مجلة جامعة الأزهر-غزة، سلسلة العلوم الإنسانية، المجلد 27، العدد 1 يونيو 2026، ص: 103-132

التنبؤ بمخاطر الإفلاس باستخدام تحليل التمييز المتعدد والشبكات العصبية الاصطناعية: دراسة مقارنة للعوامل المالية وغير المالية في قطاع الاستثمار الفلسطيني.

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(تاريخ الاستلام 2026/03/10، تاريخ القبول 2026/04/26)

Predicting Insolvency Risk Using Multiple Discriminant Analysis and Artificial Neural Networks: A Comparative Study of Financial and Non-Financial Factors in Palestine's Investment Sector

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(Received 10/03/2026, Accepted 26/04/2026)

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الملخص:

تتناول هذه الدراسة التنبؤ بمخاطر التعثر لشركات قطاع الاستثمار المدرجة في بورصة فلسطين، انطلاقاً من قصور النماذج التقليدية التي تعتمد حصراً على مؤشرات مالية تاريخية وتُغفل العوامل النوعية في بيئة متقلبة كالبيئة الفلسطينية، وسعت الدراسة إلى بناء نموذج هجين يدمج العوامل المالية وغير المالية ومقارنته بالنماذج التقليدية، مستخدمةً منهجية كمية وتقنيتَي تحليل التمييز المتعدد (MDA) والشبكات العصبية الاصطناعية (ANN)، وقد تضمنت البيانات 18 نسبة مالية تغطي السيولة والربحية والكفاءة والهيكل المالي والقيمة السوقية، أُكملت بمؤشرات الحوكمة العالمية، والناتج المحلي الإجمالي، وصراع الوكالة، وهيكل الملكية وهي متغيرات غير مالية ، وقد كشفت النتائج تحسّناً في دقة التنبؤ عند دمج العوامل غير المالية: ارتفعت دقة MDA من 71.3% إلى 76.3%، ودقة ANN من 70.8% إلى 77.3% ،ويعكس تفوّق النموذج القائم على الذكاء الاصطناعي قدرته على التقاط العلاقات غير الخطية، فيما برزت نسبة السوق إلى القيمة الدفترية وربحية السهم كأقوى المتنبئين بالمخاطر، وهو ما يعكس ثقل معنويات المستثمرين في السياق الناشئ، تُقدّم الدراسة إطاراً عملياً لدعم قرارات المستثمرين والمحلّلين والجهات الرقابية في التقييم الاستباقي للمخاطر المالية.

الكلمات المفتاحية: التنبؤ بالإفلاس، تحليل التمييز، العوامل غير المالية، صراع الوكالة، مؤشرات الحوكمة العالمية.

Abstract:

The purpose of this study is to forecast the insolvency-risk of investment-sector companies listed on the Palestinian Exchange. This study is based on the fact that the conventional models based on the historical financial ratios are not effective in a volatile environment of the Palestinian one. The study constructs a hybrid specification of both financial and non-financial inputs and compares it with traditional models by two methodologies: Multiple Discriminant Analysis (MDA) and Artificial Neural Networks (ANN). The dataset includes 18 financial ratios related to liquidity, profitability, efficiency, financial structure, and market value. Additionally, the dataset contains Worldwide Governance Indicators, GDP, agency conflicts, and ownership structure.

Results indicate significant improvement when non-financial factors are added to the specification with MDA accuracy improving from 71.3% to 76.3% and ANN accuracy improving from 70.8% to 77.3%. The superiority of the AI-based model suggests the ability of the model to detect non-linear relationships in the data. The market-to-book ratio and earnings per share were the most influential predictors of insolvency risk emphasizing the significance of investor sentiment in emerging-market environments. This study provides a practical framework for investors, financial analysts, and regulator risk, emphasizing active financial risk assessments.

Keywords: Bankruptcy Forecasting, Discriminant Analysis, Non-Financial Factors, Agency Conflict, Worldwide Governance Indicators.

Introduction:

Predicting financial distress and bankruptcy risk represents one of the most critical challenges confronting both academic and professional communities, given its far-reaching economic and social implications for investors, creditors, employees, and the overall macroeconomic stability of nations. This field has gained increasing prominence in the context of emerging markets characterized by acute economic and political volatility, rendering their corporate sectors particularly vulnerable to financial shocks. Historically, traditional statistical models, such as the Altman Z-Score developed by (Altman, 1968) and the Logit models pioneered by (Ohlson, 1980), have dominated the bankruptcy prediction literature, relying primarily on financial ratios extracted from firms' historical financial statements. Despite the notable successes these models achieved in stable economic environments, successive financial crises ranging from the Asian Financial Crisis to the Global Financial Crisis of 2008 have exposed their limitations in accurately predicting failure under complex and rapidly changing conditions (Altman & Hotchkiss, 2018). In recent years, research has witnessed a qualitative shift toward integrating non-financial factors into prediction models, including corporate governance indicators, management quality, and macroeconomic conditions (Chan et al., 2016). This evolution stems from the recognition that higher-quality predictions must incorporate qualitative factors that may serve as root causes of quantitative outcomes such as financial ratios. Weak governance or economic instability are factors that precede and precipitate financial deterioration. Concurrently, the application of artificial intelligence, machine learning techniques, and hybrid models has emerged, demonstrating superior capability in capturing complex nonlinear patterns in data, thereby enhancing prediction quality beyond traditional models based on linear assumptions (Dasilas, 2024; Samara, 2025). The study by (Ansah-Narh et al., 2024) confirmed the effectiveness of hybrid models integrating Domain Adaptation Learning with machine learning in improving bankruptcy prediction accuracy, while (Mojdehi et al., 2025) highlighted that combining Topological Data Analysis with Graph Neural Networks provides an innovative framework for credit risk assessment.

Within the Palestinian context, the corporate sector faces unique challenges arising from political and economic instability, heightening firms' susceptibility to insolvency risk. Companies listed on the Palestine Exchange (PEX) constitute a vital economic artery for the Palestinian economy, with the investment sector occupying a pivotal position due to its role in capital allocation and its direct impact on financial market stability. Although prior studies have addressed financial failure prediction in the Palestine Exchange, most have relied exclusively on traditional financial ratios, neglecting the crucial role of non-financial factors and macroeconomic conditions in an environment characterized by extreme volatility. The study by (Vukčević et al., 2024) noted that countries with low to medium levels of economic development, including emerging markets, continue to suffer from insufficient research in bankruptcy prediction modeling. Hence, the significance of this study lies in its endeavor to bridge this gap by developing a proposed model that integrates financial indicators with qualitative factors, focusing on the investment sector in the Palestine Exchange, with the aim of providing a more accurate and reliable predictive tool for decision-makers and investors in this vital market.

Research Problem and Questions:

The research problem emanates from the evident inadequacy of current bankruptcy risk prediction models when applied to firms operating in volatile economic environments such as Palestine. This problem can be analyzed by tracing its causes and effects (problem tree), where the ultimate effect manifests in increased unexpected financial failures and their consequent losses to investors and creditors, as well as market destabilization. The root causes primarily stem from the prevailing models' reliance on traditional methodologies. The first cause is the exclusive dependence on financial ratios, which constitute lagging quantitative indicators reflecting financial deterioration that has already occurred rather than predicting it, and fail to explain failure resulting from qualitative factors such as weak governance or macroeconomic shocks (Wu et al., 2010). The second cause is the neglect of non-financial factors; despite contemporary literature emphasizing the critical importance of variables such as corporate governance, agency conflicts, and ownership concentration in bankruptcy prediction, these factors remain overlooked in studies applied to the Palestinian context. The study by (Chan et al., 2016) demonstrated that incorporating governance variables significantly enhances bankruptcy prediction model performance, while (Almaskati, 2019) confirmed that integrating governance indicators improves classification and prediction accuracy. Finally, the third cause is the absence of a sector-specific model that accounts for the unique characteristics of the investment sector in the Palestine Exchange, as applying generic models may not provide the required accuracy given the variation in risk nature across sectors.

These causes converge to form a clear research gap, manifested in the scarcity of studies offering a comprehensive hybrid model that integrates financial and non-financial factors, employs modern methodologies, and is specifically designed for volatile emerging market environments such as Palestine, with a focus on a vital sector like investment. (Zhao et al., 2024) indicated that utilizing board of directors' network relationships as governance indicators represents an innovative approach to bankruptcy prediction, while (Dasilas, 2024) emphasized that "the inclusion of non-financial ratios alongside financial ratios in hybrid models enables a more comprehensive evaluation of a firm's financial health." Based on the foregoing, the study seeks to answer the following main research question: "To what extent can a proposed model, integrating both financial and non-financial variables, effectively and accurately predict insolvency risk for investment sector firms listed on the Palestine Exchange"?

To address this central question, several interconnected narrative sub questions emerge: The study begins by identifying which financial ratios exert the greatest influence in distinguishing between distressed and non-distressed firms in this sector. It then proceeds to explore the incremental role that non-financial factors, such as governance indicators and macroeconomic variables, play in enhancing prediction accuracy. Finally, the study compares the predictive capability of advanced statistical models when incorporating these multiple factors against that of traditional models confined to financial indicators alone.

Research Objectives:

The investment sector companies listed on the Palestine Exchange face significant challenges stemming from economic and political instability, which heightens their exposure to financial insolvency risk. Although traditional models that rely solely on financial ratios have proven effective in various contexts, they remain limited in their ability to capture the qualitative and nonlinear effects of non-financial factors. Therefore, there is a clear need to develop hybrid models that combine classical statistical analysis (discriminant analysis) with artificial intelligence techniques (artificial neural networks), while integrating non-financial indicators, to enhance the accuracy of predicting insolvency risk levels (low, moderate, high). Motivated by this problem, the present study pursues the following objectives:

- To develop and compare two baseline predictive models for insolvency risk among investment sector companies listed on the Palestine Exchange one based on discriminant analysis and the other on artificial neural networks utilizing a selected set of financial ratios and non-financial factors.

- To identify and rank the most influential indicators (both financial and non-financial) that best explain and classify insolvency risk levels (low, moderate, high) within the investment sector.

- To evaluate the predictive performance of the proposed hybrid model and compare it against models that rely exclusively on financial factors, thereby demonstrating the added value of incorporating non-financial factors.

Literature Review:

1. The Historical Evolution of Insolvency Prediction Models: From Traditional Approaches to Artificial Intelligence. The field of financial insolvency prediction has undergone a remarkable methodological evolution over the past six decades, transitioning from a reliance on univariate analysis of financial ratios to the deployment of sophisticated artificial intelligence and hybrid models. This evolution represents a direct response to successive financial crises and global economic shifts that have exposed the limitations of traditional methods in capturing the complex dynamics of financial distress. This review examines the seminal research literature in this domain, with a particular focus on discriminant analysis and artificial intelligence techniques, analyzing prediction quality and the most influential indicators, and culminating in the identification of existing research gaps.
2. The Foundational Stage: Discriminant Analysis and Classical Statistical Models (1960-2000)

3. The methodological roots of insolvency prediction trace back to the 1960s, when (Beaver, 1966) presented the first systematic study using univariate analysis of financial ratios to distinguish between distressed and non-distressed firms. Beaver defined financial failure as "the inability of a firm to pay its financial obligations as they mature" and tested 30 financial ratios classified into six main groups. He concluded that five ratios possessed high predictive power, most notably the ratio of net income to total assets and the ratio of debt to total assets. However, the true methodological leap came with the pioneering study by (Altman, 1968), which developed the Z-Score model using Multiple Discriminant Analysis (MDA) on a sample of 33 bankrupt and 33 non-bankrupt manufacturing firms. Altman selected five variables from a pool of 22 potential candidates, including working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of debt, and sales to total assets. The model achieved a predictive accuracy of 95% one year prior to bankruptcy, establishing it as the gold standard in the field for decades.
4. Continuing on this path, (Altman et al., 1977) developed the more advanced ZETA model, which extended the prediction horizon to five years before failure, using seven variables that included earnings stability, interest coverage, and firm size. The model achieved a classification accuracy of 93% one year prior to failure and 70% five years prior, reflecting the increasing challenge of long-term prediction. However, (Ohlson, 1980) criticized the strict statistical assumptions of discriminant analysis, particularly the requirement of normal distribution for variables and equality of variance-covariance matrices between groups—assumptions rarely met in actual financial data. Therefore, he introduced the Logit model as a more flexible alternative, using a much larger sample (105 bankrupt and 2,058 non-bankrupt firms) and nine financial variables. The study by (Zavgren, 1985) reinforced this direction, noting that

"most prior studies played loose with the assumptions of discriminant analysis" and proposed using the Logit technique as a more appropriate methodology for developing models that assess the probability of financial risk over a five-year period.

5. These methodologies were extended to non-U.S. markets during the 1980s and 1990s, as illustrated in Table 1. In Australia, (Messier & Hansen, 1988) used Neural Networks (NN) and achieved 100% classification accuracy on a small hold-out sample, while (McNamara et al., 1988) achieved 85% accuracy using MDA. In the UK, (Wilson et al., 1995) compared neural networks with Logit models, using 18 financial and non-financial variables, and concluded that "neural network simulation produces a higher predictive accuracy and is more robust than conventional logit models," with accuracy ranging from 70% to 95% for distressed firms. Furthermore, (Lennox, 1999) showed in the UK that Logit and Probit models performed similarly, with a predictive accuracy of 49% for bankrupt firms and 97% for healthy firms one year prior. In Canada, (Springate et al., 1983) developed a model using only four financial ratios that achieved 90% accuracy for failed firms and 95% for successful ones.

Table (1): Summary of International Insolvency Prediction Studies (1980-1999)

Study	Country	Methodology	Key Indicators	Prediction Accuracy (Distressed/Healthy)
Messier & Hansen, 1988	Australia	Neural Networks	12 financial ratios	100% / 100%
McNamara et al., 1988	Australia	MDA	6 ratios (Retained Earnings, Debt, Liquidity)	86% / 83%
Keasey & Watson, 1994	UK	MDA	Multiple financial ratios	70% / 80%
Wilson et al., 1995	UK	NN + Logit	18 financial & non-financial variables	70-95% / 82.5-95%
Lennox, 1999	UK	Logit + Probit	9 factors (ratios + economic conditions)	49% / 97%
Takahashi et al., 1984	Japan	MDA	8 financial ratios	100% / 53-75%
Tsukuda & Baba, 1994	Japan	Neural Networks	Multiple financial ratios	83-100% / 60-100%
Springate et al., 1983	Canada	MDA	4 ratios (WC, ROA, Liquidity, Turnover)	90% / 95%
Altman & Lavallee, 1980	Canada	MDA	5 financial ratios	70-94.1% / 64.5-90%
Poddig, 1995	France	Neural Networks	Multiple financial ratios	89-93% (1 year)

It is evident from the table that predictive accuracy varied significantly across studies, peaking at 100% in some cases and dropping to 49% in others, especially when predicting over longer time horizons. It is also noteworthy that models based on neural networks demonstrated a relative superiority over traditional statistical models in most cases, paving the way for the shift towards artificial intelligence techniques in subsequent decades.

The Transitional Stage: Re-evaluation of Classical Models and Integration of Non-Financial Factors(2012-2000) :

The early years of the third millennium witnessed a critical re-evaluation of classical models, especially in light of major corporate collapses such as Enron in 2001 and WorldCom in 2002, which exposed the shortcomings of traditional financial analysis in detecting accounting fraud and qualitative risks. (Grice & Ingram, 2001) conducted a comprehensive examination of the generalizability of Altman's Z-Score model across different time periods and industries. They found a significant decline in the model's accuracy from 95% in its original development period to about 72% when applied to contemporary data. The authors noted that "the coefficients that worked well in the 1960s were less effective in the 1990s and early 2000s," highlighting the temporal sensitivity of bankruptcy prediction models and the need for periodic recalibration.

In response to this limitation, (Shumway, 2001) introduced a dynamic hazard model that addressed several statistical shortcomings of previous approaches. Unlike static models that rely on single-period data, Shumway's model incorporated time-varying covariates, allowing it to capture the gradual financial deterioration over multiple periods. This methodological innovation significantly improved predictive accuracy to 80-85%, with the author demonstrating that "hazard models produce more consistent, more efficient, and more accurate forecasts than single-period models." The importance of integrating non-financial factors also came to the forefront during this stage. Studies by (Altman & Hotchkiss, 2006), (Altman et al., 2010), and (Altman et al., 2017) emphasized that including qualitative variables such as legal actions against the firm, audit reports, and company-specific historical data significantly enhances risk assessment accuracy, especially for small and medium-sized enterprises (SMEs).

The Global Financial Crisis of 2008, which saw the collapse of giants like Lehman Brothers, Washington Mutual, and General Motors, served as a catalyst for a fundamental rethinking of existing models. It became clear that an exclusive reliance on historical financial ratios was insufficient to capture systemic risks and macroeconomic factors affecting corporate stability, setting the stage for a new era of methodological innovation.

The Era of Artificial Intelligence and Hybrid Models(2023-2013) :

The period between 2013 and 2023 marked a true revolution in insolvency prediction methodologies, driven by tremendous advancements in machine learning, artificial intelligence, and the availability of big data. Research shifted from relying on linear statistical models to employing complex algorithms capable of handling non-linear relationships and intricate patterns in data. Multiple studies, including (Ciampi, 2015), (Sun et al., 2014), and (Madrid-Guijarro et al., 2013), demonstrated that integrating qualitative factors such as managerial experience, legal records, market competition, and internal governance substantially improves the performance of predictive models.

A key development in this era was the emergence of hybrid models that combine the strengths of different approaches. (Ansah-Narh et al., 2024) introduced an innovative approach that integrates Domain Adaptation Learning with machine learning techniques, significantly enhancing bankruptcy prediction accuracy. In a similar vein, (Mojdehi et al., 2025) developed a hybrid model combining Topological Data Analysis (TDA) and Graph Neural Networks (GNN) to assess credit risk in supply chain finance. Furthermore, the comprehensive study by (Dasilas, 2024) on machine learning techniques in bankruptcy prediction asserted that "the inclusion of non-financial ratios alongside financial ratios in hybrid models enables a more comprehensive evaluation of a firm's financial health".

(Samara, 2025) demonstrated that machine learning models, particularly Random Forest, can significantly improve prediction accuracy compared to traditional models, achieving accuracy rates exceeding 90% in some applications. Moreover, (Zhao et al., 2024) indicated that using a complex network analysis approach based on corporate governance, especially board of directors' networks, represents an innovative method for bankruptcy prediction that captures institutional interlocks and systemic risks.

Table (2): Comparison of Modern Prediction Methodologies and Their Accuracy (2013-2025)

Study	Methodology	Key Influential Indicators	Prediction Accuracy
Ansah-Narh et al., 2024	Domain Adaptation + ML	Financial ratios + Environmental factors	88-92%
Mojdehi et al., 2025	TDA + Graph Neural Networks	Network data + Financial ratios	85-90%
Dasilas, 2024	Hybrid ML Models	Financial + Non-financial ratios	87-93%
Samara, 2025	Random Forest	Specific financial indicators	90-94%
Zhao et al., 2024	Complex Network Analysis	Board networks + Governance	84-89%
Vukčević et al., 2024	Logistic Regression	Debt ratio + Asset turnover	85-88%

The Impact of the COVID-19 Pandemic and Digital Transformation(2023-2020)

The COVID-19 pandemic in 2020 introduced a new set of challenges for insolvency prediction models, causing unprecedented economic disruptions and severe market volatility. Researchers responded by developing models capable of adapting to rapidly changing conditions and incorporating alternative data sources, including digital footprints, online behavior, and broader macroeconomic indicators. Studies showed that models integrating macroeconomic indicators and industry-specific variables demonstrated greater resilience, with accuracy declines of only 5-8% compared to pre-pandemic performance, whereas traditional models suffered larger drops.

In this context, (Zięba et al., 2020) developed a Transfer Learning framework to adapt pre-trained bankruptcy prediction models to new economic contexts, asserting that "transfer learning can preserve model accuracy even when economic conditions shift dramatically." Their transfer learning models maintained accuracy rates of 85-90% during the pandemic, compared to 75-80% for conventional models, highlighting the importance of methodological flexibility in the face of economic shocks.

Research Gap and Future Directions:

Despite the significant progress in the field of insolvency prediction, substantial research gaps remain. First, most advanced studies have focused on developed markets and large economies, while emerging markets and smaller economies suffer from a clear scarcity of specialized research. (Vukčević et al., 2024) noted that "countries with low to medium levels of economic development, including emerging markets, still suffer from a lack of research in bankruptcy prediction modeling," creating a significant knowledge gap in understanding insolvency dynamics in these volatile environments.

Second, despite the growing consensus on the importance of non-financial factors, most models applied in emerging markets still rely exclusively on traditional financial ratios, ignoring critical variables such as governance quality, agency conflicts, ownership concentration, and macroeconomic conditions. Studies by (Chan et al., 2016) and (Almaskati, 2019) have proven that incorporating governance variables significantly improves model performance and classification accuracy, yet this integration remains limited in practical applications.

Third, there is a scarcity of sector-specific models that account for the unique characteristics of each economic sector. The nature of risks and influential factors differs fundamentally across sectors, making the application of generic models less accurate and effective. Finally, despite the significant advancements in AI, the interpretability of complex models (the "Black Box Problem") remains a challenge, limiting their acceptance by decision-makers and regulators who require a clear understanding of the factors driving the prediction.

In light of these gaps, there is a pressing need to develop specialized hybrid models that combine the power of AI techniques with methodological transparency, while comprehensively integrating financial and non-financial factors. These models should be specifically designed for the characteristics of emerging markets and specific economic sectors, thereby providing more accurate, reliable, and practically applicable predictive tools.

Sample Selection Methodology:

The scope of this study is strictly focused on the companies listed under the Investment Sector on the Palestine Stock Exchange (PSE). To establish a final sample that ensures methodological robustness and data integrity, a series of rigorous criteria were applied to the initial population of firms, resulting in the following systematic selection process:

The first criterion, related to Listing Status and Temporal Scope, required all included companies to have been officially listed and actively trading on the PSE until the end of 2022. The subsequent period, spanning 2023–2024, was deliberately excluded from the analysis due to the unprecedented wartime disruptions, particularly those affecting the southern provinces, which resulted in operational halts and significant delays in the timely publication of auditable financial statements. Secondly, the Trading Continuity criterion was implemented, mandating that the firms must demonstrate consistent share trading throughout the entire ten-year study period, from 2012 to 2022. This requirement was essential for ensuring the comprehensive availability of market data and serves to reflect the economic resilience of the included companies amidst Palestine’s protracted political and economic instability. Finally, the Data Availability criterion demanded that companies possess consistently published, audited financial statements for the full 2012–2022 period. Adhering to this ensures the reliability and validity of the key financial ratios derived and utilized for the empirical analysis.

Following the application of these specific methodological filters, no further exclusions were necessary. Consequently, the final sample comprises 9 companies, which effectively represents a census of the study's target population within the Investment Sector.

Data Sources:

This study relies on both quantitative and qualitative data specific to firms within the Investment Sector listed on the Palestine Stock Exchange (PSE) over the eleven-year period spanning 2012–2022. The requisite data for the analysis were primarily sourced from reliable secondary sources and are categorized into three main types:

I. Financial Data.

To construct the essential Financial Ratio Indicators for the companies, quantitative financial data were collected from Annual Reports and Audited Financial Disclosures of the listed Investment Sector companies, accessible through the official website of the Palestine Stock Exchange (www.pse.ps).

II. Corporate Governance and Decision-making.

To analyze the specific qualitative indicators directly relevant to Corporate Governance and managerial decision-making, such as Agency Conflict issues and the degree of Ownership Concentration, the study utilized the qualitative Notes and Non-financial Disclosures extracted directly from the Supplements to the Annual Reports and Board of Directors' reports. These documents provide crucial insights into ownership structure, board composition, and specific governance practices, available on the PSE website (www.pse.ps).

III. Macroeconomic Indicators.

To incorporate macroeconomic factors that serve as control variables in the study (such as GDP and global governance metrics), data were sourced from Standard Economic Metrics (e.g., Palestinian Gross Domestic Product - GDP) obtained from the Palestinian Monetary Authority (www.pma.ps) and the Palestinian Central Bureau of Statistics (www.pcbs.gov.ps). Worldwide Governance Indicators (WGI) specific to Palestine, utilized to proxy the country's governance environment, which were obtained from the official website of the World Bank (www.worldbank.org).

Steps to Apply:

This study embarks on a systematic journey to forge a precise predictive model for bankruptcy risk, focusing specifically on the investment sector within the Palestinian market. The research pathway is a carefully sequenced, three stage expedition, moving from the foundational gathering of data to the ultimate evaluation of sophisticated predictive tools.

Phase 1: Data Preparation and Compilation.

Our journey begins with the critical task of data preparation. We first delve into the financial statements of the listed companies, where we calculate a comprehensive set of 18 financial ratios.

These ratios are not chosen at random; they are the key indicators spread across five critical dimensions of corporate health: Liquidity, Asset Management, Debt Management, Profitability, and Market Value. Together, they form a quantitative portrait of a company's financial vitality. Recognizing that a company's fate is not dictated by numbers alone, we simultaneously cast a wider net to capture non-financial indicators. We identify and gather crucial qualitative and quantitative metrics that lie beyond the balance sheet measures of agency conflict, the concentration of ownership, standards of global governance, and the overarching influence of GDP growth. This holistic approach ensures our model is grounded in both the internal mechanics and the external pressures that shape a company's future.

Phase 2: Setting the insolvency risk rating

With the raw data in hand, the study moves to its second phase: establishing a clear and standardized map to categorize firms according to their insolvency risk. Here, we construct a definitive classification framework by synthesizing two authoritative sources. The first is the concrete world of Palestinian legislation, which provides legally stipulated criteria for financial solvency and distress. The second is the established body of academic literature on corporate bankruptcy, which offers proven theoretical benchmarks. This newly forged framework is then applied to each company in our sample, sorting them into preliminary risk categories such as Low, Medium, or High. This crucial step creates a reliable, real-world benchmark, a "ground truth" against which the predictive power of our subsequent models will be rigorously tested and measured.

Phase 3: The Analytical Core:

The final and most pivotal phase of our journey is dedicated to building, testing, and comparing the predictive models themselves. We construct two distinct analytical instruments: one rooted in traditional statistical science a model based on Discriminant Analysis and another harnessing the cutting-edge power of Artificial Intelligence, specifically an Artificial Neural Network (ANN). To precisely gauge the value of our non-financial data, we put each model through a deliberate testing regimen under two separate scenarios. First, we task them with making predictions using only the 18 financial ratios. Then, we challenge them again, this time providing the integrated dataset that combines both the financial ratios and the non-financial indicators. This sets the stage for a comprehensive analytical comparison. The performance of the traditional statistical model is pitted against the modern AI counterpart. Most importantly, by observing how each model's accuracy shifts between the two testing scenarios, we can isolate and quantify the unique, incremental power that non-financial indicators hold in illuminating the path toward corporate distress, ultimately determining the most accurate and robust predictor for bankruptcy risk in the Palestinian investment landscape.

The Insolvency risk rating Result:

Based on financial and non-financial data spanning from 2014 to 2022. Under the legal framework established by the Palestinian Companies Law of 2021, which defines bankruptcy as a company's inability to meet its financial obligations as they fall due, no company in the sample recorded a full legal bankruptcy during the study period. Accordingly, this analysis adopts a methodology of classifying companies based on bankruptcy risk or "financial distress" rather than actual bankruptcy, providing a proactive and forward-looking view of the financial health of the sector as a whole. To assess the degree of risk faced by firms, a multi-dimensional analytical framework was employed, rooted in key indicators derived from seminal academic studies in the field of financial failure prediction. The methodology is predicated on the concept that financial distress is not an abrupt event but rather a cumulative process that can be monitored through a set of warning signals embedded in financial statements and other corporate reports. Academic thought in this domain has evolved significantly, from the early use of financial ratios as predictors of failure, as pioneered by Beaver (1966), to the multivariate models introduced by Altman (1968), which became a cornerstone of modern distress prediction. Subsequent research has incorporated other critical indicators, such as cash flow patterns (Ohlson, 1980; Hillegeist et al., 2021), dividend policies as a signal of a firm's strength or weakness (Lintner, 1956;

Fama & French, 2020), and the structure of a company's assets and its impact on financial flexibility (Myers, 1977; Brealey et al., 2022). Furthermore, the importance of non-financial indicators, such as the quality of auditor reports (Geiger et al., 2005; PCAOB, 2022) and the transparency of financial disclosures (Leuz & Wysocki, 2016), has been increasingly emphasized as crucial factors in risk assessment. Building on this academic legacy, each firm in the sample was evaluated annually against eight indicators and classified into one of three categories: Low Risk, a Gray Zone requiring monitoring, or High Risk indicating potential financial distress.

The aggregate results paint a picture of relative stability within the Palestinian investment sector. The risk distribution demonstrates that the vast majority of firm-year observations fall within a safe range, while the proportion of high-risk cases remains notably limited. The following table illustrates the percentage distribution of risk categories across the entire study period:

Risk Category	Percentage of Total Observations
Low Risk	62.8%
Gray Zone	29.6%
High Risk	7.2%
Total	100%

Figure (1):

These figures indicate that nearly two-thirds of the observations pertained to firms with a strong and stable financial position. Conversely, approximately 30% of the cases were classified in the "Gray Zone," an intermediate category for firms that may not be in imminent danger but exhibit some signs of weakness that warrant cautious monitoring to prevent financial deterioration. Most significantly, the proportion of cases classified as "High Risk" did not exceed 7.2%, reflecting the rarity of severe financial distress within the sector.

Statistical Analysis and Interpretation of Insolvency Risk Prediction Models:

This section presents and analyzes the statistical outputs of the two models employed in this study: Discriminant Analysis (DA) and Artificial Neural Networks (ANN). The commentary on the results is enhanced by integrating them within the theoretical framework and the existing body of academic literature.

Discriminant Analysis (DA) Outputs:

Discriminant Analysis represents a classical statistical method that was extensively used in the foundational studies of financial failure prediction, most notably the Z-Score model developed by Altman (1968). Despite the emergence of more advanced techniques, DA still offers valuable insights into the variables that most effectively differentiate between distinct groups (e.g., distressed vs. non-distressed firms). The following is a presentation and interpretation of the model's application to the investment sector companies.

Model Significance and Classification Power:

Before delving into the specifics of the variables, it is imperative to ascertain the model's overall statistical significance in discriminating between the three risk groups (Low, Gray, High). The table below presents the results of the Wilks' Lambda test.

Test	Wilks' Lambda	Chi-square	Sig.
	0.396	64.773	0.000

Figure (2):

The low Wilks' Lambda value (0.396) and the high Chi-square value (64.773) at a significance level of 0.000 indicate that the model is highly effective in distinguishing between the groups, and the observed differences are not due to chance. This result validates the model as a sound basis for analysis. In terms of classification power, the model demonstrated promising results, particularly with the integration of non-financial factors, as detailed below:

Table (3): Discriminant Analysis (Investment Sector)

Sorting	Factors X	financial factors		financial & Non financial factors	
		1	2	1	2
financial	Earnings Per Share	.607*	-.068-	.516*	0.141
	Asset Turnover Ratio	.534*	0.114	.463*	0
	Market-to-Book Ratio	.469*	-.130-	.396*	0.164
	Equity Turnover Ratio “b”	.464*	0.118	.403*	-.014-
	Return on Equity “b”	.444*	-.129-	.374*	0.16

Table (3): Discriminant Analysis (Investment Sector)

Sorting	Factors X	financial factors		financial & Non financial factors	
		1	2	1	2
	Return on Assets	.427*	-.175-	.357*	0.19
	Debt to Equity Ratio	.392*	0.335	.352*	-.180-
	Days Sales Outstanding (DSO) “b”	.118*	0.038	.103*	-.009-
	Operating Cash Flow to Sales Ratio	.094*	0.031	.082*	-.008-
	Net Profit Margin “b”	.080*	0.026	.070*	-.006-
	Debt to Assets Ratio	0.363	.551*	.338*	-.338-
	Cash Ratio	0.052	-.389-*	0.025	.286*
	Gross Profit Margin “b”	-.209-	-.343-*	-.196-	.213*
	Quick Ratio	-.063-	-.335-*	-.073-	.231*
	Current Ratio “b”	-.067-	-.329-*	-.073-	.225*
	Price-to-Earnings (P/E) Ratio	-066.-	*-200.-	-067.-	*133.
	Free Cash Flow (FCF)	-184.-	*315.	-157.-	*301.
Non financial	Ownership Ratios			-299.-*	-177.-
	Worldwide Governance Indicators			*-258.-	-003.-
	Agency conflict			*-165.-	-102.-
	GDP “b”			*149.	0.072
	TEST	Wilks' Lambda	Chi-square	Sig.	
		0.396	64.77	0	
	Classification Results	71.3% of original grouped cases correctly classified		76.3% of original grouped cases correctly classified	
	*. Largest absolute correlation between each variable and any discriminant function				
	"b". This variable not used in the analysis.				

- **Using Financial Variables Only: The classification accuracy was 71.3%.**
- **Upon Adding Non-Financial Variables: The accuracy significantly increased to 76.3%.**

This enhancement in accuracy underscores the growing importance of non-financial factors in predictive modeling, a finding that aligns perfectly with contemporary research trends. Numerous studies, such as those by Chan et al. (2016) and Almaskati (2019), have confirmed that incorporating governance and institutional quality variables substantially improves the predictive power of traditional models that were once confined to financial ratios. As Dasilas (2024) noted, "the inclusion of non-financial ratios alongside financial ratios in hybrid models enables a more comprehensive evaluation of a firm’s financial health."

Influential Variables and the Prediction Equation:

The following tables identify the most influential variables in discriminating between the groups, ranked by the strength of their correlation with the discriminant functions. They also present the coefficients of the canonical discriminant function, which can be used to construct the prediction equation.

Table (4):Canonical Discriminant Function Coefficients Investment Sector

Factors	Function		Factors	Function	
	1	**2**		1	2
Quick Ratio	-0.06	0	Operating Cash Flow to Sales Ratio	-8.918	-3.889
Cash Ratio	0.849	0.075	Earnings Per Share	3.782	-1.77
Debt to Assets Ratio	7.353	-30.62	Price-to-Earnings (P/E) Ratio	0.003	-0.001
Debt to Equity Ratio	-1.824	14.11	Market-to-Book Ratio	1.565	-0.298
Asset Turnover Ratio	0.127	12.536	AG conflict	-0.452	-0.562
Free Cash Flow (FCF)	0.097	-5.822	Ownership Ratios	-0.136	-0.328
			WGI	-4.702	1.479
Return on Assets	20.208	7.355	(Constant)	-3.042	-0.461
Function	Eigenvalue		Canonical Correlation		
1	0.879		0.684		
2	0.343	28.1%	0.505		

Through discriminant analysis, it was found that 13 out of 21 financial and non-financial indicators were successful in prediction. The successful qualitative indicators were those related to corporate governance, such as agency conflict and ownership concentration. From the political-economic indicators, the Worldwide Governance Indicators (WGI) was successful; however, the Palestinian GDP indicator was not influential in the model, as the Palestinian economy is a dependent economy tied to Israel and not independent like other countries worldwide. As for the financial indicators that were successful in the model, they were: Quick Ratio, Cash Ratio, Debt to Assets Ratio, Debt to Equity Ratio, Asset Turnover Ratio, Free Cash Flow (FCF), Operating Cash Flow to Sales Ratio, Earnings Per Share, Price-to-Earnings (P/E)

Ratio, and Market-to-Book Ratio. Clearly, these covered various analysis dimensions such as profitability, liquidity, debt management, efficiency, and market performance.

From the previous table, it is evident that the variance proportion for the first function reached 71.9%, while for the second function it was 28.1%. The same table also showed that the canonical correlation between the independent variables and the dependent variable was 68.4% for the first discriminant function, indicating a strong correlation, and 50.5% for the second discriminant function, indicating a moderate correlation. Therefore, the first discriminant function was adopted to construct the discriminant equation for the successful financial and non-financial indicators. The discriminant equation can be derived as follows:

Z = -3.042 - 0.06(Quick Ratio) + 0.849(Cash Ratio) + 7.353(Debt to Assets Ratio) - 1.824(Debt to Equity Ratio) + 0.127(Asset Turnover Ratio) + 0.097(FCF) + 2.208(Return on Assets) - 8.918(Operating Cash Flow to Sales Ratio) + 3.782(Earnings Per Share) + 0.003(Price-to-Earnings (P/E) Ratio) + 1.565(Market-to-Book Ratio) - 0.452(AG Conflict) - 0.136(Ownership Concentration) - 4.702(WGI) + e

Artificial Neural Network (ANN) Model Outputs:

Artificial Neural Networks represent a paradigm shift from traditional statistical methods, distinguished by their ability to model complex, non-linear relationships between variables without requiring strict statistical assumptions. In contrast to traditional models that may pre-select or exclude variables, the Artificial Neural Network (ANN) methodology holistically integrates both financial and non-financial indicators, allowing the model to learn and assign their optimal relative influence on the prediction outcome.

Model Performance and Predictive Accuracy.

The table below details the model's accuracy in classifying firms within the training and testing samples, both before and after the inclusion of non-financial variables.

Table (5): Investment Performance and Forecasting Accuracy

<table>
<tr><th></th><th></th><th colspan="4">Financial indicators</th><th colspan="4">Financial and non-financial indicators</th></tr>
<tr><th rowspan="2">Sample</th><th rowspan="2">Observed</th><th colspan="4">Predicted</th><th colspan="4">Predicted</th></tr>
<tr><th>Low Risk</th><th>Gray Risk</th><th>High Risk</th><th>Percent Correct</th><th>Low Risk</th><th>Gray Risk</th><th>High Risk</th><th>Percent Correct</th></tr>
<tr><td rowspan="4">Training</td><td>Low Risk</td><td>21</td><td>8</td><td>0</td><td>72.40%</td><td>30</td><td>3</td><td>0</td><td>90.90%</td></tr>
<tr><td>Gray Risk</td><td>7</td><td>12</td><td>0</td><td>63.20%</td><td>3</td><td>16</td><td>0</td><td>84.20%</td></tr>
<tr><td>High Risk</td><td>0</td><td>8</td><td>0</td><td>0.00%</td><td>0</td><td>6</td><td>0</td><td>0.00%</td></tr>
<tr><td>Overall Percent</td><td>50.00%</td><td>50.00%</td><td>0.00%</td><td>58.90%</td><td>56.90%</td><td>43.10%</td><td>0.00%</td><td>79.30%</td></tr>
<tr><td rowspan="4">Testing</td><td>Low Risk</td><td>11</td><td>3</td><td>0</td><td>78.60%</td><td>9</td><td>1</td><td>0</td><td>90.00%</td></tr>
<tr><td>Gray Risk</td><td>3</td><td>6</td><td>0</td><td>66.70%</td><td>1</td><td>8</td><td>0</td><td>88.90%</td></tr>
<tr><td>High Risk</td><td>0</td><td>1</td><td>0</td><td>0.00%</td><td>0</td><td>3</td><td>0</td><td>0.00%</td></tr>
<tr><td>Overall Percent</td><td>58.30%</td><td>41.70%</td><td>0.00%</td><td>0.708</td><td>45.50%</td><td>54.50%</td><td>0.00%</td><td>0.773</td></tr>
</table>

The results clearly show a significant leap in model accuracy upon integrating non-financial factors. In the testing sample the most critical measure of a model's ability to generalize the overall accuracy rose from 70.8% to 77.3%. This performance, which surpasses that of the DA model, confirms the power of neural networks in extracting complex patterns and strongly supports the hypothesis that hybrid models integrating diverse data types are the most effective. This conclusion is echoed in recent studies by Ansah-Narh et al. (2024) and Mojdehi et al.(2025) .

Ranking the Importance of Influential Variables

One of the key advantages of ANN models is their ability to determine the relative importance of each variable in the prediction process. The following table ranks the variables according to their impact on the model.

Table (6): Variable ranking by impact

<table>
<tr><th rowspan="2">Financial and non-financial indicators</th><th colspan="2">Investment Ranking factors</th><th rowspan="2">non- Financial and financial indicators</th><th colspan="2">Investment Ranking factors</th></tr>
<tr><th>Importance</th><th>Normalized Importance</th><th>Importance</th><th>Normalized Importance</th></tr>
<tr><td>Market-to-Book Ratio</td><td>0.11</td><td>96.00%</td><td>Equity Turnover Ratio</td><td>0.04</td><td>36.60%</td></tr>
</table>

Financial and non-financial indicators	Investment Ranking factors		non- Financial and financial indicators	Investment Ranking factors	
	Importance	Normalized Importance		Importance	Normalized Importance
Earnings Per Share	0.096	86.90%	Days Sales Outstanding (DSO)	0.039	35.70%
Price-to-Earnings (P/E) Ratio	0.095	86.00%	Return on Assets	0.034	30.90%
WGI	0.073	66.20%	GDP	0.034	30.70%
Cash Ratio	0.073	65.70%	Current Ratio	0.023	21.00%
Debt to Assets Ratio	0.067	60.50%	Net Profit Margin	0.023	20.90%
Return on Equity	0.066	59.60%	Asset Turnover Ratio	0.017	15.60%
Free Cash Flow (FCF)	0.064	57.80%	Operating Cash Flow to Sales Ratio	0.014	12.30%
Quick Ratio	0.058	52.50%	Debt to Equity Ratio	0.013	11.50%
AG conflict	0.043	38.90%	Gross Profit Margin	0.011	9.90%
Ownership Ratios	0.006	5.70%			

It is striking that three of the top five most influential variables are market-based metrics (Market-to-Book Ratio, EPS, P/E Ratio), suggesting that investor perceptions and market sentiment play a decisive role in forecasting the future of investment sector firms. The inclusion of the World Governance Indicators (WGI) in the top five further reinforces the pivotal role of non-financial factors. Although financial indicators such as the debt-to-equity ratio and profit margin are fundamental for assessing solvency, they held relatively lesser importance for bankruptcy prediction compared to non-financial indicators like agency conflict and ownership concentration, which retained a moderate level of influence .These weights can be used to construct a composite risk index, where the value of each indicator is multiplied by its importance weight to generate an aggregate risk score for each company, allowing for objective comparisons and ranking based on risk exposure.

Conclusions:

This study embarked on a critical investigation into the prediction of financial insolvency within the unique and volatile economic environment of the Palestine Exchange, focusing specifically on the investment sector. The research was motivated by the recognized limitations of traditional prediction models, which have historically relied almost exclusively on financial ratios and have often proven inadequate in contexts of high uncertainty. By developing and comparing hybrid models that integrate both financial and non-financial variables, this study has generated a series of conclusions that not only address the initial research questions but also contribute meaningfully to the broader academic and professional discourse on corporate failure prediction.

First Conclusion: Validation of Non-Financial Factors Importance:

The first and most unequivocal conclusion is the validation of the central hypothesis: the integration of non-financial factors significantly enhances the predictive power of insolvency models. The empirical results demonstrated a marked increase in classification accuracy for both the Discriminant Analysis (DA) and Artificial Neural Network (ANN) models upon the inclusion of variables related to corporate governance and macroeconomic conditions. This finding resonates strongly with a growing body of contemporary literature. For instance, the research by (Chan et al., 2016) and (Wu et al., 2010) has consistently highlighted the shortcomings of models that ignore the qualitative aspects of a firm's operations and its surrounding environment. Our study provides robust, localized evidence from an emerging market that corroborates these global trends, confirming that a purely quantitative approach, focused on historical financial data, provides an incomplete and often misleading picture of a firm's true vulnerability to financial distress. The inclusion of factors like agency conflict and ownership structure provides a more nuanced and forward-looking assessment of risk, moving beyond the symptoms of financial trouble to its potential root causes.

Second Conclusion: Superiority of Machine Learning Techniques:

Secondly, this study concludes that advanced machine learning techniques, specifically Artificial Neural Networks, offer a superior alternative to traditional statistical methods for the task of insolvency prediction. The ANN model consistently outperformed the DA model, achieving a higher overall accuracy in classifying firms. This superiority can be attributed to the inherent ability of neural networks to model complex, non-linear relationships and interactions between variables without the restrictive assumptions that underpin classical statistical models like DA. This conclusion is in alignment with a significant stream of research dating back to the work of pioneers like (Wilson et al., 1995) and more recent studies such as (Dasilas, 2024), which have championed the use of AI in finance. The findings suggest that as financial markets become more complex and data becomes more abundant, the adoption of such sophisticated analytical tools is no longer just an academic curiosity but a practical necessity for accurate risk management. The model's ability to learn from the data provides a dynamic and adaptable framework that is better suited to the ever-changing nature of financial markets than the static, linear assumptions of older models.

Third Conclusion: Dominance of Market-Based Indicators:

Thirdly, the research provides a compelling conclusion regarding the specific drivers of insolvency risk within the Palestinian investment sector. The analysis of variable importance revealed the striking dominance of market-based indicators, namely the Market-to-Book Ratio, Earnings Per Share (EPS), and the Price-to-Earnings (P/E) Ratio. This finding underscores the profound influence of investor sentiment and market perception in shaping the destiny of firms, particularly in an emerging market context.While traditional accounting-based ratios related to liquidity, debt, and profitability remain relevant, their predictive power was found to be secondary to how the company is perceived and valued by the market. This conclusion harks back to the foundational work of (Altman, 1968), who included market value in his original Z-score, but it gains new significance in the context of a volatile market where information asymmetry may be high and investor confidence can be fragile. It suggests that for stakeholders and analysts, monitoring the market's pulse is as crucial, if not more so, than a retrospective analysis of financial statements.

Based on the empirical findings of this study, the following recommendations are proposed to enhance financial distress prediction models and governance practices within the Palestinian context, structured around model development, sectoral analysis, and policy oriented reforms as follows: -

• Replacing GDP with the Ratio of Imports from Israel: Given the weak explanatory power of Palestinian GDP in previous models, this study recommends adopting the variable "ratio of imports from Israel to total foreign trade" as a key economic indicator. This variable should be included as a mandatory control variable in the classification model.

- Incorporating Additional Economic and Social Indicators: The study recommends adding other economic indicators such as unemployment rates, inflation, and the Gini coefficient (as a measure of inequality), alongside qualitative indicators related to the business environment, including job satisfaction, customer satisfaction, and corporate governance indicators derived from official reports.

- Employing AI Techniques to Explore Predictive Accuracy: The study recommends utilizing artificial intelligence-based methods, such as Decision Trees and Random Forest, to test prediction accuracy when using hybrid variables (financial and qualitative combined) compared to cases where each set of variables is used separately.

- Predicting insolvency Risk Across Sectors and Conducting Cross-Sectoral Comparisons: The study recommends extending the prediction scope to include other sectors, such as industry and services. Cross-sectoral comparisons should be conducted using both traditional and advanced models, with the necessary integration of financial indicators and qualitative factors, given that each sector has its own distinct financing structure and inherent risks.

- Enhancing Disclosure of Market Indicators: As the results show that market indicators (such as stock prices and dividend yields) were the strongest predictors, this study recommends reviewing current disclosure requirements to ensure data transparency and timeliness, while reducing the time lag between the occurrence of an event and its disclosure.

- Developing Qualitative Indicators Specific to the Palestinian Context: Instead of relying solely on global governance indicators such as the WGI, the study recommends developing local qualitative indicators that reflect the specificity of the Palestinian environment. These should include variables such as the impact of movement and trade restrictions, economic dependence on Israel, and crossing and customs costs.

- Improving Internal Governance Indicators as an Early Warning Tool: Companies should recognize that weak governance (e.g., agency conflicts and excessive ownership concentration) is not merely a regulatory shortcoming but an early warning indicator of financial distress. Therefore, the study recommends adopting sound governance practices, including enhancing board independence, activating internal audit and control mechanisms, and linking executive compensation to long-term performance.

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