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Integrating Algorithmic Decision Making into Small Business Credit Initiatives: a path to Enhanced Efficiency and Inclusive Economic Growth

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Abstract

Purpose: This paper addresses the challenges faced by small businesses in accessing credit through Small Business Credit Initiatives (SBCI) in the United States. Despite the success of SBCI in creating jobs and fostering economic growth, there are limitations in the evaluation process.

Methodology: The research design integrates advanced algorithmic decision-making, machine learning, and LLMs into existing credit evaluation process. Primary data is collected from various sources, including financial and business history, market sentiments, external factors, and utilization of sampling techniques if required. Document review, surveys and digital platforms are used for collecting data for LLMs to extract insightful information from complex sources. This comprehensive approach, combining with traditional and innovative methods, aims to establish a robust foundation for developing and evaluating a fair, efficient, and adaptive credit evaluation system for small business credit initiatives.

Findings: The proposed framework integrates external market factors and use of LLMs for document review on top of primary data sources currently in adaption. Data processing could be amended by extracting features by using advanced natural language processing to enhance feature space by collecting valuable information which is expected to enhance predictive power, adjustment of thresholds and decision making along with a feedback loop.

Unique Contribution to Theory, Policy, and Practice: Unique framework to accelerate small business credit initiatives by developing a new process of selecting and evaluating machine learning model centered on addressing associated risks, adapting to changes in government policy, improving current procedures, and incorporating feedback from stakeholders and applicants. This is done in an organized manner, with a focus on monitoring and maintaining algorithmic decision models.

Keywords: *Small Business Credit Initiative, Algorithmic Decision Making (ADM), Large Language Models (LLMs), Machine Learning, Credit Risk*

1 Introduction

In the United States, years between 1995 to 2021, small businesses created 17.3 million net new jobs, accounting for 62.7% of net jobs created since 1995 [1]. Since small businesses carry a lion share of job creations, governments have taken initiatives to support local enterprises by Small Business Credit Initiatives (SBCI) to foster economic growth. The initiation of this process typically begins with small business owners expressing their credit requirements and financial needs. They submit applications to participating financial institutions or government agencies overseeing the SBCI program. These applications undergo a thorough evaluation, considering factors such as the financial health of the small business, its creditworthiness, and its potential for sustainable growth. These initiatives were the pillar of recovery after the economic crisis of 2008 and covid 2019 [2]. Empowering small enterprises to broaden their operations, invest in innovation, achieve cost savings, and generate employment opportunities is achieved through targeted support in making credit accessible via government initiatives or by participation of government with NGOs and financial institutions.

Understanding the inherent risks associated with small business ventures, the SBCI incorporates risk mitigation strategies. This ensures that financial support is not only accessible but is also sustainable, contributing to the long-term success and stability of the supported enterprises. A review of these reports is done by the accountability officers. Effectiveness of such initiatives is subject to some level of noise and potential human error, which give space for use of some unbiased approaches with the advent of large-language models and scoring methods such as propensity scoring [3]. The ideas suggested in this paper aim to shed light on the efficacy of existing SBCI programs, identify challenges, and propose strategies for improvement by integrating use of innovative technologies like machine learning and generative AI.

2 Background

Small businesses form the backbone of economies, contributing significantly to employment and innovation. However, accessing credit remains a persistent challenge for many small enterprises. Capital is the lifeblood of any small business, and according to NSBA's most recent data, which was pre-pandemic, there was a drop in bank lending to smaller firms. 35 percent said that lack of capital is hindering their ability to grow their business or expand operations [5]. Traditional credit assessment methods often fall short in capturing the nuanced and dynamic nature of small business operations. As a result, there is a growing interest in leveraging algorithmic decision-making to enhance the accuracy and efficiency of credit evaluation processes for small businesses.

In recent years, Algorithmic Decision Making (ADM) processes have gained prominence, and revolutionized various industries. Algorithms have the power to transform traditional institutions in manners that hold important implications for power, accountability [6], efficiency, and sustainability. Big Data and algorithmic governance are transforming traditional institutions and media of transnational governance in manners that hold important implications for power, accountability and effectiveness.

The integration of advanced technologies, such as large language models (LLMs), can be seamlessly integrated into downstream machine learning (ML) or deep learning (DL) pipelines [5]. This has allowed for more sophisticated and data-driven approaches to critical decision-making tasks. One particularly impactful domain is small business credit initiatives.

3 Motivation

The motivation behind this work stems from the need to address the challenges such as bureaucratic hurdles, insufficient funding, complexity, inadequate support etc. in small business credit initiatives [7]. Traditionally, the credit initiatives rely on fixed criteria, may overlook potential of emerging business, or fail to adapt to a rapidly challenging business environment.

Government initiatives in this space have an underwriting model with definition of small businesses. With often vague definitions and influence of the policies, it is unlikely to have a consistent metric necessary for automated underwriting and tend to be underwritten manually when requesting credit [8]. Despite increasing use of large language models (LLMs) across various domains, their potential applications in the financial sector remain largely unexplored [9]. Integration of these technologies along with machine learning have an immense scope to foster accelerated growth in small business initiatives with algorithmic decision making (ADM)

Typical process of SBCI involves a lot of documents, forms and personal information from applicants. With the advent of large language models (LLMs), and advancements in machine learning (ML) techniques, there is a room for improvement to make these initiatives more decisive, efficient, and simplified by using ADM. This process presents an opportunity to create a more adaptable, data-driven, and predictive evaluation system for applicants. There are multiple factors drive the motivation for this work:

Enhanced Predictive Power: Algorithmic models, with available data sources can analyze a diverse set of data points. This has the potential to enhance the predictive power of credit assessment.

Real-time Adaptability: Small businesses often face dynamic market conditions. Algorithmic models can be designed to adapt in real-time, incorporating the latest financial information and market trends to make credit decisions that align with the current state of the business.

Reduced Bias and Increased Fairness: By leveraging advanced algorithms, there is an opportunity to mitigate biases present in traditional credit assessment methods. The research aims to explore methodologies that promote fairness and inclusivity in credit evaluation processes.

Efficiency and Cost-Effectiveness: Automated decision-making processes can significantly reduce the time and resources required for credit assessments. This research seeks to explore ways to enhance the efficiency and cost-effectiveness of small business credit initiatives.

Integration of Language Models: The incorporation of large language models (LLMs) in decision-making processes introduces a new dimension. Natural language processing capabilities can be utilized to extract insights from unstructured data sources, contributing to a more holistic understanding of a small business's operations.

4 Literature Review

Accessing credit for small business is a persistent challenge due to risk aversion from the lenders especially after the 2007-2009 economic crisis. To overcome this problem governments around the world have started small business credit initiatives. These government backed programs, lenders are provided some guarantees to foster economic growth and generate employment.

In recent years, the rise of Algorithmic Decision Making (ADM) processes and advanced technologies, such as large language models (LLMs), has transformed various industries. While these technologies have been widely adopted in sectors like healthcare and marketing [10], their potential applications in the financial sector, particularly in the context of SBCI, remain largely unexplored. The integration of ADM, machine learning (ML), and LLMs into small business credit assessment processes presents a novel approach to address the challenges inherent in traditional methods.

Motivated by the need to overcome bureaucratic hurdles, insufficient funding, and the complexity of small business credit initiatives [11], this literature review aims to explore the current state of algorithmic decision-making in the context of SBCI. By examining existing research, we aim to highlight the gaps and limitations in the adoption of ADM and propose how our work can contribute to fostering this sector. Getter [9] emphasizes the challenges in small business credit markets, with underwriting often done manually due to vague and inconsistent definitions of small business and policy influences. This manual process poses hurdles in consistency and scalability. Despite the increasing use of LLMs across various domains [9], there is a lack of comprehensive exploration of their potential applications in small business credit initiatives.

The existing literature highlights the need for innovative approaches to credit assessment. Wu et. al. [12] showcase the power of text in credit default prediction, indicating the potential for leveraging textual data in risk assessments. Our work seeks to build upon this idea, exploring how LLMs and machine learning (ML) can enhance the predictive power of credit assessment to automate the approval process and help to make fast decisions for such credit needs. Verduyn and Porter [6] discuss the implications of Big Data and algorithmic governance, emphasizing the need for transparency and accountability. Our research aims to address these ethical considerations by proposing frameworks for clear communication of decision-making processes. Myers et al. [5]

provide insights into the fundamentals, challenges, and opportunities of large language models. Our work aims to leverage these models to enhance the efficiency and cost-effectiveness of small business credit initiatives.

In conclusion, the current literature suggests a significant gap in the adoption of algorithmic decision-making in small business credit initiatives. Our work seeks to bridge this gap by proposing innovative approaches that leverage ADM, machine learning, and large language models to transform and optimize credit assessment processes, contributing to the development of fair, efficient, and adaptive systems that better serve the needs of small businesses and foster economic growth.

5 Contribution

In this work, our contribution to the field of small business credit initiative focuses on assessment of the credit risk and approval by employing advanced algorithmic decision-making, machine learning and large language models (LLMs). This research addresses the pressing challenges faced by small businesses in accessing the credit and outlines a comprehensive framework for enhancing the accuracy, removal of bias, introducing efficiency, and improved decision making over time. Leveraging LLMs, we propose a feature selection approach from document [13] in addition to the existing information to build machine learning models along with a feedback system to enhance decision making with changing dynamics in this field.

The significance of our research lies in its potential to revolutionize traditional credit assessment models. By incorporating LLMs, we achieve a more nuanced understanding of the textual information provided by businesses, allowing us to extract relevant features that may be indicative.

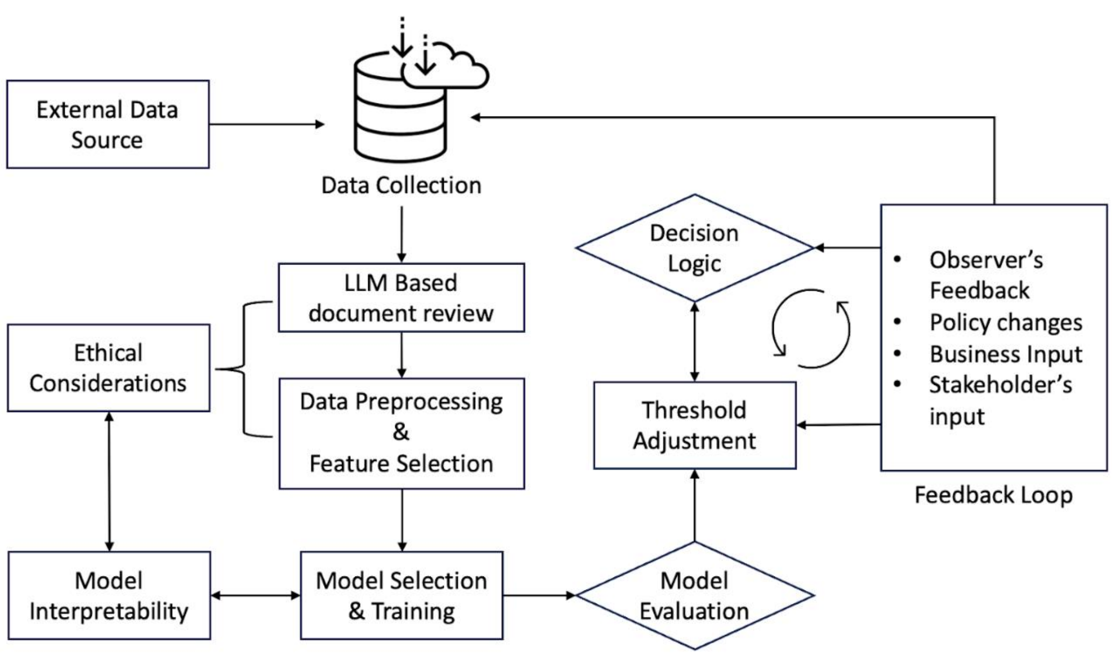

Figure 1. Algorithmic decision-making in the context of small business credit initiatives

This paper also introduces considerations for real-time adaptability, ethical considerations, and the integration of language models in the decision-making process. The proposed framework not only enhances the efficiency of credit assessments but also contributes to the broader discourse on fairness, transparency, and accountability in algorithmic decision-making. Our findings hold promise for creating more inclusive and responsive credit evaluation systems, fostering economic growth through better support for small businesses.

Data Collection:

Primary data comes from the applicant's financial and business history, user information, financial institution's data. There is a potential to club readily available external market factors [14] such as market factors, interest rates, sentiments about specific businesses etc. In addition, a significant amount of data for such loans are in the form of complex documentation submitted by the businesses and governments.

Identify the data sources and variables that will be used in your model. This could include financial data, credit history, business plans, etc.

LLM based document review and data processing:

Traditionally text mining techniques or using entity detection techniques such as Hidden Markov Models (HMM) [15] have given high performance results. Such rule-based approaches are only applicable when documents are in standard format and follow some kind of structure and that is why such approaches are rarely used in small business credit initiatives. For our case, use of large language models to extract valuable information from such unstructured data from different standards or order, enabling more informed decision making in risk modeling [16].

Feature Selection:

The adaptable nature of LLMs enables us to perform sentiment analysis, summarization, and keyword extraction from the documents. In addition, in this step new features are created from existing ones, for example, calculation of debt-to-income ratio, age, or to generate time-series features to have monthly/weekly trends in financial data.

Model Selection and Evaluation:

Typical small business loans are about credit risk for the institution and the bank, in current framework the models are expected to provide probability of default. In this step models are fine-tuned by comparison of outputs from multiple machines learning techniques, scoring methods, and optimizing parameters to minimize associated risk. A model with best scores may not be the most cost-effective model [17].

Decision Logic and Threshold Adjustment:

To properly define a decision logic in a machine learning pipeline, which could be based on either minimization of the losses, maximization of the profit or by adjusting the probability threshold depending on the choice of optimization parameter. Probability threshold for approval is > 0.5, to be more conservative, it could be as high as 0.9 and as low as 0.1 for being lenient depending on the appetite of taking risk and evaluation inputs in an iterative fashion.

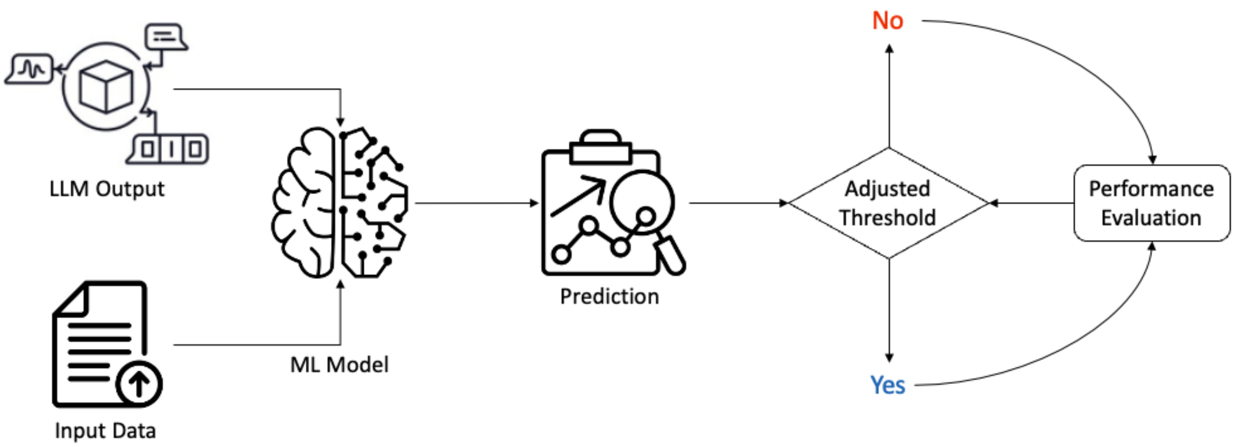

Figure 2. ML Pipeline with Decision Logic

One shall ensure proper monitoring and maintenance to address any drift in the data or model performance over time and retrain the models as new data comes in. This threshold adjustment should be dynamic in nature and flexible with changing times, and demand from the economy of a particular governmental jurisdiction.

Model Explainability:

Within the context of small business credit initiatives, ensuring the interpretability of binary classifiers is crucial for ethical considerations and technical transparency. Integrating methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) enhances our ability to provide clear insights into the factors influencing credit decisions. SHAP, through its Shapley values, quantifies the contribution of each feature to the model's output, facilitating a comprehensive understanding of credit assessment criteria. Similarly, LIME generates locally faithful explanations, offering insights into individual predictions by perturbing input data points.

Research, as exemplified by Lundberg and Lee [18] underscores the effectiveness of SHAP values in revealing feature importance and discriminatory patterns. LIME, introduced by Ribeiro et al. [19], further complements interpretability efforts by providing locally faithful approximations of complex models, making it applicable to a range of classifiers, including those used in credit assessment. By incorporating SHAP, LIME, and other advanced interpretability methods, small business stakeholders, such as owners, lenders, and regulators, gain the technical tools necessary to validate and understand credit decisions. This approach not only bolsters transparency and trust in the credit evaluation system but also enables the identification and rectification of potential biases, aligning with ethical considerations. Ultimately, these interpretability methods contribute to the creation of a fair and accountable small business credit ecosystem, promoting an environment conducive to growth and success.

Ethical Considerations and Transparency: Algorithmic decision-making processes could result in more objective and potentially fairer decisions compared to those made by humans. However, ethical considerations, including transparency and accountability, arise in the context of algorithmic decision-making [20]. The research aims to tackle these concerns by proposing frameworks that ensure a clear communication of decision-making processes to stakeholders.

The overarching objective of this research is to harness algorithmic decision-making, machine learning, and language models to revolutionize and optimize small business credit initiatives. By doing so, the research seeks to make significant contributions to the development of credit assessment systems that are not only fair, efficient, and adaptive but also better aligned with the specific needs of small businesses, ultimately contributing to economic growth.

In summary, this research is motivated by the overarching goal of leveraging algorithmic decision-making, machine learning, and language models to transform and optimize small business credit initiatives. By doing so, it seeks to contribute to the development of fair, efficient, and adaptive credit assessment systems that better serve the needs of small businesses and contribute to economic growth.

Feedback Loop:

The incorporation of feedback mechanisms into Small Business Credit Initiatives (SBCI) is a pivotal element aimed at honing and optimizing the efficacy of credit support programs for small businesses. The establishment of a robust feedback system empowers stakeholders, including small business owners, financial institutions, and community organizations, to actively contribute their insights and experiences.

This feedback collectively has information on the application process, credit accessibility, overall impact on the business growth, effectiveness, community impact etc. Research done by Schmisseur [4] on program evaluation of small business credit initiatives sheds light on the importance of feedback in assessing program effectiveness and impact. Studies by Oh et al. [3] and Getter [9] emphasize the significance of feedback in evaluating credit guarantee policies and addressing challenges in small business credit markets. US government accountability office [2] supports having valuable insights into effectiveness of credit evaluation, timeline and challenges encountered in implementation of these programs.

The integration of feedback from online surveys, digital platforms, and data analytics streamlines the collection and analysis of feedback, facilitating faster and more informed decision-making. Barnett and Diakopoulos [8] explore the utility of crowdsourcing impacts, offering insights into leveraging diverse feedback sources for anticipating societal impacts of algorithmic decision-making. Regular reporting and transparent communication channels further augment the effectiveness of the feedback loop.

Such insights are invaluable for refining program parameters, ensuring a closer alignment with the needs and challenges faced by small enterprises. Integration of feedback from financial institutions and lenders participating in the SBCI sheds light on the effectiveness of credit evaluation processes, loan approval timelines, and any challenges encountered in credit program implementation. By actively seeking and incorporating input from diverse stakeholders, the program gains the ability to adapt to evolving needs, address challenges, and continuously improve its impact on supporting the growth and sustainability of small businesses.

6 Conclusion

This research proposes a transformative approach to small business credit initiatives by integrating algorithmic decision-making, machine learning, and large language models. The comprehensive framework addresses challenges in credit assessment, focusing on accuracy, efficiency, and fairness. By leveraging advanced technologies, the proposed model aims to create a more adaptive and data-driven evaluation system for small businesses, contributing to economic growth.

7 Recommendations

While this research provides a comprehensive framework for small business credit initiatives, there are inherent limitations that warrant further investigation. Future work should involve the implementation and testing of the proposed framework in real-world SBCI programs to validate its effectiveness and identify potential challenges. Additionally, exploring the impact of feedback mechanisms on program adaptation and improvement would be crucial. Further research is needed to address ethical considerations and transparency in algorithmic decision-making for credit evaluations. Ongoing monitoring and evaluation of the model's performance, coupled with adjustments to ensure its relevance in dynamic business environments, will be essential for sustained success.

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