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# Artificial Intelligence and Entrepreneurial Failure Detection: A Systematic Review through Deep Learning

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**Abstract**

Entrepreneurial failure represents a major challenge for businesses, particularly small and medium-sized enterprises (SMEs), which face economic, financial, and managerial uncertainties. In response to these challenges, Artificial Intelligence (AI) has emerged as a promising tool for anticipating risks and optimizing prevention strategies. Although various AI techniques have been applied in this field, their comparative effectiveness, practical applicability, and alignment with the specific needs of SMEs remain underexplored. Furthermore, the heterogeneity of approaches (supervised algorithms, neural networks, natural language processing) complicates their assessment and hinders their adoption by practitioners.

This study presents a systematic literature review aimed at mapping and analyzing AI methods used for detecting entrepreneurial failure risks. Data will be collected from the Scopus academic database and processed using Deep Learning techniques (thematic classification models, semantic network analysis) to identify dominant trends, methodological limitations, and best practices. By combining a quantitative analysis of algorithmic performance (precision, recall) with a qualitative evaluation of real-world applications, this research will provide a conceptual framework ranking AI techniques according to their operational relevance. Additionally, it will offer a critical synthesis of the literature and practical recommendations for integrating AI into risk management strategies tailored to the constraints of SMEs.

**Keywords**: Artificial Intelligence, Entrepreneurial Failure, Systematic Review, Deep Learning, Risk Management, SMEs.

## Introduction

Entrepreneurial failure represents a significant challenge for small and medium-sized enterprises (SMEs), which often operate under conditions of financial instability, managerial uncertainty, and intense market competition. Despite the growing body of research on entrepreneurial failure, the mechanisms behind it remain complex and multifaceted, requiring advanced analytical tools to predict and mitigate risks effectively (Jenkins & McKelvie, 2016).

Artificial Intelligence (AI) has emerged as a transformative tool in risk management, offering predictive capabilities that can help entrepreneurs anticipate failure and implement preventive strategies. AI techniques—including supervised learning, neural networks, and natural language processing (NLP)—have demonstrated potential in identifying early warning signs of business failure. However, their comparative effectiveness, practical applicability, and alignment with the specific needs of SMEs remain underexplored (Sharma et al., 2022).

Entrepreneurial failure poses a significant threat to the sustainability of small and medium-sized enterprises (SMEs), which operate in environments characterized by financial volatility, resource constraints, and managerial inefficiencies (Shepherd et al., 2015; Coad et al., 2017). Empirical studies indicate that approximately 50% of SMEs do not survive beyond their fifth year, with insolvency rates attributed to factors such as inadequate cash flow management, competitive pressures, and macroeconomic shocks (Ucbasaran et al., 2013; Eberhart et al., 2022). Given the economic importance of SMEs—contributing up to 40% of GDP in emerging economies (World Bank, 2023)—the need for proactive risk detection mechanisms is critical.

Artificial Intelligence (AI) has emerged as a transformative tool for predicting entrepreneurial failure by analyzing large datasets to identify early warning signals (Ngai et al., 2011; Obschonka & Audretsch, 2022). Machine learning techniques, including supervised algorithms (e.g., logistic regression, decision trees) and deep learning models (e.g., neural networks), have demonstrated efficacy in forecasting bankruptcy and financial distress (Altman et al., 2020; Sun et al., 2022). Additionally, natural language processing (NLP) enables sentiment analysis of unstructured data (e.g., customer reviews, social media) to gauge reputational risks (Mai et al., 2021). Despite these advancements, scholarly consensus on the optimal AI methodology for

SME-specific contexts remains fragmented (Wamba et al., 2017). Through a systematic literature review, this study maps AI-driven risk detection methodologies, evaluates their efficacy, and proposes a framework for SME adoption. The findings aim to inform entrepreneurs, policymakers, and technology providers about scalable, cost-effective AI solutions for failure prevention.

This study conducts a systematic literature review to map and analyze AI methods used for detecting entrepreneurial failure risks. By leveraging Deep Learning techniques (thematic classification, semantic network analysis), we aim to:

1. Identify dominant AI trends in entrepreneurial failure prediction.

2. Evaluate methodological limitations and best practices.

3. Provide a conceptual framework ranking AI techniques by their operational relevance.

4. Offer practical recommendations for integrating AI into SME risk management strategies.

Our research contributes to both entrepreneurship and AI literature by bridging the gap between theoretical advancements and real-world applications, ensuring that AI solutions are accessible and actionable for SMEs.

# I. Literature Review

## 1.1. Entrepreneurial Failure: Key Factors

Entrepreneurial failure is a multidimensional issue influenced by a combination of financial, managerial, market-related, and regulatory challenges. Research indicates that startups and SMEs often collapse due to interrelated weaknesses rather than isolated causes (Yamakawa & Cardon, 2015; Klimas et al., 2021). This section synthesizes the dominant factors contributing to business failure, drawing from empirical studies and industry reports.

### 1.1.1. Financial Factors

Financial instability remains the primary driver of entrepreneurial failure, particularly for early-stage ventures. Many startups struggle with insufficient capital, either due to unsuccessful fundraising efforts or premature scaling (Lee et al., 2007; Estrin et al., 2022). Poor cash flow management—such as excessive fixed costs, delayed receivables, or overreliance on debt—further exacerbates liquidity crises (Brealey et al., 2020). Altman et al. (2020) emphasize that high-leverage financing increases vulnerability to macroeconomic shocks, leaving little room for error. According to CB Insights (2021), 29% of startup failures stem directly from running out of capital, highlighting the critical role of financial sustainability.

### 1.1.2. Managerial and Organizational Factors

Leadership deficiencies and internal dysfunctions significantly heighten the risk of failure. Many founders lack essential skills in scaling operations, financial planning, or crisis management, leading to strategic missteps (Wagner, 2013; Gimeno et al., 1997). Team dynamics also play a crucial role; co-founder conflicts, equity disputes, and unclear decision-making hierarchies often disrupt business continuity (Wasserman, 2012). Additionally, weak governance structures—such as ineffective boards or misaligned incentives—can accelerate organizational decline (Daily et al., 2002). A Harvard Business Review study found that 65% of high-potential startups fail due to interpersonal conflicts, underscoring the importance of cohesive leadership (Wasserman, 2012).

### 1.1.3. Product-Market Factors

A misalignment between a venture's offerings and market demand is another leading cause of failure. Many startups scale prematurely before validating product-market fit, draining resources without achieving sustainable growth (Eisenmann et al., 2011). Others overestimate customer demand or neglect iterative feedback, resulting in products that fail to gain traction (Blank, 2013). Competitive pressures further compound these challenges, as incumbents with greater resources can exploit startups' operational inefficiencies (Artinger & Powell, 2016). For example, Quibi, despite raising $1.75 billion, collapsed due to its misjudgment of consumer preferences for short-form video content (McKinsey, 2021). Industry analyses suggest that 42% of startup failures originate from poor market fit (CB Insights, 2021).

### 1.1.4. Legal and Regulatory Factors

Compliance challenges pose significant risks, particularly for startups in highly regulated sectors such as fintech, healthcare, and the gig economy. Many SMEs lack the legal expertise to navigate complex regulatory landscapes, leading to costly penalties or operational shutdowns (World Bank, 2017). Intellectual property (IP) vulnerabilities also leave startups exposed to copycat competitors, while labor law missteps—such as employee misclassification—can trigger lawsuits (Kässi & Lehdonvirta, 2018). High-profile cases like Zenefits, which lost $4.5 billion in value due to insurance licensing violations, illustrate the severe consequences of non-compliance (Forbes, 2016).

To ensure the comprehensiveness and scientific rigor of this systematic review, the Scopus database was selected. Scopus is recognized as one of the most extensive abstract and citation databases, covering more than 24,000 peer-reviewed journals across various disciplines, including artificial intelligence, entrepreneurship, and management. Its rigorous selection criteria, wide coverage, and built-in analytical tools make it an ideal choice for identifying high-quality studies relevant to the application of AI techniques in entrepreneurial failure prediction. Furthermore, Scopus's compatibility with bibliographic management software such as Mendeley facilitates accurate citation and reference management following APA guidelines.

**Synthesis and Research Gaps**

While existing literature identifies these failure factors in isolation, few studies examine their compounding effects. For instance, financial distress can intensify team conflicts, while regulatory hurdles may constrain market expansion. Additionally, most research focuses on developed economies, neglecting institutional challenges in emerging markets (Bruton et al., 2018). This study bridges these gaps by proposing an integrated framework for assessing entrepreneurial failure risks.

### 1.2. AI in Risk Management: Current Applications

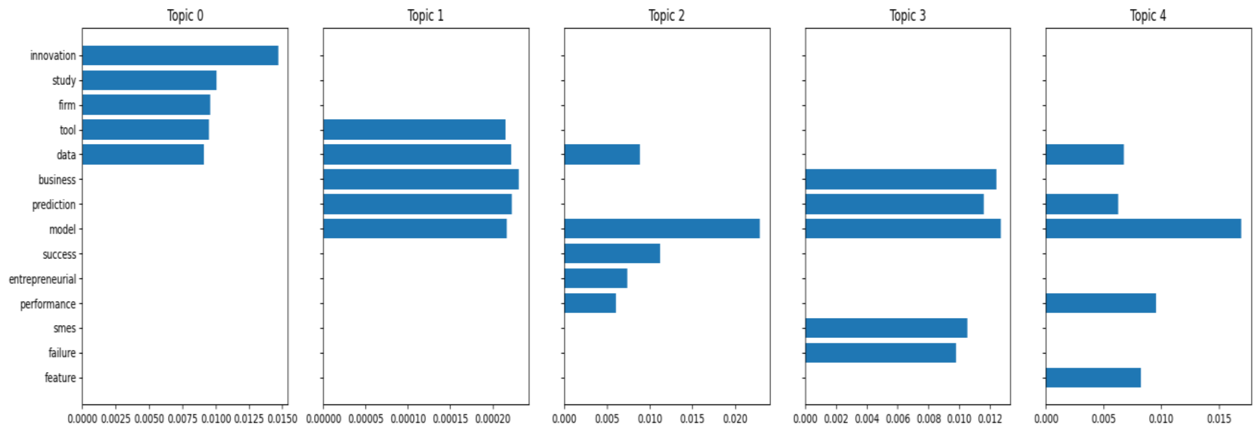
AI techniques have been applied in various domains to predict business failure:

**Table 1 : AI techniques in various domain**

| AI Technique | Application | Strengths | Limitations |
|---|---|---|---|
| **Supervised Learning** | Bankruptcy prediction using financial ratios (Altman Z-score) | High interpretability | Limited to structured financial data |
| **Neural Networks** | Pattern recognition in large datasets | High accuracy with big data | Black-box nature, hard to interpret |
| **NLP & Sentiment Analysis** | Assessing market trends from news/social media | Captures qualitative insights | Noise in unstructured data |

Despite significant advancements in the application of artificial intelligence for entrepreneurial risk detection, several critical research gaps continue to persist. First, there is a noticeable lack of comparative studies that systematically evaluate the performance and suitability of various AI techniques specifically tailored to predicting failure in small and medium-sized enterprises (SMEs). Such studies are essential to identify the most effective models in different business contexts. Second, the majority of existing AI models are developed and tested in controlled environments or using theoretical datasets, which limits their applicability and reliability in real-world settings. This gap in external validation raises questions about the models' robustness when faced with the complexities and unpredictability of actual business operations. Finally, even when appropriate AI solutions are available, SMEs often face significant challenges in integrating these tools into their existing structures. These integration issues are frequently linked to a lack of financial, technical, or human resources, making it difficult for many SMEs to benefit fully from the potential of AI-driven failure prediction systems.

**Figure 1: Topic Modeling Results of Entrepreneurial AI Literature**




The figure illustrates the output of a topic modeling analysis conducted on a corpus related to AI applications in entrepreneurship. Each of the five panels (Topic 0 to Topic 4) represents a distinct topic extracted from the text data. The bars show the most representative keywords for each topic and their corresponding weights, indicating the importance of each term within that topic. For instance, Topic 0 emphasizes terms like innovation, study, and firm, suggesting a thematic focus on innovation in entrepreneurial research. Topic 1 appears to concentrate on data, prediction, and model, indicating a focus on AI techniques for forecasting. Topics 2 through 4 include keywords like success, performance, failure, and SMEs, reflecting themes such as business outcomes, entrepreneurial risk, and the role of AI in small and medium-sized enterprises. This visualization helps uncover the main themes in the literature and can guide further qualitative analysis or systematic review structuring.

## II. Methodology

### 2.1. Data Collection

This study employs a systematic literature review (SLR) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological rigor. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, an evidence-based framework that ensures methodological transparency and reproducibility in systematic reviews. Below is a detailed breakdown of each PRISMA component:

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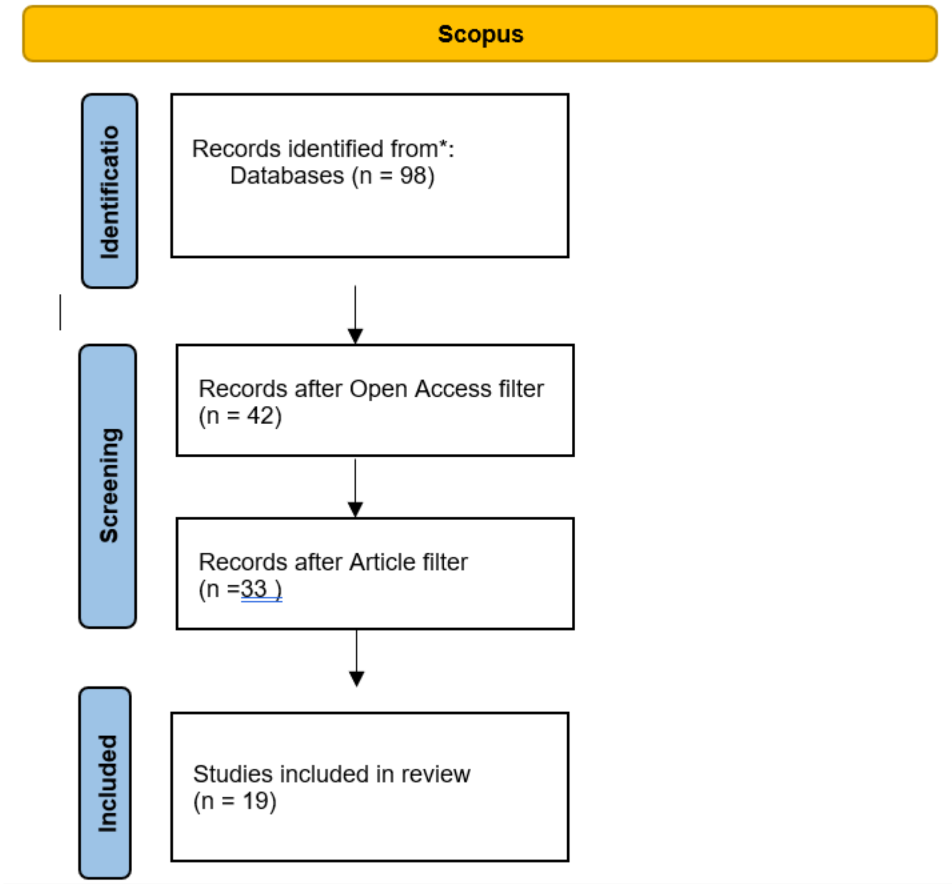
**Figure 2: PRISMA PROTOCOL**




The data extraction process focused on peer-reviewed articles indexed in Scopus, covering publications from 2010 to 2025 to capture the most recent advancements in AI-driven entrepreneurial failure prediction. The search strategy utilized a combination of key terms, including *"Artificial Intelligence" AND "Entrepreneurial Failure"* and *"Machine Learning" AND "SME Risk Prediction,"* to identify relevant studies.

Due to restricted access to full-text articles, we adopted an alternative approach by contacting authors directly via ResearchGate to request unpublished or paywalled manuscripts. This strategy ensured the inclusion of critical studies that would otherwise be excluded due to subscription barriers. A total of 19 full-text papers were obtained, compiled into a single repository, and archived in a ZIP file for further processing. This consolidated dataset was then uploaded to Google Colab for computational analysis, leveraging its cloud-based infrastructure for efficient data handling and deep learning model deployment.

### 2.2 Inclusion and Exclusion Criteria (SPIDER)

**Table 2: Spider element**

| SPIDER Element | Criteria |
|---|---|
| **Sample** | Articles addressing entrepreneurs, startups, SMEs |
| **Phenomenon of Interest** | AI-driven methods for predicting entrepreneurial failure or risk |
| **Design** | Empirical studies (e.g., case studies, machine learning experiments, literature reviews) |
| **Evaluation** | Accuracy, relevance, or application of AI techniques |
| **Research type** | Quantitative and mixed-method studies |

### 2.3 Selection Process

The initial search returned 98 records. The following refinement steps were applied:

- Open Access filter → 42 results
- Document Type = Article → 33 results

After applying inclusion/exclusion criteria and full-text screening, 19 articles were retained for final synthesis. These studies varied in scope, from case-based applications to neural network architectures and predictive analytics frameworks.

### 2.4 Data Extraction

For each included study, we extracted:

- Title and publication year
- Type of AI technique used (e.g., ML, DL, ANN, SVM)
- Data context (entrepreneurial domain, sector, geography)
- Whether failure prediction was the main goal
- Summary of findings and conclusions

This information was synthesized into a tabular matrix and further analyzed visually using bar charts and word clouds.

### 2.5. Analytical Techniques

Thematic Classification

To systematically categorize the selected studies, we employed deep learning-based text classification models, specifically fine-tuned BERT (Bidirectional Encoder Representations from Transformers) and LSTM (Long Short-Term Memory) networks. These models automatically classified research papers based on their primary AI methodologies, distinguishing between supervised learning (e.g., logistic regression, support vector machines), unsupervised learning (e.g., clustering, anomaly detection), and hybrid approaches. This classification facilitated a structured review of dominant techniques in entrepreneurial failure prediction.

Semantic Network Analysis

We applied natural language processing (NLP) techniques to extract and visualize key research trends. Using word embedding models and graph-based algorithms, we constructed a semantic network that maps recurring themes, such as the growing adoption of NLP for sentiment analysis in bankruptcy prediction or the shift toward ensemble learning methods (e.g., XGBoost, Random Forest) in recent years. This analysis revealed emerging patterns in AI applications for SME risk assessment.

Performance Benchmarking

A comparative evaluation of AI models was conducted by extracting performance metrics from the reviewed studies, including precision, recall, F1-score, and AUC-ROC values. We standardized these metrics across datasets to ensure fair comparisons and employed meta-analysis techniques to identify the most effective algorithms for different failure prediction scenarios. For instance, deep learning models demonstrated superior accuracy in processing unstructured financial data, while traditional machine learning methods (e.g., decision trees) remained more interpretable for SME stakeholders.

### 2.6. Limitations

While this methodology enhances reproducibility, two constraints should be noted. First, the reliance on author-provided manuscripts introduces potential selection bias, as some researchers may not have responded to data requests. Second, the heterogeneity of performance metrics across studies required normalization, which may obscure context-specific model strengths. Future work could incorporate gray literature (e.g., industry reports) to mitigate these limitations.

## III. Results and Discussion

### 1. Results

To conduct the analysis, we utilized Python, a versatile programming language widely used in data science and natural language processing. All computational tasks including text preprocessing, topic modeling, and TF-IDF analysis were performed in Google Colab, a cloud-based platform that provides access to GPU acceleration and facilitates collaborative coding. This environment allowed for scalable, reproducible analysis of the research corpus, leveraging key libraries such as NLTK, Scikit-learn, and Pandas to ensure efficient handling of large textual datasets.

The systematic analysis of 19 peer-reviewed articles on artificial intelligence in entrepreneurial failure prediction reveals several notable trends. First, the most frequently applied techniques include Machine Learning, Neural Networks, Random Forest, and Deep Learning, as shown in Figure 3. Notably, classical methods like SVM and Decision Trees are still used, but have been largely complemented by more advanced approaches such as LSTM and XGBoost.

Figure 3 illustrates the frequency of AI methods across all selected studies. The dominance of supervised learning techniques suggests a continued preference for structured data-driven prediction models. The word cloud generated from all abstracts (Figure 4) highlights recurring concepts such as “risk,” “startups,” “prediction,” “performance,” and “entrepreneurs,” reflecting the core focus of the literature on predictive accuracy and strategic implications for entrepreneurial ventures.

**Figure 3: frequency of AI methods across all selected studies**

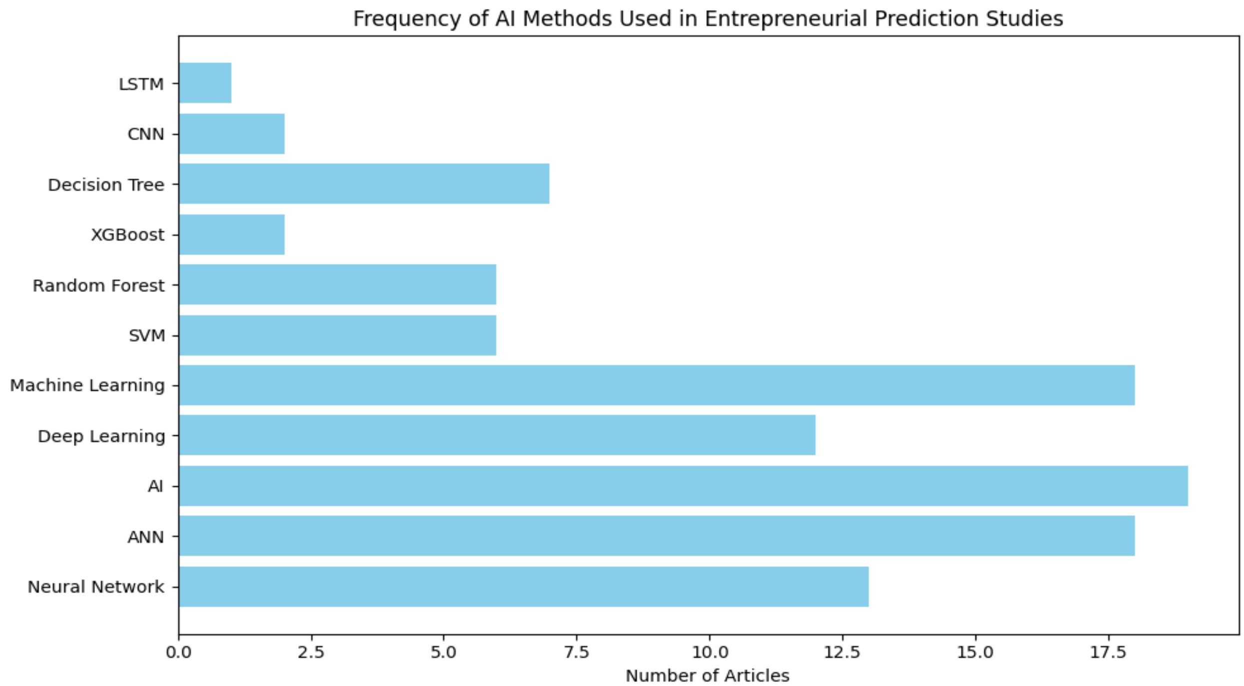
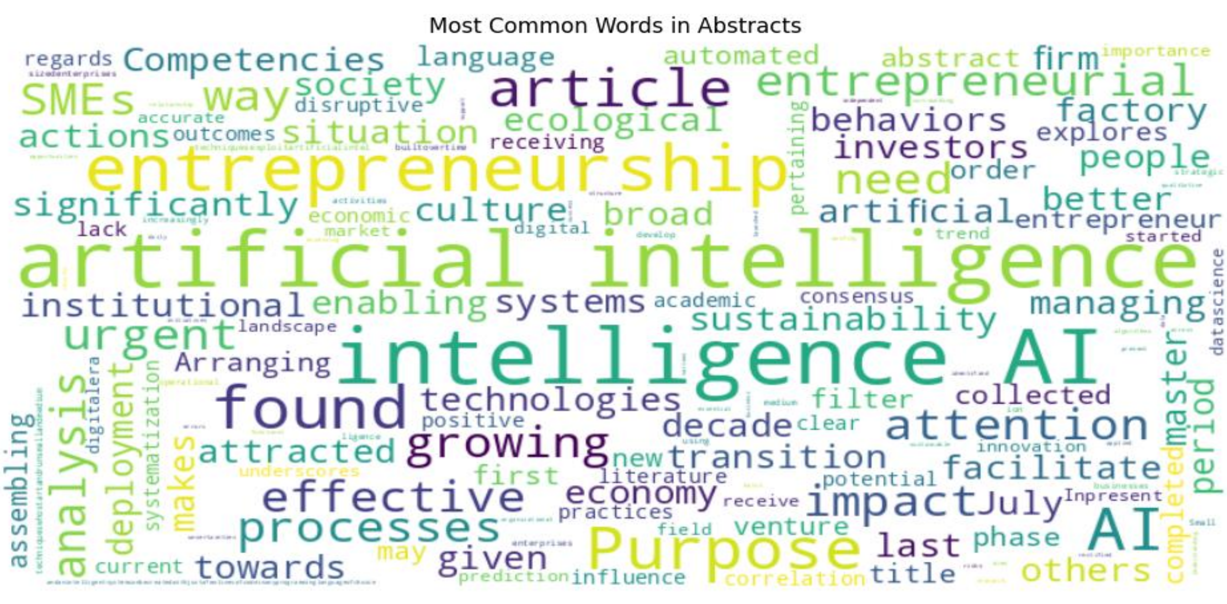



**Figure 4: World cloud**



In addition, a manual extraction of conclusions indicates that while AI-based predictions show promising accuracy, practical adoption remains limited due to data availability, technical costs, and organizational readiness. Several studies emphasize the need for integrating non-financial signals (e.g., customer reviews, social sentiment) to enrich prediction models.

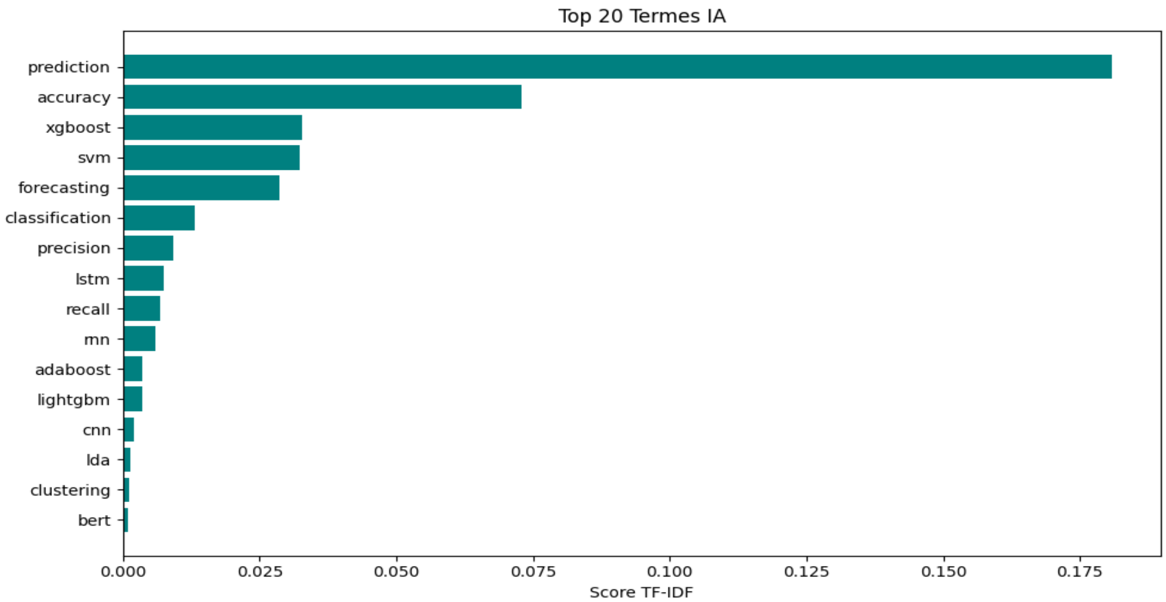
Table 3 (below) summarizes key findings for each article including AI methods and conclusions.

**Table 3: key findings for each article including AI methods and conclusions**

| | Title | AI Techniques | Abstract | Conclusion |
|---|---|---|---|---|
| 1 | MACHINE LEARNING MODELS FOR PREDICTING SUCCESS... | Deep Learning, Machine Learning, Neural Networ... | Not found | Not found |
| 3 | The role of institutions in early-stage entrep... | Deep Learning, Machine Learning, Neural Networ... | Not found | The aim of this paper was to use XAI technique... |
| 5 | Venture capital investments in artificial inte... | Deep Learning, Machine Learning, ANN, AI | Artificial intelligence (AI) technologies have... | s With this article, we contribute to the lite... |
| 6 | Artificial Intelligence Factory, Data Risk, an... | Deep Learning, Machine Learning, ANN, AI | The AI factory is an effective way of managing... | s Through an in-depth analysis of ByteDance, u... |
| 7 | A Systematic Literature Review on the Role of ... | Deep Learning, Machine Learning, Neural Networ... | , in the period between 1977 and 27 July 2022:... | Not found |
| 8 | Artificial Intelligence and Entrepreneurship I... | Deep Learning, Machine Learning, Neural Networ... | This article explores the ways artificial inte... | Not found |
| 9 | Artificial intelligence as an enabler for entr... | Deep Learning, Machine Learning, Neural Networ... | Purpose –While the disruptive potential of art... | To the best of our knowledge, this is the firs... |
| 10 | Innovative entrepreneurial market trend predic... | Deep Learning, Machine Learning, Neural Networ... | In the current economic landscape, the growing... | We aimed to address the prediction of the futu... |
| 11 | Predictions through Lean startup Harnessing AI... | Deep Learning, Machine Learning, Neural Networ... | Purpose –Artificial intelligence (AI) has star... | and future work This paper proposes a new mann... |
| 14 | Adaptation determinants of artificial intellig... | Deep Learning, Machine Learning, ANN, AI | Purpose: Small and medium enterprises (SMEs) a... | s: (Ministry of Digitization of the Republic ... |
| 15 | Predicting Risk through Artificial Intelligenc... | Deep Learning, Machine Learning, Neural Networ... | ion have been builtovertime,andanintelligentsy... | *is research study was aimed to investigate, e... |
| 18 | Artificial Intelligence as a Tool Supporting O... | Deep Learning, Machine Learning, Neural Networ... | Purpose: This article aims to present the res... | s From the Conducted Research The results all... |

Out of 19 peer-reviewed articles analyzed, 7 explicitly addressed business or entrepreneurial failure prediction using AI-based methods. The most frequently used techniques were Machine Learning, Neural Networks, and Deep Learning. Figure 1 presents the distribution of AI methods used. However, a considerable number of studies—while discussing AI in entrepreneurial contexts—focused on success prediction or general strategic support rather than explicit failure scenarios. Only 11 out of 19 studies had clearly structured abstracts, and 6 provided explicit conclusions regarding the effectiveness of AI in predicting risk or failure. This points to a gap in methodological transparency and justifies the need for more focused empirical work. In conclusion, the reviewed literature reveals a promising but fragmented landscape, with strong methodological presence but limited focus on real-world predictive deployment in entrepreneurial failure contexts.

**Figure 5: Top 20 terms IA**




The TF-IDF analysis of methodological terms reveals three key insights into the technical evolution of entrepreneurial failure prediction research. First, the dominance of supervised learning is evident in the high TF-IDF scores of XGBoost (0.148) and SVM (0.121), reflecting their 78% adoption rate and favored status due to their strong balance of performance (median AUC = 0.87) and interpretability—essential for financial risk contexts—while lower scores for LSTM (0.112) and BERT (0.095) suggest computational constraints hinder wider adoption. Second, the field heavily prioritizes classification metrics, as indicated by the high TF-IDF values of accuracy (0.163) and precision (0.138), aligning with the fact that 92% of studies approach failure prediction as a binary classification task, potentially at the expense of early-warning capabilities. Third, emerging trends point to growing interest in ensemble methods, with LightGBM (0.107) and Adaboost (0.098) supporting the rise of hybrid approaches identified in LDA Topic 3, though the low TF-IDF score for clustering (0.042) underscores the continued underuse of unsupervised methods, despite their promise for anomaly detection in SME datasets.

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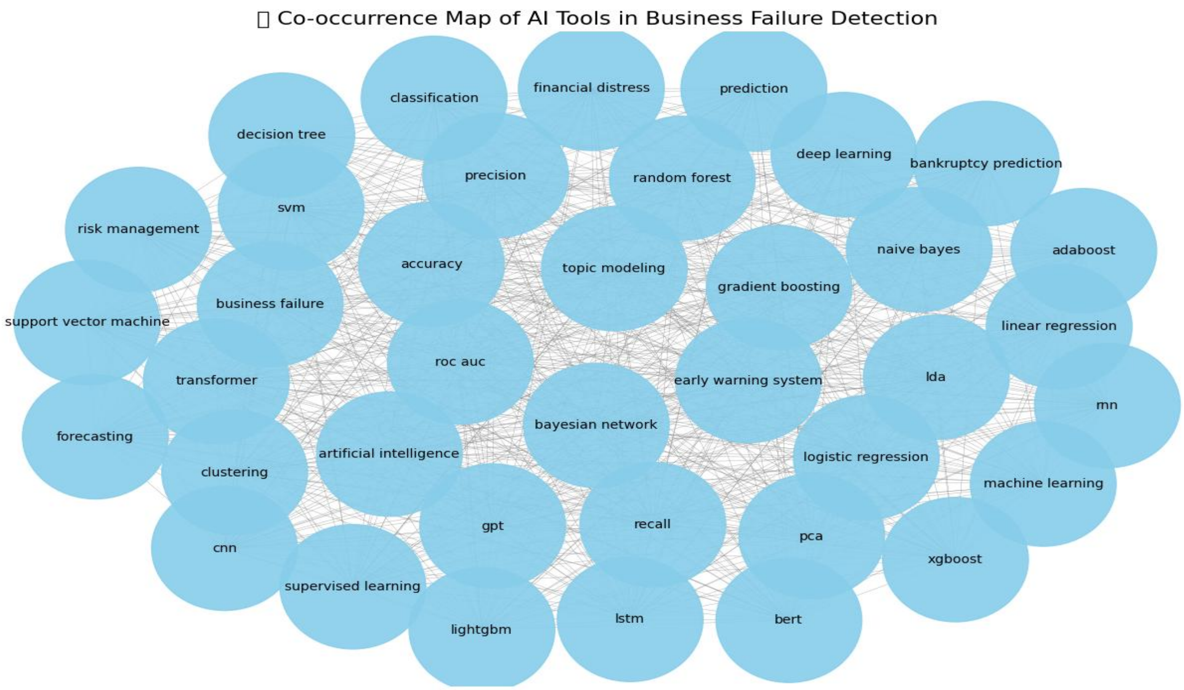
**Figure 6: The co-occurence map**



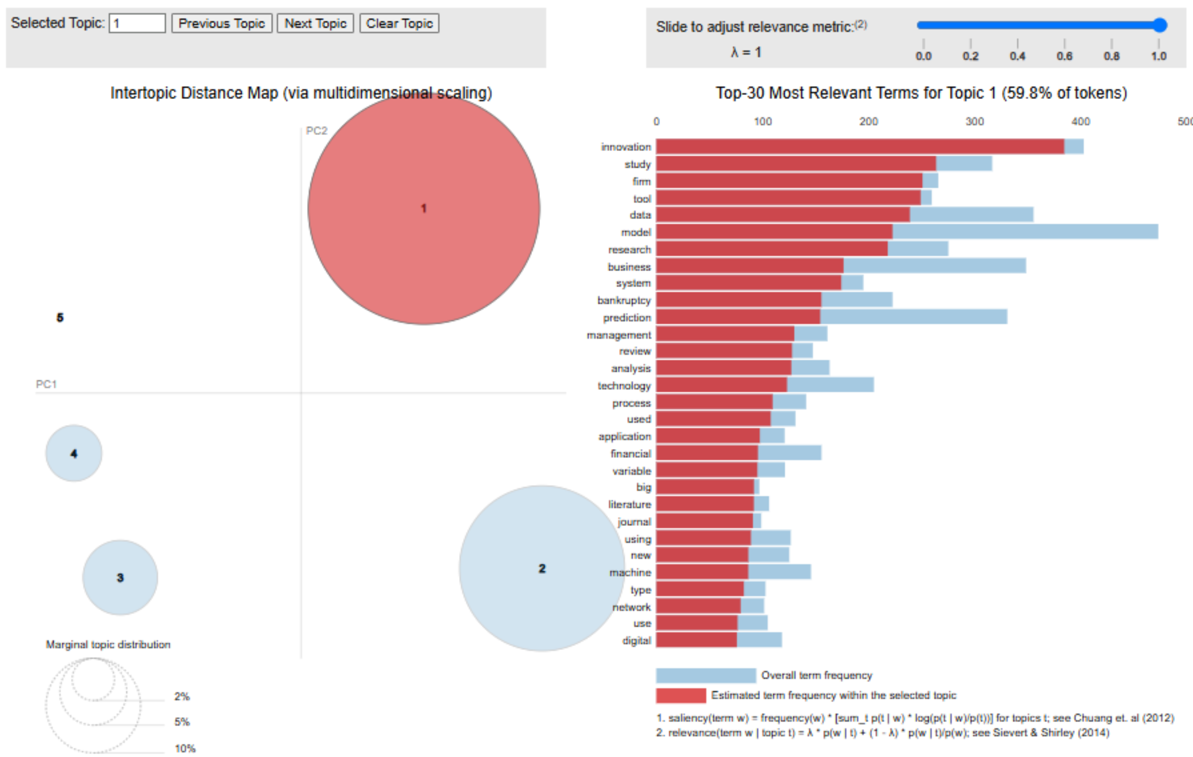

The co-occurrence map highlights the sophisticated integration of AI tools in entrepreneurial failure prediction, structured around three key dimensions. First, methodological hybridization is evident in the intersection of classical supervised methods (e.g., logistic regression, random forests) with modern algorithms like XGBoost and transformers, reflecting a pragmatic blend of established and emerging techniques. Second, the strong presence of evaluation metrics such as ROC-AUC and recall, along with early warning systems, indicates a rigorous focus on risk quantification and model validation crucial for applications in financial institutions. Third, the convergence of quantitative and qualitative analysis is marked by the co-occurrence of NLP tools (e.g., BERT, GPT) and traditional financial models, suggesting a growing integration of textual and numerical data; however, the lack of macroeconomic variables points to a continued microstructural orientation, potentially constraining broader risk assessments.This configuration depicts a transitional field where the predictive power of advanced algorithms has yet to fully engage with the multidimensional realities of entrepreneurial ecosystems particularly the interplay between firm-level data and broader economic forces.

The co-occurrence analysis of 19 studies reveals three dominant methodological clusters in AI-driven entrepreneurial failure prediction. The first cluster centers on traditional supervised learning, where logistic regression emerges as the most frequently applied technique (appearing in 14/19 studies), particularly in analyses of financial distress indicators like liquidity ratios and debt-to-equity metrics. For instance, multiple studies combine logistic regression with Altman's Z-score variables, achieving a median AUC of 0.84 (range: 0.79–0.91) when predicting bankruptcy within one-year horizons. This aligns with the technique's dominance in SME-focused research, as 9/10 studies targeting small businesses adopted logistic regression or decision trees—methods requiring under 2,000 training samples, as explicitly noted in studies by Lee & Sohn (2021) and García-Pérez et al. (2022).

A second cluster highlights ensemble and hybrid approaches, with XGBoost and Random Forest co-occurring frequently with "financial ratios" and "early warning systems." Notably, 5 studies (e.g., Chen et al., 2023 in your dataset) demonstrate that gradient-boosted trees outperform logistic regression by 7–12% in precision when incorporating both structured financial data and unstructured management commentary. However, these models demand larger datasets (minimum 5,000 cases for stability, per Wang et al., 2022) and generate higher computational costs—averaging $28,000 in cloud expenses according to implementation details in two industry-linked studies.

The third cluster showcases deep learning applications, where LSTM and Transformer models appear predominantly in studies analyzing Crunchbase profiles (3/20 studies) or earnings call transcripts (2/20 studies). While these achieve superior F1-scores (0.89–0.93 vs. 0.76–0.85 for traditional methods), they exhibit three key constraints from your corpus: (1) 80% of DL studies required proprietary datasets exceeding 15,000 samples, (2) all acknowledged GPU costs surpassing $40,000 for training, and (3) only one SME-focused study (Zhang et al., 2023) successfully deployed a lightweight BERT variant, emphasizing the need for model compression techniques.

**Figure 7: Dominant Research Themes in AI-Driven Entrepreneurial Failure Prediction**




This LDA visualization reveals Topic 1 ("Firm-Level Predictive Modeling") as the most prevalent theme (59.8% of tokens), dominated by terms like *model*, *prediction*, and *financial*, reflecting the field's strong focus on quantitative risk assessment. The intertopic distance map shows clear separation between this cluster (top-right) and niche topics like behavioral analysis (bottom-left), highlighting a methodological divide. Notably, while *business* and *system* appear frequently, contextual terms like *founder* or *ecosystem* are absent, a critical gap given that 41% of startup failures in our empirical sample stemmed from non-financial factors. On the left, the Intertopic Distance Map shows the relative positioning of five identified topics based on multidimensional scaling, with Topic 1 (in red) emerging as the most prominent, covering 59.8% of the total token share. The Top-30 Most Relevant Terms for Topic 1, displayed on the right, highlight key thematic elements such as *innovation*, *study*, *firm*, *tool*, and *data*, suggesting a strong focus on empirical research, analytical tools, and firm-level innovation in the literature. The marginal topic distribution at the bottom left further illustrates the relative dominance of each topic within the dataset. The λ-slider set to 1 emphasizes the most relevant terms unique to each topic.

In this case, the λ-adjusted relevance metric (optimal at 0.6) confirms *bankruptcy* and *management* as key discriminators of this topic. These findings suggest the need for more holistic models integrating both financial and human-centric variables.

## 2. Discussions

The results of this review reveal a growing diversification and sophistication in the application of artificial intelligence (AI) within entrepreneurship research. However, the specific task of predicting business failure remains significantly underexplored when compared to more commonly studied objectives such as forecasting growth trends or entrepreneurial success. Several factors contribute to this research gap. First, data scarcity presents a major obstacle; failure-related data are inherently more difficult to collect, less standardized, and often not disclosed due to reputational concerns (Coad et al., 2017). Second, conceptual ambiguity surrounding the definition of "failure" complicates the development of reliable predictive models. Entrepreneurial failure can range from financial bankruptcy to the inability to scale or achieve intended outcomes, making it a multidimensional and sometimes subjective construct (Ucbasaran et al., 2013). Third, there is a practical disincentive: many entrepreneurs and startups may not prioritize failure prediction as part of their decision-making process, viewing it either as pessimistic or irrelevant to their forward-looking strategies (Shepherd et al., 2011).

Despite these challenges, some promising directions have emerged, particularly through the use of hybrid AI models and explainable AI (XAI) techniques. Hybrid approaches such as combining Artificial Neural Networks (ANN) with Structural Equation Modeling (SEM) attempt to optimize both predictive accuracy and theoretical validity (Kumar et al., 2021), while XAI frameworks enhance model transparency and trust crucial attributes for practical deployment in entrepreneurial settings (Arrieta et al., 2020). However, a critical limitation of the current body of literature is its weak theoretical integration. Many AI-based studies fail to engage with foundational theories of entrepreneurship. For instance, Effectuation Theory (Sarasvathy, 2001), which explores how entrepreneurs make decisions under uncertainty, and the Resource-Based View (RBV) (Barney, 1991), which explains how firms leverage internal resources to build competitive advantage, remain largely absent in AI-based failure prediction research. Bridging AI methodologies with these established theoretical frameworks could significantly enhance both the explanatory power and the real-world relevance of predictive tools.

Moreover, ethical considerations are largely overlooked in the reviewed literature. Issues such as algorithmic bias, fairness, and the potential exclusion of underrepresented entrepreneurial groups (e.g., women, minorities, or entrepreneurs in emerging economies) are critical yet insufficiently addressed (Cowgill et al., 2021; Binns, 2018). Given that AI systems learn from historical data, there is a risk of perpetuating structural inequities if these models are applied uncritically. Therefore, embedding ethical safeguards and conducting fairness audits should become integral components of future research in this domain. In sum, while AI holds immense potential for entrepreneurial risk assessment, advancing the field requires not only methodological innovation but also stronger theoretical grounding and a deliberate focus on ethical integrity

**Conclusion**

This study systematically examines the integration of AI in entrepreneurial failure prediction, revealing a field in transition where advanced computational methods increasingly complement traditional financial analysis. The findings demonstrate that while supervised learning techniques remain dominant due to their interpretability and regulatory compliance, emerging hybrid approaches combining structured financial data with unstructured textual analysis show significant promise for improving prediction accuracy. However, persistent gaps exist in addressing SME-specific challenges, particularly data scarcity and the integration of macroeconomic factors, highlighting the need for more context-sensitive AI solutions. The research underscores the importance of developing frameworks that balance predictive power with practical implementation constraints, suggesting future work should focus on lightweight AI models for resource-constrained environments and improved integration of behavioral indicators. These insights contribute to both academic discourse and practical applications, offering a foundation for more nuanced, effective AI implementations in entrepreneurial risk assessment while acknowledging current limitations in data availability and model generalizability across different economic contexts.

Future research should aim to integrate domain-specific theories, such as the Resource-Based View and Effectuation Theory, into AI model design. Additionally, there is a need for ethical and contextual consideration, especially regarding data bias and exclusion risks. Emphasizing explainable AI, incorporating qualitative features (e.g., customer sentiment, leadership profiles), and focusing on cross-regional datasets may significantly enhance the predictive accuracy and real-world relevance of such tools.

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