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Administrative Sciences

Provided in Cooperation with:

MDPI – Multidisciplinary Digital Publishing Institute, Basel

Suggested Citation: Saleh, Lina; Semaan, Samer (2024) : The potential of ai in performing financial sentiment analysis for predicting entrepreneur survival, Administrative Sciences, ISSN 2076-3387, MDPI, Basel, Vol. 14, Iss. 9, pp. 1-12,
<https://doi.org/10.3390/admsci14090220>

This Version is available at:

<https://hdl.handle.net/10419/321034>

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Article

The Potential of AI in Performing Financial Sentiment Analysis for Predicting Entrepreneur Survival

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Abstract: The aim of this study is to investigate the potential of ChatGPT in analyzing the financial sentiment analysis of entrepreneurs. Sentiment analysis involves detecting if it is positive, negative, or neutral from a text. We examine several prompts on ChatGPT-4, ChatGPT-4.0, and LeChat-Mistral and compare the results with FinBERT. Then, we examine the correlation between scores given by both tools with the type, size, and age of the company. The results have shown that scores given by FinBERT are mostly significant and positively correlated with sustainable variables. By sharing these results, we hope to stimulate future research and advances in the field of financial services, particularly bank loans.

Keywords: sentiment analysis; entrepreneur sustainability; entrepreneur death; AI; LLM

1. Introduction

Lebanon is experiencing a multilevel crisis in several areas: health, economic, social, and political. The crisis is forcing Lebanese entrepreneurs to adapt their business models and rethink their internal organizations to survive. Accordingly, we have asked entrepreneurs how they are adapting to the crisis. Historical data were collected in 2021 and 2024 with a focus on the entrepreneur and their sentiments through qualitative financial data. We aim to predict the performance of ChatGPT in sentiment analysis and to compare them to transformer-trained models, mainly FinBERT. Based on the results, we use sentiment scores (neutral, positive, and negative) in entrepreneur sustainability prediction models.

Sentiment analysis, also called opinion mining, involves extracting and identifying opinions that individuals express about specific topics. These opinions and sentiments significantly influence decision-making processes among various stakeholders. Understanding the sentiments of entrepreneurs and forecasting their actions has become essential through sentiment analysis. This analysis offers valuable insights into the collective mindset of entrepreneurs, aiding in more informed and strategic decision-making. As pretrained large language models (LLMs) like ChatGPT continue to be integrated into practical applications, our findings provide valuable insights that can assist developers and researchers in effectively leveraging these models' potential.

LLMs's advanced natural language processing capabilities present significant potential for innovation in entrepreneurial sentiment analysis. Despite its significant implications, this area remains largely unexplored, providing ample opportunity for future research and development. This research advances the understanding of the potential of generative AI in specialized financial sentiment analysis tasks and their practical applications. To our knowledge, this is the first study that evaluates LLMs capabilities specifically for the financial sentiment of entrepreneurs. Therefore, our main two research questions are as follows:



Citation: Saleh, Lina, and Samer Semaan. 2024. The Potential of AI in Performing Financial Sentiment Analysis for Predicting Entrepreneur Survival. *Administrative Sciences* 14: 220. <https://doi.org/10.3390/admsci14090220>

Received: 23 July 2024

Revised: 29 August 2024

Accepted: 29 August 2024

Published: 13 September 2024



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Question 1: *What is the potential of ChatGPT compared to FinBERT in generating sentiment analysis?*

Question 2: *Could sentiment analysis predict entrepreneurs sustainably?*

A standard sentiment analysis system follows several steps: first, it ingests documents in multiple formats (such as PDF, XLS, and Word). The documents are then converted to text and pre-processed using linguistic techniques like stemming, tokenization, part-of-speech tagging, entity extraction, and relation extraction. Finally, the system uses lexicons and linguistic resources to tag the processed text with sentiment labels (Feldman 2013). Traditionally, financial sentiment analysis relied on manually curated lexicons and simple machine learning algorithms (Schumaker and Hsinchun 2009). However, advances in Natural Language Processing (NLP) have introduced more complex methods. Models specifically designed for financial contexts, such as FinBERT (Liu et al. 2021), have greatly enhanced the precision and reliability of sentiment analysis.

LLMs and related AI advancements have shown considerable promise in various fields, including financial sentiment analysis. GPT, developed by OpenAI, is a sophisticated language model trained on extensive datasets, enabling it to understand and reproduce human language patterns with high accuracy. ChatGPT offers significant potential for improving applications that analyze the financial sentiments of entrepreneurs. By utilizing its advanced natural language understanding capabilities, financial institutions can enhance the accuracy and depth of sentiment analysis. The ability to grasp and interpret complex language patterns allows for more effective analysis of large, unstructured datasets. Enhanced sentiment analysis through LLMs can lead to better decision-making in investment strategies, risk management, and entrepreneurial support services, potentially increasing success rates for entrepreneurial ventures. Moreover, the capability of LLMs like ChatGPT to simplify and communicate intricate sentiment analysis outcomes can enhance the accessibility of financial insights for users at all expertise levels (Fatouros et al. 2023). We investigate the potential of using sentiment analysis in predicting an entrepreneur's sustainability or failure. It is the first study—to our knowledge—that uses entrepreneurial financial sentiment analysis to predict failure using FinBERT. We collected data from 14 Lebanese entrepreneurs in 2021, followed them up in 2024 to evaluate their survival capabilities, and analyzed their financial sentiment analysis through the best-performing tool. Then, we measured the correlation between the date of creation of the enterprise, the age and type of the enterprise, and the sentiment scores. Part of the results were significant and could be the base for elaborating further studies of this new subject.

This paper is structured as follows: first, we review the literature on failure prediction models used, sentiment analysis, and LLMs. Then, we detail the methods used to collect and analyze the data collected. Then, we detail the results, and before concluding, we discuss the results that merit further deep studies in order to elaborate on failure prediction models.

2. Literature Review

2.1. Theoretical and Methodological Frameworks' Competing Views on the Economic Implications of AI

This study leverages AI-driven sentiment analysis tools, specifically ChatGPT and FinBERT, to assess the financial sentiments of entrepreneurs and predict their sustainability in a challenging economic environment. It is worth noting that the broader debate on the economic implications of AI sits between two prominent schools of thought: the developers, who advocate for technological advancement and entrepreneurship, and the degrowth proponents, who favor more controlled technological progress and central planning. The developers' perspective is grounded in economic theories that favor market-driven processes and innovation. This school of thought, associated with approaches like Austrian Economics and New Institutional Economics, suggests that technological advancements are key drivers of economic growth and entrepreneurship (Sánchez-Bayón et al. 2024). Austrian economists emphasize that innovation, spurred by minimal government intervention, leads to the efficient allocation of resources and long-term economic sustainability.

This perspective views technologies such as AI and digital tools as essential for enhancing productivity, creating new markets, and supporting entrepreneurial ventures. In contrast, the degrowth school of thought, which aligns with New and Post-Keynesian Economics, takes a more cautious view of technological progress (Sánchez-Bayón et al. 2024). This perspective argues that unregulated technological advancement can lead to negative social and environmental outcomes, such as increased inequality and environmental degradation. Proponents of this school advocate for greater government intervention and central planning to ensure that economic growth is sustainable and socially equitable. They emphasize the importance of regulating technological innovations to prevent job displacement and ensure that economic benefits are widely shared.

2.2. Failure Predictions

When we talk about enterprise survival, we should talk about their failure and failure prediction models that could be performed via basic linear and nonlinear methods (statistical methods) or artificial intelligence methods. Neural networks are the most known (Séverin and Véganzones 2023). Neural networks are computer models inspired by the human brain, designed to recognize patterns and make predictions based on data. They can make fast classifications. The main issue with predictive models is that they rarely consider qualitative data. Ninety-six percent of the studies on enterprise prediction models use financial ratios (Séverin and Véganzones 2023), and 46.2% of the studies are coupled with other types of variables. The variables that are most used are variables of performance, size, financial structure, liquidity, and activity. The problem with qualitative data is that they are not measured and are difficult to obtain. In this study, we are proposing tools that can measure financial, qualitative data (FinBERT) that could predict enterprise sustainability. The other variables that we used are inspired by the literature on failure:

1. Resources-based resources: it states that the deployment of resources is an important and central element in enterprise failure. The lack of resources and competencies contributes to failure (Auken 2007). Therefore, we have asked enterprises how their sales do, gain and loss variate during the crisis, and collected text data that we have analyzed the sentiment with FinBERT. Then, we measured the correlation between the age, size, and type of the enterprise and the sentiments;
2. Size and age of the enterprise: younger enterprises fail more often than the oldest (Stinchcombe 1965), cited by (Séverin and Véganzones 2023). He explains that by the fact that young enterprises lack legitimacy and resources because of the lack of expertise and knowledge on the market. These are disadvantages related to big companies that are well-established in the market.
3. Type of the enterprises: failure trajectories were elaborated by many studies (Séverin and Véganzones 2023). Failure is defined as a situation where enterprises stop their activities and lose their identity because of their incapacity to adapt. However, the trajectories that are the most similar to the one that we have detected through a previous analysis that we have performed on 14 entrepreneurs (Lina and Levy-Tadjine 2023) and through the follow-up in 2024 on the same structures performed by (Crutzen and Van Caillie 2010). In this trajectory, three main company types were identified: startups having non-mastered hypergrowth, incapacity to adapt to the environment after years of growth, and enterprises that are touched by an external shock.

2.3. Corporate Sustainability

Meuer et al. (2019) have screened 101 publications to identify definitions of corporate sustainability. However, the one that we adopt is the following: A firm's attempt to respond to environmental and social issues.

Engert (2016) considers that integrating corporate sustainability into strategic management requires a framework that considers organizational influences, internal and external drivers, and factors supporting or hindering its integration. Dyllick and Hockerts (2002) suggest that corporate sustainability requires six criteria: eco-friendly, socio-efficiency,

eco-effectiveness, socio-effectiveness, sufficiency, and ecological equity. According to (Ludwig and Sassen 2021), board diversity, independence, and transparency are key internal corporate governance mechanisms that drive corporate sustainability, with board diversity being the most discussed factor.

Atkinson (2000) considers that full-cost accounting is crucial for understanding corporate sustainability and advice on adapting and improving environmental accounting and reporting practices to contribute to national sustainability. Lozano (2015) estimates that leadership, business case, reputation, customer demands, and regulation are key internal drivers for companies to become more sustainability-oriented.

Additionally, research about nonprofit organizations' sustainability has considered the following factors when addressing this matter: the human capital gap due to qualifications and globalization and digital transformation (Radu 2024). Changing human behavior affects an NGO's sustainability, as well as a lack of continuity, short funding cycles, and unpredictable external factors (Haddy 2023). Another study by Andrei (2024) indicates that Factors influencing financial sustainability are cost and non-financial indicators. Also, approaches to NPO sustainability include financial, organizational, and partnership perspectives (Ab Samad et al. 2023).

However, these studies have not taken into consideration sentiment analysis to study corporate sustainability, which is the main contribution of this paper.

2.4. Sentiment Analysis

Sentiments refer to the emotional and cognitive responses of entrepreneurs as expressed in their financial communications. These sentiments are critical in understanding decision-making processes. The interpretation of these sentiments can be viewed through different economic lenses, each offering unique insights into how these emotional and cognitive signals impact business outcomes.

Austrian Economics emphasizes the role of human action, subjectivity, and entrepreneurial alertness in economic decision-making. Here, sentiments could be linked to the concept of entrepreneurial alertness, where entrepreneurs detect opportunities based on their intuitive understanding of the market (Sánchez-Bayón 2020). This intuition and alertness drive entrepreneurial decisions, especially in uncertain environments.

Keynes (1936) introduced the concept of "animal spirits" to describe the instincts, emotions, and psychological factors that influence economic behavior, particularly investment decisions. Sentiment analysis aligns closely with this concept, as it quantifies the "animal spirits" that drive entrepreneurs' confidence or pessimism (Sánchez-Bayón 2020). Understanding these sentiments allows for better predictions of entrepreneurial actions during economic fluctuations, as entrepreneurs' confidence levels directly affect their investment and business decisions.

According to Simon (1955), human beings have limited cognitive abilities and rely on mental shortcuts that simplify decision-making. This theory calls for more realistic decision models that consider cognitive limitations. Sentiments, in this context, represent the emotional biases and heuristics that influence entrepreneurial decisions.

Sentiment analysis in our study is performed through neural networks. Among the many facets of this transformation, sentiment analysis has emerged as a critical tool for understanding market dynamics and predicting future trends (Fatouros et al. 2023). The ability to analyze sentiments can provide valuable insights into the collective mood of the market, thus enabling more informed and strategic decision-making. Noting that, no research that predicts entrepreneurial failure through entrepreneurial sentiment analysis has been found.

Financial sentiment analysis is the process of using Natural Language Processing (NLP) and other computational techniques to analyze textual data related to financial markets and extract sentiments or opinions expressed in that data. However, sentiment analysis is mainly used on financial markets data but rarely on business sustainability inputs. This constitutes the main contribution of the project. The goal of financial sentiment

analysis is to quantify the sentiment (positive, negative, neutral) and use this information to make more informed investment decisions. It can also be helpful in identifying potential risks by analyzing negative sentiments around specific companies. Techniques used in financial sentiment analysis include the following:

1. Tokenization: Breaking down text into smaller units (tokens), such as words or phrases;
2. Sentiment Lexicons: Using pre-built dictionaries of words associated with positive or negative sentiment;
3. Machine Learning: Training models to recognize sentiment from labeled data. Common algorithms include Naive Bayes, Support Vector Machines (SVM), and neural networks;
4. Deep Learning: Using advanced neural network architectures like Long Short-Term Memory (LSTM) networks and transformers for more accurate sentiment detection;
5. Natural Language Processing (NLP): Techniques like part-of-speech tagging, named entity recognition, and dependency parsing to understand the structure and meaning of sentences;
6. Feature Extraction: Converting text into numerical features using methods like TF-IDF (Term Frequency-Inverse Document Frequency) or word embeddings (Word2Vec, GloVe, BERT).

Traditionally, financial sentiment analysis has relied on manually curated lexicons and simple ML algorithms (Schumaker and Hsinchun 2009). However, with the rapid progress in Natural Language Processing (NLP), more sophisticated techniques are now available. Deep learning-based models, such as BERT (Bidirectional Encoder Representations from Transformers) (Toutanova 2018) (Zhuang Liu et al. 2021) and its financial domain-specific counterpart FinBERT (Liu et al. 2021), have significantly improved sentiment analysis accuracy and reliability.

3. Materials and Methods

This study aims to investigate the potential of LLMs in analyzing the financial sentiment of entrepreneurs. We evaluate multiple prompts and compare the results using various AI tools such as ChatGPT and FinBERT. In our approach, a zero-shot prompting strategy is employed to evaluate the effectiveness of these tools in interpreting financial texts collected from entrepreneurs, highlighting their ability to perform without domain-specific fine-tuning.

We have considered a sample of 14 Lebanese entrepreneurs who have survived the ongoing crisis period (2021 to 2024). They have survived by adapting their business plan, moving to other regions (especially after the explosion), or seeking international clients (to obtain foreign American Dollars). Specifically, in order to classify these companies, we have used the answers to a questionnaire consisting of 41 questions posed to 14 Lebanese entrepreneurs (see description sample in Appendix A), providing a diverse set of responses for evaluation. The questionnaire covers diverse aspects such as company details (name, creation date, region, current number of employees), entrepreneurial background (age, highest diploma obtained), and the impact of recent crises and entrepreneurial reaction to them (manifestations, pandemic, August 4 explosion). The questions also delve into changes in business operations, technological adaptations, financial impacts, remote working, revenue and profit changes, investment during crises, cost alterations, currency depreciation effects, and importation of raw materials. Further inquiries address adjustments in product quality and pricing, online consultation/sales, support from civil society or government, and business plans for 2020 and 2021. The questionnaire explores the identification of new business opportunities, support from personal networks, improvements during the pandemic, business weaknesses, resilience strategies, future business and career outlooks, and personal and family health concerns. Based on the above-collected variables and data, we were able to classify our 14 companies into 3 types: dead (type 1—startups that diminished), surviving companies (type 2—companies that have difficulties surviving), and dynamic companies (type 3—growing enterprises).

To assess the performance of our sentiment classification models, we examined the correlation between the sentiment scores (neutral, positive, negative) and the type, age, and size of the enterprises.

Our first part of the analysis focuses on the sentence: “Profit has not increased; however, sales are gradually increasing”, which responds to the following question: “Did you lose or gain more (in terms of revenue and profit) during the crisis?” This context tests the models’ ability to understand and analyze nuanced financial sentiment.

We compare the performance of ChatGPT-4, ChatGPT-4.0, and LeChat-Mistral. Zero-shot prompts are utilized to generate results from each model, which are then compared to FinBERT’s output to determine the closest alignment.

We utilized two distinct sets of prompts for our analysis. The first set was applied to the sentence: “Profit has not increased; however, sales are gradually increasing”. The second set included the question and its corresponding answer: “Did you lose or gain more (in terms of revenue and profit) during the crisis? Profit has not increased; however, sales are gradually increasing”. This approach allowed us to determine if additional context influenced the sentiment analysis results. The specific prompts we employed are detailed below.

Primary Set of Prompts:

Prompt 1—Analyze the sentiment in this sentence by scoring it from 0 to 1: “Profit has not increased; however, sales are gradually increasing”.

Prompt 2—Analyze the sentiment in this sentence by scoring it between 0 and 1 for positive, neutral, and negative sentiments: “Profit has not increased; however, sales are gradually increasing”.

Prompt 3—Analyze the sentiment of this sentence using FinBERT’s method: “Profit has not increased; however, sales are gradually increasing”.

Prompt 4—Analyze the sentiment in this sentence using ChatGPT’s (if the prompt is applied to LeChat-Mistral)/LeChat-Mistral’s (if the prompt is applied in ChatGPT) method: “Profit has not increased; however, sales are gradually increasing”.

Prompt 5—Read and understand this sentence and then analyze the sentiment by scoring it between 0 and 1 for positive, neutral, and negative sentiments: “Profit has not increased; however, sales are gradually increasing”.

Prompt 6—Suppose you are a researcher, and you have to measure the sustainability of this company by performing a sentiment analysis on this sentence and assigning a score between 0 and 1 for positive, neutral, and negative sentiments: “Profit has not increased; however, sales are gradually increasing”.

Secondary Set of Prompts:

Prompt 1’—Analyze the sentiment in this paragraph by scoring it from 0 to 1: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased; however, sales are gradually increasing”.

Prompt 2’—Analyze the sentiment in this paragraph by scoring it between 0 and 1 for positive, neutral, and negative sentiments: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased, however, sales are gradually increasing”.

Prompt 3’—Analyze the sentiment in this paragraph using FinBERT’s method: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased; however, sales are gradually increasing”.

Prompt 4’—Analyze the sentiment in this paragraph using ChatGPT/LeChat-Mistral’s method: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased; however, sales are gradually increasing”.

Prompt 5’—Read and understand this paragraph and then analyze the sentiment by scoring it between 0 and 1 for positive, neutral, and negative sentiments: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased; however, sales are gradually increasing”.

Prompt 6'—Suppose you are a researcher, and you have to measure the sustainability of this company by performing a sentiment analysis on this paragraph and assigning a score between 0 and 1 for positive, neutral, and negative sentiments: “Did you lose or gain more (in terms of revenue and profit) during the crisis? Profit has not increased; however, sales are gradually increasing”.

4. Results

This section is divided into two subheadings. It provides a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn. The first part is a comparison between prompts that we have tried on ChatGPT, Co-Pilot, and FinBERT to analyze sentiment analysis. The second part details the correlation between sentiment analysis and sustainability variables.

4.1. ChatGPT-4 Compared to ChatGPT-4.0, FinBERT, and LeChat-Mistral for Sentiment Analysis

Initially, we used FinBERT to analyze the sentiment of the sentence: “Profit has not increased; however, sales are gradually increasing”. FinBERT’s sentiment analysis produced the following results: Positive (0.944), Neutral (0.043), and Negative (0.013).

When analyzing the combined question and answer: “Did you lose or gain more (in terms of revenue and profit) during the crises? Profit has not increased; however, sales are gradually increasing”, FinBERT’s results were: Positive (0.88), Neutral (0.069), and Negative (0.05).

Next, we applied the prompts to ChatGPT and LeChat-Mistral. The responses from these LLMs varied; some provided detailed scores for each sentiment category (positive, neutral, and negative), similar to FinBERT, while others offered an overall sentiment score without breaking down each category.

The results are detailed in the following Table 1:

Table 1. Prompts and sentiment analysis results (source: the authors).

Prompt	Model	Positive	Neutral	Negative	Overall Score
<i>Primary Set of Prompts: (Sentence Only)</i>					
Prompt 1	ChatGPT-4	-	-	-	0.5 to 0.6
	ChatGPT-4.0	-	-	-	0.55
	LeChat-Mistral	-	-	-	0.6
Prompt 2	ChatGPT-4	0.4	0.4	0.2	-
	ChatGPT-4.0	0.4	0.2	0.4	-
	LeChat-Mistral	0.5	0.5	0.0	-
Prompt 3	ChatGPT-4	-	-	-	Neutral/Mixed
	ChatGPT-4.0	0.45	0.2	0.35	-
	LeChat-Mistral	-	-	-	Neutral/Mixed
Prompt 4	ChatGPT-4	-	-	-	Slightly Positive
	ChatGPT-4.0	-	-	-	Mixed/Positive
	LeChat-Mistral	-	-	-	Neutral/Positive
Prompt 5	ChatGPT-4	0.6	0.3	0.1	-
	ChatGPT-4.0	0.3	0.4	0.3	-
	LeChat-Mistral	0.6	0.5	0.4	-
Prompt 6	ChatGPT-4	0.2	0.5	0.3	-
	ChatGPT-4.0	0.4	0.2	0.4	-
	LeChat-Mistral	0.6	0.2	0.2	-

Table 1. Cont.

Prompt	Model	Positive	Neutral	Negative	Overall Score
<i>Secondary Set of Prompts (Question and Sentence Together)</i>					
Prompt 1'	ChatGPT-4	-	-	-	0.5 to 0.6
	ChatGPT-4.0	-	-	-	0.5
	LeChat-Mistral	-	-	-	0.5
Prompt 2'	ChatGPT-4	0.4	0.5	0.1	-
	ChatGPT-4.0	0.3	0.4	0.3	-
	LeChat-Mistral	0.4	0.6	0.2	-
Prompt 3'	ChatGPT-4	-	-	-	Slightly Positive
	ChatGPT-4.0	-	-	-	Mixed
	LeChat-Mistral	-	-	-	Neutral/Positive
Prompt 4'	ChatGPT-4	-	-	-	Mixed/Positive
	ChatGPT-4.0	-	-	-	Mixed/Positive
	LeChat-Mistral	-	-	-	Mixed/Positive
Prompt 5'	ChatGPT-4	0.6	0.3	0.1	-
	ChatGPT-4.0	0.3	0.4	0.3	-
	LeChat-Mistral	0.4	0.5	0.1	-
Prompt 6'	ChatGPT-4	0.6	0.3	0.1	-
	ChatGPT-4.0	0.4	0.2	0.4	-
	LeChat-Mistral	0.4	0.5	0.1	-

For Prompt 1, all three models provide an overall sentiment score that indicates a slightly positive sentiment, with LeChat-Mistral showing the highest positivity (0.6). ChatGPT-4 and ChatGPT-4.0 show consistent, slightly positive scores, suggesting that all models recognize the positive trend in sales. The added context in the secondary set did not alter the overall sentiment scores.

The models diverge more in Prompt 2. ChatGPT-4 and ChatGPT-4.0 both identify significant positive and neutral elements but differ on the negative sentiment, with ChatGPT-4.0 assigning a higher negative score. LeChat-Mistral, however, sees no negative sentiment, emphasizing the positive and neutral aspects equally. The secondary set of results showed a higher emphasis on neutral sentiment.

For Prompt 3, which asked the models to use FinBERT's method, both ChatGPT-4 and LeChat-Mistral provide a general neutral/mixed sentiment. Only ChatGPT-4.0 gave specific scores like FinBERT, with a slightly positive sentiment with considerable negative weight. The secondary set results showed slight variations, with ChatGPT-4 shifting from neutral/mixed to slightly positive and LeChat-Mistral shifting from Neutral: Mixed to Neutral/Positive. The biggest change was ChatGPT-4.0 moving from detailed scores to an overall score with mixed sentiment.

As for Prompt 4 and 4', all responses provided an overall sentiment score, reflecting the general analysis nature of ChatGPT and LeChat-Mistral rather than the detailed scoring approach of FinBERT. The responses varied slightly, with all models indicating a positive sentiment.

In Prompt 5, ChatGPT-4 and LeChat-Mistral both identify a strong positive sentiment with moderate neutral and low negative sentiments. ChatGPT-4.0, however, shows a more balanced view, with significant scores in all three categories. This suggests that while ChatGPT-4 and LeChat-Mistral are more confident in the positive aspect, ChatGPT-4.0 remains cautious. The secondary set highlighted LeChat-Mistral's increased neutrality while ChatGPT-4 and 4.0 responses remained the same.

For Prompt 6, which imagined the models as researchers analyzing the sustainability of the company, LeChat-Mistral remains the most positive, seeing minimal negative sentiment. ChatGPT-4 sees a mostly neutral sentiment with some positive and negative aspects, reflecting caution. ChatGPT-4.0 again shows a balanced perspective with equal positive

and negative scores, suggesting it sees significant risks and opportunities. The secondary set reinforced the cautious approach of ChatGPT-4.0 and the optimistic outlook of LeChat-Mistral and ChatGPT-4.

Overall, the models generally recognize a slightly positive trend when they give a single score, with LeChat-Mistral being the most positive. When providing detailed sentiment scores, ChatGPT-4.0 often shows more balanced scores, reflecting caution. ChatGPT-4 and LeChat-Mistral tend to highlight positive and neutral sentiments, with LeChat-Mistral often minimizing negative sentiments. ChatGPT-4 and LeChat-Mistral are more consistent in seeing positive sentiment, while ChatGPT-4.0 is more variable, often reflecting significant neutral and negative sentiments. Overall, LeChat-Mistral appears to be the most optimistic model, consistently identifying positive sentiment, while ChatGPT-4 and ChatGPT-4.0 provide a more nuanced and cautious analysis. The secondary sets of prompts reveal that additional context tends to prompt the models to balance their sentiment analysis more cautiously. The models tend to provide an overall score rather than specific scores for each sentiment, unlike FinBERT. Whether providing specific scores or overall scores, the models gave more weight to neutral sentiment than FinBERT. Their overall results were neutral to slightly positive, which contrasts significantly with FinBERT's highly positive score for positive sentiment (around 0.9) and its low scores for neutral and negative sentiments (less than 0.1).

4.2. Sentiment Analysis Predicts Enterprises Sustainability

The next step for this analysis is to make prediction models after testing the correlation between variables. We asked entrepreneurs in 2021 (during the multi-level crises) whether they had registered gain or loss in the results sheets and whether they had noticed an augmentation or a decrease in their sales. We have collected answers (text-qualitative financial data) and analyzed them through FinBERT and ChatGPT and collected scores for each sentiment (negative, neutral, positive).

ChatGPT has indicated a perennity score for each of the enterprises after having given the score (positive, negative, neutral) for each of them for the above-mentioned question. The results that were collected through ChatGPT indicate a weak correlation (Coeff. corr. (R): 0.353) between the sustainability score and the type of enterprises. A strong correlation (Coeff. corr. (R): 0.500) between the date of creation of the enterprises and the sustainability score. And a negative correlation between the sustainability score and the size of the company (Coeff. corr. (R): -0.035).

Additionally, there is no correlation between the sentiments: negative (Coeff. corr. (R): -0.499), positive (Coeff. corr. (R): 0.497), and neutral (Coeff. corr. (R): 0.047) with the date of creation of the enterprises.

However, the results that were collected through FinBERT have shown that there is a positive moderated correlation (Coeff. corr. (R): 0.431) between the age of the enterprise and the positive sentiment toward the variation of gain/loss and variation of sales. Another main result is that there is a positive, strong correlation (Coeff. corr. (R): 0.732) between the number of employees (the size of the company) and the positive sentiment toward the variation of gain/loss and variation of sales. There is a weak-to-moderate correlation between the positive sentiment and the type of enterprise. (Coeff. corr. (R): 0.344), which means that on a large sample, we could predict the type of enterprises (dead, surviving, or dynamic) based on the entrepreneur's emotion.

To complete this reasoning, we refer to a large number of studies (Hannan and Freeman 1977, 1988; Carroll and Delacroix 1982; Hager et al. 2004; Fauchamps and Owens 2009; Burger and Owens 2013), cited by (Séverin and Veganzones 2023), that have shown that the age and the size of the enterprise have explained the death of the enterprises. It means that sentiment analysis—analyzed by FinBERT—about resources explains perennity/company's sustainability: this is an additional contribution of the study.

5. Discussion

Further studies to this paper could add a list of steps that allow us to predict—more precisely—the correlation between predicted sentiment and stage of failure trajectory. Therefore, future research directions may also be highlighted. The following steps are the main ideas that should be taken into consideration in future studies to predict the entrepreneurial sustainability of Lebanese enterprises. First, the sample should be only Lebanese (which is the case of this study) because judiciary systems differ between nations; each country has its own definition of failure and its own accounting rules. It is impossible to determine one universal criterion of failure. In addition to this, the next step concerns the selected enterprises that supply access to data, which underlines the obligation of the enterprises to diffuse data. Another element that should be taken into consideration is the sector: the pairing should be performed sector by sector. We should take into consideration elements that are strictly related to each sector. The proportion of the enterprises between wealthy enterprises and failed enterprises must be equal. Most studies consider balanced samples where the two types (failed and sustainable) are equal. But other studies ([Garcia-Gallego and Mures-Quintana 2012](#)) have criticized the paired sample as it is not representative of the population from which it is chosen and has focused on comparing the paired sample with the random sample in order to prove if the predictive power of the models is affected by the sampling method. The results show there are differences, both in the significant variables and in the classification results, which are not so high in the random sample as in the paired one, especially regarding failed firms as they have applied a logistic regression analysis where they have considered a set of financial ratios as independent variables. To solve this problem, we need to enter the field of data science called multi-classification with unbalanced data. Therefore, the next step is to make text classification through Python to be able to classify enterprises using the best tools.

Another practical element that has to be highlighted in the discussion of this paper that tackles sentiment analysis is to invite entrepreneurs to mentor their ideas and their internal talk because it translates into positive dialogue and then positive sentiment and sentiment analysis scoring ([Hay 1989](#)). Also, using NLP models, the person could act systematically as being able to realize the same performances that an expert ([Cayrol 2019](#)) has modeled; this model presumes effective communication practices. Additionally, having a growth mindset ([Dweck 2006](#)) that relies on emotional well-being and mind flexibility is highly encouraged to ensure success and avoid failure.

6. Conclusions

This study has highlighted the importance of prompt engineering, particularly zero-shot contexts, to boost sentiment analysis in financial applications, especially entrepreneurial sustainability. We have proven that FinBERT, compared to ChatGPT, gives more accurate results on financial positive sentiment analysis. Additionally, we have proved that sentiment analysis generated by FinBERT is correlated with the age, type, and size of the companies. These are the basic and main findings that allow us to generate predictive models of entrepreneurial sustainability. Knowing that, if we know the positive sentiment analysis generated by a sentence concerning the variation of sales profit/loss, we could predict the type of the enterprise (dead, surviving, or dynamic) and, therefore, its ability to survive in the future. However, the limitation of the study is that it has covered a small sample (14 entrepreneurs) in a tight context (Lebanon). The results of this exploratory study could be generalized by including a larger sample in international contexts. Future studies could also include longitudinally the same sample or separately each sector in larger samples.

Author Contributions: Conceptualization, L.S. and S.S.; methodology, L.S. and S.S.; software, L.S.; validation, L.S. and S.S.; formal analysis, L.S. and S.S.; investigation, L.S.; resources, L.S.; data curation, L.S.; writing—original draft preparation, L.S. and S.S.; writing—review and editing, L.S. and S.S.;

visualization, L.S. and S.S.; project administration, L.S. and S.S.; funding acquisition, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding and The APC was funded by ASCENCIA Business School.

Institutional Review Board Statement: As part of the research methodology of the article, a questionnaire survey was conducted, which the respondents filled out anonymously. The Ethics Committee or Institutional Review Board does not apply to the said survey.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

Appendix A. Sample Description

We have interviewed eight male entrepreneurs and six female entrepreneurs who work for a diverse clientele, notably in consulting (dietary, sports, legal, and financial), hotels (boutique hotels), apartment subletting, home delivery, printing services, and software and hardware sales. Our sample is made up almost entirely of VSEs. We should note that one VSE became an SME after the crises of 4 August 2020 and the COVID-19 crisis.

These entrepreneurs are between 26 and 51 years old and set up their businesses between 2008 and 2020. The majority (9 out of 14) have a Bac+5 or Bac+8. The others either have no qualifications or hold a Bac+3.

The particularity of our sample is that it includes both consultants and product salespeople. This may show that the multi-level crisis has had an impact on certain business sectors and contributed to the development of others.

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