (Rosner et al., 2013; Lau et al., 2014). The document coherence score is -2.11, showing a favorable decrease relative to previous outcomes.

3.3 Qualitative Content Analysis

Following up the quantitative analysis with a qualitative approach offers multiple benefits. While LDA identifies the prevalent topics in loan evaluation reports, it may not capture the contextual significance or subtle distinctions in the text due to its reliance on statistical patterns. Qualitative analysis allows for a deeper, context-sensitive exploration of topics, providing nuance to previous findings. Additionally, this step validates the initial quantitative findings by examining if the identified topics truly represent the text's themes, offering a chance to refine interpretations. Lastly, an LDA may not be able to identify all relevant patterns to the specific research question due to its inherent limitations or the structure of the texts.

The approach for qualitative content analysis is directed content analysis, which employs established theories or prior research to outline initial coding categories. Then, operational definitions for each category are determined using theory. Coding starts with these pre-established codes, and new codes can be defined during the data analysis process (Hsieh & Shannon, 2005). The unit for analysis, also referred to as the coding unit, consists of individual themes. Thus, a code may be assigned to a text chunk of any size, as long as each code represents a single theme relevant to the research question (Zhang & Wildemuth, 2017). The coding template in Kibiswa's publication (2019) was used as inspiration for the coding scheme, as the columns of theme, subtheme, and operational definition were used. Where relevant, additional observations were added to codes in the form of memos. Initially, only the factors of personality traits and social capital were included.

With a dataset of 14,000 reports and limited time available for analysis it becomes necessary to select a subset of reports for detailed examination as analyzing all reports is not feasible. Initially, a simple random sample of loan reports was created by randomly shuffling the order of the reports in the dataset. In order to do this, the sample tool from the pandas library was used (McKinney, 2010). As a result, a subset of the loan reports is randomly selected to create a sample representative of the dataset (Gheyle & Jacobs, 2017). The sample size should not be too small, as the analysis needs sufficient information, nor should it be too large, as the analysis needs to remain detailed (Sandelowski, 1995; Boddy, 2016). Therefore, the analysis continued until a degree of saturation was reached. According to Saunders et al. (2018), a priori thematic saturation, the most suitable model in this context, is achieved when enough data is gathered to illustrate the theory at hand. Moreover, the aim was to reach a level of informational redundancy, where continued analysis adds very little new information. Subsequently, a satisfactory level of saturation was reached at around one hundred and eighty analyzed reports, and two hundred reports were coded in total to confirm that this amount was sufficient.

During this analysis, it became evident that not all documents were equally valuable in answering the research question. According to Sandelowski (1995), in combined qualitative and quantitative studies, choosing a sample of particularly informational observations can be beneficial. This research suggests that purposeful sampling may result in statistically non-representative samples that are still informationally representative, providing deeper insights that remain generalizable. A correlation analysis revealed that face-to-face meetings and evaluations for investment in new businesses included the largest number of codes explaining the theory. The outcomes of this analysis can be found in the appendix. In contrast, evaluation reports concerning refinancing decisions were strongly negatively correlated with the number of quotations. Therefore, it was decided that the second round of analysis would be conducted on a randomized dataset of reports concerning face-to-face meetings for new businesses, excluding refinancing reports. During the first round of coding, the category of entrepreneurial passion was observed, prompting further research and its inclusion in the second round of analysis. Based on initial observations, this category was divided into explicit mentions of passion, other verbal cues, preparedness, and grit to provide a clear overview. Verbal cues represent the affective state of passion, while preparedness represents the cognitive and behavioral states (Chen et al., 2009). Grit represents the persistence that entrepreneurs are expected to display (Mueller et al., 2017), a category observed in the first round of coding. The final coding scheme can be found in the appendix. Since 200 reports were sufficient to reach saturation in the first round, even with reports supplying less information, it was expected that this would be the case in the second round as well. Moreover, the round number facilitates easier analysis of the results.

4. RESULTS

4.1 Quantitative content analysis

The results of the Latent Dirichlet Allocation are shown in table 1. Each row represents a topic with the ten words most relevant to that topic. Dark grey rows contain topics considered relevant to the research question and hypotheses, while light grey words are also deemed relevant. The number behind each word represents the probability that shows how strongly that word is associated with its topic. The output shows three topics relevant to the research question, while relevant terms can also be found scattered throughout the table.

A key theme that emerges from the analysis is the observation and perception process used by loan officers. Topic number five includes terms suggesting that loan officers gather information through observations to form their opinions, which in turn helps them make recommendations. Additionally, topic number nineteen includes terms that refer to the loan professional's perception and the applicant's payment morality. Words referring to a loan officer's perception, feeling, and personal opinion also appear in various topics throughout the table, highlighting the importance of these subjective factors in the decision-making process.

Another important theme is the influence of social ties on the assessment of creditworthiness. Topic fifteen includes various terms describing the entrepreneur's family, classified as strong ties (Davidsson & Honig, 2003). This suggests that the perception of the entrepreneur's strong ties plays a role in assessing the creditworthiness of SMEs. Furthermore, terms referring to the wider social network, considered weak ties (Davidsson & Honig, 2003), are dispersed throughout Table 1. This indicates that the perception of weak ties also influences the assessment of SME creditworthiness. Whether these perceptions are paired with a positive opinions depends on the context, thus requiring qualitative content analysis to draw final conclusions on hypotheses seven and eight.

Additionally, there are mentions of payment morality in topics including terms indicating observations. Payment morality falls under the honesty-humility personality dimension (Ashton & Lee, 2007), suggesting that honesty-humility plays a role in assessing creditworthiness. However, additional context is

Table 1. Latent Dirichlet Allocation (LDA) outcome

Topic Number	Topic Words 1	2	3	4	5	6	7	8	9	10
1	winkel (0.089)	vestiging (0.025)	centrum (0.014)	vestigen (0.013)	overname (0.011)	winkelcentrum (0.010)	huurcontract (0.009)	kleding (0.009)	pand (0.009)	openen (0.008)
2	onderschrijven (0.017)	betalingsmoraliteit (0.015)	betaalmoraal (0.010)	voorstel (0.010)	overeenkomstig (0.009)	historisch (0.008)	twijfel (0.008)	realistisch (0.007)	voorliggen (0.007)	alternatief (0.007)
3	track (0.014)	record (0.013)	stabiel (0.011)	realisatie (0.011)	fors (0.011)	faciliteit (0.010)	kredietbehoefte (0.010)	aangeleverd (0.010)	balans (0.009)	onttrekking (0.008)
4	salon (0.038)	kapsalon (0.026)	huur (0.022)	ruimte (0.019)	pand (0.018)	behandeling (0.018)	opleiding (0.015)	schoonheidssalon (0.013)	vestigen (0.011)	kapper (0.010)
5	mening (0.038)	ervaren (0.023)	marketing (0.015)	signalen (0.014)	opleiden (0.013)	schuld (0.012)	casus (0.012)	deskundig (0.012)	netwerk (0.011)	adviseren (0.011)
6	ouder (0.096)	moeder (0.058)	jong (0.045)	overname (0.044)	thuiswonen (0.026)	thuis (0.023)	leeftijd (0.015)	opleiding (0.014)	overnemen (0.012)	vader (0.010)
7	signalen (0.037)	ondernemerskwaliteit (0.020)	codering (0.018)	ongewijzigd (0.018)	orde (0.018)	bevoegdheid (0.015)	lijken (0.013)	restschuld (0.013)	relevant (0.011)	extern (0.011)
8	marketing (0.017)	website (0.015)	webshop (0.012)	lastig (0.010)	netwerk (0.010)	leverancier (0.009)	voorraad (0.007)	productie (0.007)	doelgroep (0.006)	merk (0.006)
9	opdrachtgever (0.033)	transport (0.015)	gevoel (0.013)	voorstel (0.012)	bevoegdheid (0.011)	chauffeur (0.010)	opleiding (0.010)	werkkapitaal (0.010)	verwachten (0.010)	huwen (0.009)
10	pand (0.064)	hypotheek (0.027)	verhuur (0.023)	verbouwing (0.019)	waarde (0.014)	verhuren (0.013)	overwaaren (0.011)	huur (0.010)	inschrijving (0.010)	overwaarde (0.010)
11	gemeente (0.044)	sociaal (0.039)	evenement (0.021)	mens (0.021)	stichting (0.017)	organiseren (0.016)	jong (0.012)	festival (0.011)	cliënt (0.009)	groep (0.009)
12	voorraad (0.052)	webshop (0.025)	inkoop (0.019)	marge (0.018)	winkel (0.016)	trackrecord (0.011)	leverancier (0.009)	artikel (0.008)	uitbreiden (0.008)	groothandel (0.008)
13	opleiding (0.029)	praktijk (0.022)	mens (0.013)	afronden (0.012)	uitkering (0.009)	traject (0.008)	netwerk (0.008)	zelfstandig (0.008)	verleden (0.008)	schuld (0.007)
14	horeca (0.054)	restaurant (0.038)	keuken (0.016)	centrum (0.010)	café (0.009)	terras (0.009)	eten (0.008)	pand (0.008)	overname (0.008)	open (0.007)
15	vader (0.208)	zoon (0.111)	broer (0.073)	dochter (0.028)	moeder (0.020)	boot (0.020)	overlijden (0.015)	overnemen (0.012)	familie (0.012)	familiebedrijf (0.010)
16	holding (0.046)	persoonlijk (0.014)	waarneming (0.012)	faillissement (0.011)	personeel (0.011)	dossier (0.010)	zichtbaar (0.009)	tekenen (0.009)	management (0.008)	structuur (0.008)
17	eenmanszaak (0.036)	persoonlijk (0.026)	achten (0.020)	trouwen (0.019)	aflopen (0.018)	schuld (0.017)	verwachten (0.016)	acht (0.015)	toekomst (0.013)	auto (0.013)
18	reparatie (0.033)	machine (0.025)	onderhoud (0.025)	auto (0.023)	service (0.014)	motor (0.013)	elektrisch (0.013)	gebruiken (0.012)	garage (0.012)	onderdeel (0.010)
19	lijken (0.034)	helder (0.020)	betalingsmoraliteit (0.019)	ogen (0.019)	opleiden (0.014)	verplichting (0.014)	reëel (0.013)	kiezen (0.013)	indiener (0.013)	privélast (0.013)
20	orde (0.073)	persoonlijk (0.029)	exploitatie (0.027)	jong (0.024)	faciliteit (0.020)	achterstand (0.019)	wajong (0.016)	limiet (0.015)	melding (0.014)	vertragen (0.014)
21	overbrugging (0.024)	open (0.016)	uitstel (0.015)	huur (0.013)	normaal (0.013)	crisis (0.012)	lockdown (0.011)	maatregel (0.010)	overbruggingskrediet (0.009)	verwachten (0.009)
22	bevoegdheid (0.029)	auto (0.022)	uitkering (0.022)	acceptatiescore (0.016)	sociaal (0.014)	twijfel (0.013)	voordeel (0.012)	school (0.011)	mens (0.010)	trouwen (0.010)
23	training (0.027)	franchise (0.017)	personal (0.012)	sportschool (0.011)	netwerk (0.011)	mens (0.011)	marketing (0.010)	opleiding (0.009)	persoonlijk (0.009)	trainer (0.009)
24	dekking (0.045)	ogen (0.033)	verpanding (0.030)	begroting (0.029)	leunen (0.027)	legitiem (0.026)	realistisch (0.024)	onderbouwen (0.023)	activa (0.022)	case (0.017)
25	spaargeld (0.016)	koopwoning (0.012)	indruk (0.012)	lijken (0.012)	stabiel (0.011)	achten (0.011)	fors (0.010)	keurig (0.010)	uitgave (0.009)	onttrekking (0.009)
26	helder (0.008)	beoordeling (0.008)	remweg (0.007)	breekpunt (0.007)	balans (0.007)	extern (0.006)	bespreken (0.006)	navraag (0.006)	fors (0.005)	facto (0.005)
27	opdrachtgever (0.037)	zzper (0.037)	bouw (0.028)	netwerk (0.016)	uurtarief (0.013)	zelfstandig (0.010)	materiaal (0.010)	werkgever (0.009)	personeel (0.008)	gereedschap (0.008)

needed to gain further insights into loan professionals' perceptions and indicators of payment morality, necessitating qualitative analysis to investigate hypothesis one further.

Lastly, the other personality dimensions and entrepreneurial passion are not clearly presented in the LDA results. The output lacks specific personality traits describing the loan applicants, which may be due to the diverse range of terms available for describing people. Similarly, descriptors of passion, which can also be indicated by preparedness and grit, are not prominently featured. If the corpus uses a wide array of descriptors sparingly or inconsistently, the model might not flag them as significant. Some terms indicating neatness and orderliness can be found scattered throughout the model. However, these descriptors can also refer to the paperwork or financial ratings. Alternatively, they can refer to the preparedness of the applicant, which could indicate passion. Therefore, qualitative analysis might be necessary to identify the specific traits and qualities evaluators consider more clearly.

4.2 Qualitative content analysis

The mixed-method approach, combining both quantitative and qualitative analyses, provides a basis for validating research findings. The Latent Dirichlet Allocation helped in identifying help in identifying broad patterns and prevalent themes within the large dataset. However, this method might miss the contextual subtleties and deeper meanings embedded in the dataset. This is where qualitative analysis proves invaluable. By examining the content's nuanced context, the qualitative analysis ensures a comprehensive understanding of the data, validating and enriching the insights obtained from quantitative methods. This combination enhances the reliability of the findings while providing a more holistic view of the factors influencing lending decisions.

The qualitative analysis succeeded in providing more nuanced insights into the specific traits of entrepreneurs that influence loan decisions. Personality emerged as the most frequently reported category. The results are highly dependent on the interpretation and subsequent classification of the texts. To accurately assign descriptions of an entrepreneur's personality traits, publications providing descriptions and lexicons of the HEXCAO model in the Dutch language were used (De Vries et al., 2009; De Vries & Born, 2013). Lists of facets and adjectives belonging to each personality dimension were consulted when categorizing descriptions into subthemes. Out of the 632 quotes, 269, or 42.56%, were related to the theme of personality. 74 quotes, making up around 27% of the personality theme, could not be specified. This means that personality traits were considered likely to affect the outcome, but they were not described in detail. An example would be an applicant who is said to leave a positive impression and is simply described as being a real entrepreneur with strong entrepreneurial qualities. As a result, it is unclear what specific traits are deemed suitable. Nevertheless, it is evident that subjective perceptions based on observations of the applicant's personality influence the lending decision. The most frequently described personality traits are extraversion and conscientiousness, accounting for approximately 23.4% and 19.7%, respectively. Extraversion traits include being sociable, having high energy, and having an open personality. Traits associated with conscientiousness include perfectionism, thoughtfulness, and discipline. Conscientiousness and extraversion are the most frequently described personality traits, both linked to positive perceptions by loan professionals. Therefore, hypotheses two and three can be supported.

Openness, honesty-humility, and emotionality each comprised about 8-10% of the personality theme. The dimensions of openness and honesty-humility are associated with favorable opinions of the entrepreneur and are considered in lending decisions, while emotionality is linked to negative perceptions. Therefore, all other dimensions were counted as normal when a positive opinion was expressed about the trait, and a note was added when the trait was described in other contexts. The reverse was done for emotionality. However, loan officers take these dimensions into account less frequently than conscientiousness and extraversion. Consequently, hypotheses one, four, and five are validated, but with a smaller amount of compelling evidence. Additionally, in thirty of the two hundred documents the payment morality, categorized by honesty-humility, was examined with the use of financial indicators. Therefore, the dimension of honest-humility is assessed through a combination of soft information and hard information.

The agreeableness dimension made up only 1.1% of the personality theme. Agreeableness is rarely mentioned in the reports, indicating that it does not significantly influence the loan professionals' perceptions of the entrepreneur. In the instances where the perception of agreeableness was mentioned by the loan officer, it was discussed as a positive factor. Therefore, the qualitative analysis findings support hypothesis four. In conclusion, the findings validate all six hypotheses regarding the association between perceptions of entrepreneurs' personality traits and the gut feeling they evoke.

Negative perceptions were mostly reported within the theme of personality. Specifically, there were five negative cases in each of the categories of unspecified traits, honesty-humility, and conscientiousness. Additionally, there was one negative perception reported for each of the categories of grit, extraversion, and emotionality. Negative opinions arose from the perception of the entrepreneur either having a negative trait or exhibiting an excess of a generally positive trait. For example, negative opinions of the honesty-humility dimension could arise if the entrepreneur is perceived as arrogant or overly honest, resulting in frequent conflicts. In the conscientiousness category, negative descriptions included being disorganized or a control freak. In the unspecified category, detailed reasons for why the entrepreneur's personality is thought to lower their expected chance of success are often lacking.

Social capital, although it has the fewest subthemes, emerged as the most frequently reported category. Within the entire coding scheme, weak ties and strong ties were the most frequently and second most frequently reported subthemes, respectively. A distinction was made between strong ties and weak ties. This distinction is observed both in the literature and in this dataset (Davidsson & Honig, 2003; Granovetter, 2005). Weak ties comprised approximately 60% of the social capital category, with strong ties accounting for around 40%. Examples of weak ties are having a large network in general, being acquainted with many potential customers and fellow entrepreneurs, and knowing many industry contacts who can provide information. Weak ties can be exemplified by coming from a supportive family of entrepreneurs, receiving financial support from a wealthy family, and having a spouse who handles administrative tasks. Since most reports discussed guarantors for a loan, these descriptions were excluded. Therefore, the quotes only include information about strong ties that increase the chances of becoming a successful entrepreneur, rather than those that lower the financial institution's risk of loan defaults. Both strong and weak ties were described as factors that improve the entrepreneur's chances of success and were seen as indicators of credibility. Therefore, the perception of large social capital positively impacts the loan officer’s opinion. Subsequently, both hypotheses seven and eight are supported.

During the analysis of the first sample, the theme of entrepreneurial passion emerged, creating the least frequently reported category. The first subtheme includes expressions that describe the entrepreneur as passionate, very enthusiastic about their new business, or as fulfilling their dream. Chen and colleagues (2019) refer to this category as “verbal cues”. This is the subtheme that most explicitly refers to passion, while also comprising almost half of the entrepreneurial passion theme. Initially, preparedness and grit were seen as distinct aspects, but they were later found to also be part of the entrepreneurial passion theme (Chen et al., 2009; Mueller et al., 2017). Descriptions of preparedness include being knowledgeable about a thoroughly researched plan, having already made business preparations, and presenting a neat, well-thought-out plan. Examples of grit include being driven and determined to persevere. As mentioned earlier, some of these behaviors may be related to traits like extraversion and conscientiousness (Lee & Ashton, 2004). Therefore, it was important to make a distinction. Quotes under the theme of personality refer to descriptions of the overall personality of the nascent entrepreneur, while quotes under the theme of entrepreneurial passions refer to their behavior and attitude towards the new business. Verbal cues and preparedness emerged a comparable number of times, while grit was reported somewhat less frequently. Each of the three subthemes was viewed positively and mentioned as a justification for expressing trust in the entrepreneurs’ capabilities. Therefore, support for hypotheses nine, ten, and eleven is found, although support for hypothesis eleven is somewhat scarcer.

Understanding of the dataset and the descriptions grew over time. Therefore, the first round of analysis was useful as a training round, and to gain deeper insights to add and redefine the themes as described by Hsieh and Shannon (2005). The final frequency counts displayed in table 2 come from the second sample. To ensure consistency, the sample was revisited after the initial coding.

Table 2. Content analysis results

Theme	Subtheme	Count	%
Personality	Honesty-humility	26	
	Emotionality	22	
	Extraversion	63	
	Agreeableness	3	
	Conscientiousness	53	
	Openness	28	
	Miscellaneous	0	
	Unspecified	74	
	Total	269	42.56
Social capital	Strong ties	95	
	Weak ties	137	
	Total	232	36.71
Passion	Verbal cues	50	
	Preparedness	48	
	Grit	33	
	Total	131	20.73
Total		632	100

5. DISCUSSION

These results provide an opportunity to discuss the conclusions concerning the research question: “What perceived traits of SME founders affect creditworthiness evaluations of opaque borrowers?”. To answer this question, a mixed-method approach was employed, combining quantitative and qualitative analyses. The quantitative segment utilized Latent Dirichlet Allocation to identify prevalent topics within a dataset of upwards of 14,000 loan evaluation reports compiled by Qredits. This was followed by a detailed qualitative content analysis that provided a deeper understanding of the context of the soft information and how it is used by loan officers in their assessments.

The Latent Dirichlet Allocation revealed several key themes that are pertinent to the research question. Notably, it indicates that loan professionals gather information through observation to form opinions. This is mainly observed in topic number five, but key words supporting this finding also appear in topic nineteen and scattered across other topics not directly relevant to the research question. Subjective perceptions of the entrepreneur, as described in this finding, fall under the category of soft information (Huang & Pearce, 2015; Liberti & Petersen, 2019). The LDA shows that loan officers use this soft information to form opinions that influence their lending decisions. Therefore, it can be concluded that soft information about the entrepreneur is indeed considered during the decision-making process when assessing the creditworthiness of SMEs.

Moreover, indicators of social capital can be observed in the outcome of the Latent Dirichlet Allocation. Notably, indicators of social capital, such as strong and weak ties, emerged as influential factors in the assessment process. Qualitative analysis was necessary in order to understand whether these factors positively or negatively influenced perceptions of the entrepreneur before a conclusion regarding hypotheses seven and eight could be drawn. In the qualitative analysis, strong and weak ties were the most frequently reported subcategories. Both strong and weak ties were recognized as enhancing the entrepreneur's credibility and success chances, thereby positively influencing loan officers' opinions of the entrepreneur. As a result, support for hypotheses seven and eight was found. In conclusion, the perception of substantial social capital in an entrepreneur positively influences the loan officer's gut feeling during the loan assessment process.

The LDA presented terms hinting at personality traits, but not enough evidence was found to draw any concrete conclusions. The presence of terms related to payment morality hinted at the role of personality dimensions, particularly honesty-humility, in creditworthiness evaluations, though further qualitative context was required to deepen the understanding. The qualitative analysis proved to be far more effective in providing information regarding personality traits. Personality emerged as the most significant category, with conscientiousness and extraversion being the most frequently associated with positive lending decisions. Other traits like honesty-humility, openness, and emotionality also played roles, albeit less frequently. Therefore, all hypotheses concerning personality traits could be supported. This underscores the broader understanding that the subjective observation of personality traits can influence the loan-officers gut feeling.

Since the LDA revealed no indicators of entrepreneurial passion, the discussion of this theme depends entirely on the qualitative analysis. Even in the qualitative analysis, the theme of entrepreneurial passion was reported the least number of times. Though reported less frequently, loan officers also described passion as a positive indicator. All three subthemes—verbal cues, preparedness, and grit—contributed to a favorable perception of the entrepreneur. Therefore, support was found for the last three hypotheses. Therefore, the loan officer's perception of entrepreneurial passion has a positive impact of their gut feeling during the loan assessment process.

Overall, the study validates the significant influence of subjective perceptions of personality traits, social capital, and entrepreneurial passion on the decision-making process of loan officers when assessing the creditworthiness of opaque borrowers. The findings underscore the importance of soft information, suggesting that high levels of honesty-humility, extraversion, conscientiousness, openness, substantial social capital, and visible entrepreneurial passion positively impact loan officers' gut feelings and their subsequent lending decisions. Conversely, emotionality negatively influences these feelings, while agreeableness does not play a significant role.

Personality traits, social capital, and entrepreneurial passion all influence the perception of loan officers and contribute to entrepreneurial success. Understanding how these traits interact can help identify potential synergies and correlations. Studies suggest that extraverted individuals are more likely to develop significant social capital, aiding their entrepreneurial success (Baron & Markman, 2000). Their ability to connect with others, build relationships, and leverage networks can enhance their perceived creditworthiness. Additionally, there is a relationship between passion, extraversion, and social networks. Chen et al. (2009) discovered that passionate entrepreneurs were more expressive, a characteristic of extraversion (Lee & Ashton, 2004), which aids in acquiring social capital. Preparedness, an essential element of entrepreneurial passion, involves thorough planning and meticulous execution, traits that are linked to conscientiousness (Lee & Ashton, 2004). Therefore, it can be concluded that extraversion and conscientiousness, social capital, and entrepreneurial passion are interconnected. Recognizing these connections provides a more comprehensive understanding of how various traits influence entrepreneurial success. Loan officers may be influenced by these relationships when forming impressions. For instance, they may perceive extraverted individuals as more expressive and engaging, which could translate to a perception of higher passion and enthusiasm for their business. Consequently, the interconnectedness of these traits can enhance the loan officer's overall positive impression, increasing the likelihood of favorable opinions of the entrepreneur.

6. IMPLICATIONS

6.1 Theoretical implications

The current literature recognizes that gut feelings play a crucial role in early-stage investment decisions. However, it falls short in identifying the specific soft criteria that shape these intuitions. Similarly, the subjective perception of loan officers is widely accepted as a key factor in the loan approval process. Ciampi et al. (2021) emphasize the importance of investigating the non-financial attributes of SMEs to improve lending decision quality. They highlight that the unique characteristics of emerging entrepreneurs and their influence on the perceptions of financial institution professionals have not been thoroughly examined. This study explored what specific traits conveyed by soft information may affect the gut-feeling of those making investment decisions. It offers an indication that certain personality traits, social capital, and entrepreneurial passion may be among those traits that positively influence gut feeling when perceived.

Studies have demonstrated that specific personality traits, social capital, and entrepreneurial passion boost entrepreneurial success (Brandstätter et al., 2011; Mueller et al., 2017; Murnieks et al., 2014; Murnieks et al., 2020; Stam et al., 2014). The hypotheses were developed on the relationship between these traits and entrepreneurial success demonstrated in previous research. However, it was uncertain whether loan officers believed these traits enhanced the likelihood of a nascent entrepreneur's success and if they evoked a positive impression of the entrepreneur. The findings support the statement that the perception of these traits indeed leads to favorable opinions of the entrepreneur. Moreover, some studies have demonstrated that expressions of passion evoke positive gut feelings (Chen et al., 2009). The findings from these studies support this result.

By examining how subjective observations of traits influence opinions, this study enhances the broader literature on behavioral finance by highlighting the psychological and social dimensions of financial decision-making. This perspective can inform a more expansive theoretical model of credit assessment that integrates qualitative factors alongside traditional financial metrics (Huang & Pearce, 2015). Such integration offers a more comprehensive framework for understanding loan officers' decision-making processes and can contribute to the development of more robust models for credit risk.

6.2 Practical implications

The findings of this research have practical implications for both SME founders and loan officers. For entrepreneurs it can be beneficial to understand the soft criteria that influence investor decisions. By acknowledging which personal attributes may affect the outcome of their application, entrepreneurs can adjust their behavior to achieve more favorable outcomes. They could strategically highlight the traits that positively impact the evaluators gut feeling (Lavi & Yaniv, 2023). SME founders can strategically highlight traits such as conscientiousness and extraversion during loan applications, for example by displaying diligence and expressing liveliness. Moreover, they could emphasize strong professional connections, resources made available through family members, and prominence in their community. Additionally, focusing on being better prepared and expressing passion for the business and entrepreneurship during the meeting could improve the opinion of the loan professional. Research shows that people can change their personality traits through conscious efforts, both with and without professional intervention like therapy (Magidson et al., 2014). As a result, founders could even purposefully cultivate personality traits that could lead to greater success securing funding, and therefore improve their chances of becoming a successful entrepreneur.

Incorporating soft information, such as personality traits including integrity, into the credit assessment process has been demonstrated to enhance default prediction rates (Baklouti & Bouri, 2014; Goel & Rastogi, 2023; Rauch & Frese, 2007; Zhao et al., 2010). These qualitative factors often provide crucial insights into an entrepreneur's reliability and potential for business success, insights that traditional financial metrics alone may not capture. By integrating these elements, loan officers can uncover both strengths and potential risks that might otherwise be missed, leading to more accurate assessments and better prediction of defaults. Understanding which aspects of soft information influence personal opinions can help loan officers recognize and mitigate their biases. For example, being aware that traits like conscientiousness and extraversion are positively perceived can encourage officers to look for objective evidence of these traits rather than relying solely on gut feelings. This awareness can lead to more standardized and fair evaluations, as officers can focus on specific, observable behaviors and attributes instead of vague impressions. By systematically including soft information, loan officers can form more comprehensive and nuanced views of applicants.

7. LIMITATIONS AND FUTURE RESEARCH RECOMMENDATIONS

7.1 Limitations

While this study provides valuable insights into the influence of soft information on lending decisions for SMEs, it is important to acknowledge several limitations that may impact the findings and their generalizability. These limitations highlight areas for future research and improvements in methodology. One key limitation of LDA is the need to define the number of topics and filter an appropriate number of words from the dataset, both of which significantly impact the outcome. There is no universally accepted strategy that fits every situation. Determining suitable parameters involves a process of trial and error (Blei et al., 2003). While coherence and perplexity scores can serve as guidelines, the final decision still requires human judgment. Therefore, it is impossible to choose a set of parameters that can be objectively considered the best or the only possible choice. Moreover, LDA assumes that topics are independent and that documents always have a smooth mixture of topics, which may not always reflect reality. In real-world data, topics can be interrelated or hierarchical, leading to topics that are less meaningful or interpretable in certain situations. In reality, documents can contain a differing number of topics. Finally, LDA assumes that the distribution of topics in a document is insignificant, based on the bag-of-words assumption. This may not be valid for all documents or datasets, leading to less optimal results (Blei et al., 2003).

The qualitative analysis relies on the interpretation of texts, which can introduce subjectivity. Different researchers might categorize and interpret the data differently. Ensuring consistency in coding across large datasets can be challenging, potentially leading to variations in the analysis results. This limitation was amplified by the lack of a second coder to ensure consistency and the nature of the data (Zhang & Wildemuth, 2017). Soft information is inherently subjective, making it difficult to ensure consistency and comparability in assessments (Liberti & Petersen, 2019). Though the literature has defined aspects such as social capital and entrepreneurial passion, the interpretation of the descriptions of loan officers remains subjective. Additionally, though the HEXACO model is one of the most measures of personality available, it is still not a standardized measure that is accepted among all scholars in the field (Lee & Ashton, 2007). Additionally, loan officers' descriptions of traits can be vague and open to interpretation, which can complicate the analysis and lead to ambiguous findings.

The limitations associated with the dataset and sampling methods used in this study are crucial to consider, as they may affect the representativeness and comprehensiveness of the findings. Due to time and resource constraints, the analysis was conducted on a subset of the available reports. Analyzing only a portion of the dataset may not capture all relevant patterns and variations, potentially leading to incomplete or biased conclusions. Moreover, the results are highly dependent on the dataset from Qredits. The dataset primarily includes loan reports from a specific period and institution, which may not capture the full range of factors influencing lending decisions across different settings and times. Therefore, the results may not be generalizable to other financial institutions, different cultural contexts, different clientele, or different time periods.

Lastly, mixed-method and iterative approach of the methods comes with its own limitations. Combining quantitative and qualitative methods can introduce complexity and potential biases. The transition from quantitative to qualitative analysis requires careful interpretation to ensure coherence. Additionally, the iterative process used to refine the analysis and coding may introduce biases based on the researcher's evolving understanding and interpretations.

7.2 Future research

Building on the limitations identified in this study, several future research directions can be pursued to enhance the understanding and robustness of findings. Firstly, other quantitative techniques that account for hierarchical and related topics, as well as word order and context, can be explored to improve the interpretability of results. Second, standardized measures and frameworks for assessing soft information could be developed to enhance consistency and comparability across studies. Third, the rigor of the qualitative analysis could be improved. Utilizing multiple coders and conducting inter-rater reliability checks can enhance the consistency and reliability of qualitative content analysis, particularly when there is sufficient time to analyze a larger sample. This could also help in uncovering additional patterns and factors. They could use triangulation methods to validate qualitative findings through multiple data sources and analytical approaches (Zhang & Wildemuth, 2017). Fourth, the scope of the dataset could be expanded to represent a wider range of financial institutions and clientele. Incorporating data from multiple financial institutions across different regions and during different time periods could enhance the generalizability of the findings.

This paper explored the soft information influencing a loan officer's perception of the entrepreneur. However, the lending decision is not solely based on the loan officer's subjective perception. Other factors, most notably hard information such as credit scores, play a significant role in the final decision regarding the loan disbursement and lending terms. Currently, it is unknown how much influence soft information, including the factors discussed in this thesis, has on the final lending decision. Further research could investigate the correlation between soft information and loan disbursement and lending terms, to determine to what degree the loan officer's perception of the entrepreneur affects the final decision.

To deepen our understanding of loan officers' decision-making processes, it could be beneficial to explore the psychological and behavioral mechanisms that underpin their evaluations, including the role of biases and heuristics. Since the dataset only shows the conclusions that the loan officers arrived at, it does not provide comprehensive insight into their cognitive processes. For example, it would be insightful to gain knowledge about their observations and how they process these observations to arrive at their conclusions. This exploration can provide valuable insights into the cognitive processes that influence lending decisions and identify areas where improvements can be made to enhance objectivity and fairness. Loan officers, like all humans, are susceptible to cognitive biases that can influence their perceptions. These biases can affect how loan officers interpret soft information and make lending decisions, especially when little hard information is available (Campbell et al., 2019). Heuristics, while helpful for efficiency, can also lead to systematic errors, underlining the importance of understanding the cognitive processes involved. However, little is currently known about the potential specific biases of loan officers. Further research into this topic could provide more insights about the objectivity and fairness of loan officers, and whether their subjective opinions positively impact loan decisions.

Future research could delve into the intricate relationships between specific traits discussed in this thesis to provide a more nuanced understanding of how specific traits can correlate or interact to influence lending decisions. These relationships have been previously described, but a brief summary will be provided again. Research indicates that extraverts are more likely to build extensive social capital, aiding entrepreneurial success (Baron & Markman, 2000). Extraversion, linked to expressiveness and social networks, helps secure social capital (Chen et al., 2009). Additionally, the behavioral aspect of preparedness, crucial for entrepreneurial passion, is tied to conscientiousness through thorough planning and execution. Future research could examine these relationships further and investigate potential syntheses, providing deeper insights into how these combined traits influence loan officers' evaluations and lending decisions.

8. CONCLUSION

Based on the research conducted, the study concludes that subjective perceptions of personality traits, social capital, and entrepreneurial passion significantly influence loan officers' decisions when assessing the creditworthiness of opaque borrowers. The findings highlight that traits such as high levels of honesty-humility, extraversion, conscientiousness, and openness positively impact loan officers' gut feelings, thereby enhancing the likelihood of loan approval. Additionally, substantial social capital, indicated by strong and weak ties, and visible entrepreneurial passion, including preparedness and grit, also favorably affect lending decisions. Conversely, emotionality tends to negatively influence these perceptions, while agreeableness appears to play an insignificant role. Overall, the study underscores the critical role of soft information in the SME lending process, providing valuable insights into the subjective criteria used by loan officers.

9. REFERENCES

Ashton, M. C., & Lee, K. (2007). Empirical, theoretical, and practical advantages of the HEXACO model of personality structure. *Personality and Social Psychology Review*, *11*(2), 150–166. https://doi.org/10.1177/1088868306294907

Baklouti, I., & Bouri, A. (2014). The loan officer's subjective judgment and its role in microfinance institutions. *Int. J. Risk Assessment and Management*, *17*(3). https://doi.org/https://doi.org/10.1504/ijram.2014.062778

Baron, R. A., & Markman, G. D. (2000). Beyond social capital: How social skills can enhance entrepreneurs' success. *Journal of Small Business Management*, *14*, 106–116. https://doi.org/10.5465/AME.2000.2909843

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. In *Journal of Machine Learning Research* (Vol. 3).

Block, J. (1995). A Contrarian View of the Five-Factor Approach to Personality Description. In *Psychological Bulletin* (Vol. 117, Issue 2).

Boddy, C. R. (2016). Sample size for qualitative research. *Qualitative Market Research*, *19*(4), 426–432. https://doi.org/10.1108/QMR-06-2016-0053

Brandstätter, H. (2011). Personality aspects of entrepreneurship: A look at five meta-analyses. *Personality and Individual Differences*, *51*(3), 222–230. https://doi.org/10.1016/j.paid.2010.07.007

Campbell, D., Loumioti, M., & Wittenberg-Moerman, R. (2019). Making sense of soft information: interpretation bias and loan quality. *Journal of Accounting and Economics*, *68*(2–3). https://doi.org/10.1016/j.jacceco.2019.101240

Chen, X.-P., Yao, X., & Kotha, S. (2009). Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions. *Academy of Management Journal*, *52*(1), 199–214. https://doi.org/https://doi.org/10.5465/amj.2009.36462018

Chen, Y., Huang, R. J., Tsai, J., & Tzeng, L. Y. (2015). Soft Information and Small Business Lending. *Journal of Financial Services Research*, *47*(1), 115–133. https://doi.org/10.1007/s10693-013-0187-x

Ciampi, F., Giannozzi, A., Marzi, G., & Altman, E. I. (2021). Rethinking SME default prediction: a systematic literature review and future perspectives. *Scientometrics*, *126*(3), 2141–2188. https://doi.org/10.1007/s11192-020-03856-0

Cornée, S. (2019). The Relevance of Soft Information for Predicting Small Business Credit Default: Evidence from a Social Bank. *Journal of Small Business Management*, *57*(3), 699–719. https://doi.org/10.1111/jsbm.12318

Costa, P. T., & McCrae, R. R. (1995). Solid ground in the wetlands of personality: A reply to Block. *Psychological Bulletin*, *117*(2), 216–220. https://doi.org/10.1037/0033-2909.117.2.216

Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing*, *18*(3), 301–331. https://doi.org/10.1016/S0883-9026(02)00097-6

de Vries, R. E., Ashton, M. C., & Lee, K. (2009). De zes belangrijkste persoonlijkheidsdimensies en de HEXACO Persoonlijkheidsvragenlijst. *Gedrag En Organisatie*, *22*(3), 232–274. https://doi.org/10.5117/2009.022.003.004

de Vries, R. E., & Born, M. P. (2013). De vereenvoudigde HEXACO: Persoonlijkheidsvragenlijst en een additioneel interstitieel Proactiviteitsfacet. *Gedrag En Organisatie*, *26*(2), 223–245. https://doi.org/10.5117/2013.026.002.223

Denny, M. J., & Spirling, A. (2018). Text Preprocessing for Unsupervised Learning: Why It Matters, When It Misleads, and What to Do about It. *Political Analysis*, *26*(2), 168–189. https://doi.org/10.1017/pan.2017.44

Eurostat. (2023). *Key figures on European business 2023 edition*. Publications Office of the European Union. https://doi.org/10.2785/873469

Gheyle, N., & Jacobs, T. (2017). *Content Analysis: a short overview Unpacking (de)politicization View project Trade policy with the lights on. The origins, dynamics, and consequences of the politicization of TTIP View project Content Analysis: a short overview*. https://doi.org/10.13140/RG.2.2.33689.31841

Goel, A., & Rastogi, S. (2023). Understanding the impact of borrowers' behavioural and psychological traits on credit default: review and conceptual model. In *Review of Behavioral Finance* (Vol. 15, Issue 2, pp. 205–223). Emerald Publishing. https://doi.org/10.1108/RBF-03-2021-0051

Golberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist*, *48*(1), 26–34. https://doi.org/10.1037/0003-066X.48.1.26

Granovetter, M. (2005). The Impact of Social Structure on Economic Outcomes. *Journal of Economic Perspectives*, *19*(1), 33–50. https://doi.org/10.1257/0895330053147958

Grunert, J., & Norden, L. (2012). Bargaining power and information in SME lending. *Small Business Economics*, *39*(2), 401–417. https://doi.org/10.1007/s11187-010-9311-6

Honnibal, M., Montani, I., van Landeghem, S., & Boyd, A. (2020). *spaCy: Industrial-strength Natural Language Processing in Python*. https://doi.org/10.5281/zenodo.1212303

Hsieh, H. F., & Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research*, *15*(9), 1277–1288. https://doi.org/10.1177/1049732305276687

Huang, L. (2018). The role of investor gut feel in managing complexity and extreme risk. *Source: The Academy of Management Journal*, *61*(5), 1821–1847. https://doi.org/10.2307/26528923

Huang, L., & Pearce, J. L. (2015). Managing the Unknowable: The Effectiveness of Early-stage Investor Gut Feel in Entrepreneurial Investment Decisions. *Administrative Science Quarterly*, *60*(4), 634–670. https://doi.org/10.1177/0001839215597270

Jacobi, C., van Atteveldt, W., & Welbers, K. (2016). Quantitative analysis of large amounts of journalistic texts using topic modelling. *Digital Journalism*, *4*(1), 89–106. https://doi.org/10.1080/21670811.2015.1093271

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications*, *78*(11), 15169–15211. https://doi.org/10.1007/s11042-018-6894-4

Kibiswa, N. K. (2019). Directed Qualitative Content Analysis (DQlCA): A Tool for Conflict Analysis. *Qualitative Report*, *24*(8), 2059–2079. https://doi.org/10.46743/2160-3715/2019.3778

Koestner, R., & Losier, G. F. (1996). Distinguishing Reactive versus Reflective Autonomy. *Journal of Personality*, *64*(2), 465–494. https://doi.org/10.1111/j.1467-6494.1996.tb00518.x

Lau, J. H., Newman Google, D., & Baldwin, T. (2014). Machine Reading Tea Leaves: Automatically Evaluating Topic Coherence and Topic Model Quality. In S. Wintner, S. Goldwater, & S. Riezler (Eds.), *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics* (pp. 530–539). Association for Computational Linguistics. https://doi.org/10.3115/v1/E14-1056

Lavi, A. H., & Yaniv, E. (2023). The Effect of Entrepreneur Attributes on Investment Evaluations in Pitch Competitions. *Journal of Entrepreneurship*, *32*(1), 39–74. https://doi.org/10.1177/09713557231160325

Lee, K., & Ashton, M. C. (2004). Psychometric properties of the HEXACO personality inventory. *Multivariate Behavioral Research*, *39*(2 SPEC. ISS.), 329–358. https://doi.org/10.1207/s15327906mbr3902_8

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1–41. https://doi.org/10.1093/rcfs/cfy009

Magidson, J. F., Roberts, B. W., Collado-Rodriguez, A., & Lejuez, C. W. (2014). Theory-driven intervention for changing personality: Expectancy value theory, behavioral activation, and conscientiousness. *Developmental Psychology*, *50*(5), 1442–1450.

McAdams, D. P. (1992). The Five-Factor Model *In* Personality: A Critical Appraisal. *Journal of Personality*, *60*(2), 329–361. https://doi.org/10.1111/j.1467-6494.1992.tb00976.x

McCrae, R. R. (2020). The Five-Factor Model of Personality: Consensus and Controversy. In *The Cambridge Handbook of Personality Psychology* (pp. 129–141). Cambridge University Press. https://doi.org/10.1017/9781108264822.013

McCrae, R. R., & Costa, P. T. (1997). Personality Trait Structure as a Human Universal. *American Psychologist*, *52*(5), 509–516. https://doi.org/10.1037/0003-066X.52.5.509

Mccrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McKinney, W. (2010). Data structures for statistical computing in Python. In S. van der Walt & J. Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (pp. 56–61).

Ministerie van Algemene Zaken. (2020, April 28). *Coronavirus: overbruggingskrediet gericht op startups en scale-ups vanaf 29 april beschikbaar*. Nieuwsbericht | Rijksoverheid.Nl. https://www.rijksoverheid.nl/actueel/nieuws/2020/04/25/coronavirus-overbruggingskrediet-gericht-op-startups-en-scale-ups-vanaf-29-april-beschikbaar

Mueller, B. A., Wolfe, M. T., & Syed, I. (2017). Passion and grit: An exploration of the pathways leading to venture success. *Journal of Business Venturing*, *32*(3), 260–279. https://doi.org/10.1016/j.jbusvent.2017.02.001

Murnieks, C. Y., Klotz, A. C., & Shepherd, D. A. (2020). Entrepreneurial motivation: A review of the literature and an agenda for future research. In *Journal of Organizational Behavior* (Vol. 41, Issue 2, pp. 115–143). John Wiley and Sons Ltd. https://doi.org/10.1002/job.2374

Murnieks, C. Y., Mosakowski, E., & Cardon, M. S. (2014). Pathways of Passion: Identity Centrality, Passion, and Behavior Among Entrepreneurs. *Journal of Management*, *40*(6), 1583–1606. https://doi.org/10.1177/0149206311433855

OECD. (2024). *Financing SMEs and Entrepreneurs 2024*. OECD. https://doi.org/10.1787/fa521246-en

Pirolo, L., & Presutti, M. (2010). The impact of social capital on the start-ups' performance growth. *Journal of Small Business Management*, *48*(2), 197–227. https://doi.org/10.1111/j.1540-627X.2010.00292.x

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.1037/a0014996

Portes, A. (1998). Social Capital: Its Origins and Applications in Modern Sociology. In *Annu. Rev. Sociol* (Vol. 24). https://doi.org/10.1146/annurev.soc.24.1.1

Qredits. (n.d.). *Proces aanvraag tot aflossing | Meer dan alleen krediet*. Retrieved June 16, 2024, from https://www.qredits.nl/zakelijk-krediet/proces-aanvraag-tot-aflossing

Qredits. (2022). *Sociaal Jaarverslag 2022*. https://online.flippingbook.com/view/176126496/8/

Rauch, A., & Frese, M. (2007a). Let's put the person back into entrepreneurship research: A meta-analysis on the relationship between business owners' personality traits, business creation, and success. *European Journal of Work and Organizational Psychology*, *16*(4), 353–385. https://doi.org/10.1080/13594320701595438

Rauch, A., & Frese, M. (2007b). Let's put the person back into entrepreneurship research: A meta-analysis on the relationship between business owners' personality traits, business creation, and success. *European Journal of Work and Organizational Psychology*, *16*(4), 353–385. https://doi.org/10.1080/13594320701595438

Řehůřek, R., & Sojka, P. (2010). Software Framework for Topic Modelling with Large Corpora. *In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, 45–50.

Rosner, F., Hinneburg, A., Röder, M., Nettling, M., & Both, A. (2013, December). Evaluating topic coherence measures. *Topic Models: Computation, Application and Evaluation*.

Sandelowski, M. (1995). Sample size in qualitative research. *Research in Nursing & Health*, *18*(2), 179–183. https://doi.org/10.1002/nur.4770180211

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: exploring its conceptualization and operationalization. *Quality and Quantity*, *52*(4), 1893–1907. https://doi.org/10.1007/s11135-017-0574-8

Stam, W., Arzlanian, S., & Elfring, T. (2014). Social capital of entrepreneurs and small firm performance: A meta-analysis of contextual and methodological moderators. *Journal of Business Venturing*, *29*(1), 152–173. https://doi.org/10.1016/j.jbusvent.2013.01.002

Zhang, Y., & Wildemuth, B. M. (2017). Qualitative Analysis of Content. In *Applications of social research methods to questions in information and library science* (2nd ed., pp. 318–329). Libraries Unlimited.

Zhao, H., Seibert, S. E., & Lumpkin, G. T. (2010). The relationship of personality to entrepreneurial intentions and performance: A meta-analytic review. In *Journal of Management* (Vol. 36, Issue 2, pp. 381–404). https://doi.org/10.1177/0149206309335187Coding scheme

10. APPENDIX

10.1 Correlation table with two-sided t-test

Column	Number of quotations	t-statistic	p-value
Capital Requirement	0.1266	1.7954	0.0741
Disbursed	0.0967	1.3665	0.1733
Amount disbursed	0.1287	1.8258	0.0694
Credit score	-0.0358	-0.5041	0.6148
Investment into new business	0.1747	2.4973	0.0133*
Acquisition	0.0075	0.1051	0.9164
Refinancing	-0.2567	-3.7371	0.0002*
Corona credit	0.0292	0.4117	0.6810
Face-to-face meeting	0.1732	2.4747	0.0142*

* $p < 0.05$

10.2 Coding scheme

Themes	Subthemes	Operational Defintions
Personality	Unspecified	Descriptions of the entrepreneur's personality that influences their ability to be a successful entrepreneur and pay off loans, but where the personality traits are not described in detail.
	Honesty-Humility	Writing describing the entrepreneur as having personality traits that fall under the honesty-humility dimension that may affect business outcomes and loan repayment.
	Emotionality	Writing describing the entrepreneur as having personality traits that fall under the emotionality dimension that may affect business outcomes and loan repayment. Traits indicating stability are considered to be positive observation, whereas traits indicating neuroticism are considered to be negatives.
	Extraversion	Writing describing the entrepreneur as having personality traits that fall under the extraversion dimension that may affect business outcomes and loan repayment.
	Agreeableness	Writing describing the entrepreneur as having personality traits that fall under the agreeableness dimension that may affect business outcomes and loan repayment.
	Conscientiousness	Writing describing the entrepreneur as having personality traits that fall under the conscientiousness dimension that may affect business outcomes and loan repayment.
	Openness for Experiences	Writing describing the entrepreneur as having personality traits that fall under the openness for experiences dimension that may affect business outcomes and loan repayment.
	Miscellaneous	Descriptions of the entrepreneur's personality traits that may affect business outcomes but do not explicitly fall under any HEXACO dimensions.
Social Capital	Strong Ties	Descriptions of the close circle of the entrepreneur and its ability to affect business outcomes. For example: parents, partner, spouse, siblings, close friends.
	Weak Ties	Descriptions of the larger social network of the entrepreneur and its ability to affect business outcomes. For example: customer base, industry contacts, powerful weak ties.
Entrepreneurial Passion	Verbal Cues	Verbal cues that indicate that the entrepreneur displayed passion during the meeting. For example: explicit mentions of passion, entrepreneurs fulfilling their dream, and showing enthusiasm about their new venture.
	Preparedness	Mentions and descriptions of the entrepreneur being well-prepared for their new business or the meeting with the loan officer.
	Grit	Mentions and descriptions of the entrepreneur exhibiting grit. The loan officer expects that the entrepreneur is likely to show perseverance to long-term goals and show persistence to overcome challenges.