A Hybrid Model for Supporting Auditors' Professional Judgment in Going Concern Evaluation Using Traditional Techniques and AI-Based Big Data Analytics

Research Extracted from PHD. Of Accounting

By

Mohamed Essam Tamam Osman

Assistant Lecturer of Accounting

Faculty of Commerce, Damietta University

m_essam@du.edu.eg

Dr. Yasser Mohamed Abdelaziz Samra

Professor of Accounting & Auditing

Faculty of Commerce, Damietta University

yasser.samra69@gmail.com

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A Hybrid Model for Supporting Auditors' Professional Judgment in Going Concern Evaluation Using Traditional Techniques and AI-Based Big Data Analytics

Mohamed Essam Osman and Dr. Yasser Abdelaziz Samra

Abstract

This study proposes a hybrid model that integrate the Altman Z-score— A traditional financial distress prediction Techniques -with six AI based Big Data Analytics (Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN) to enhance the professional judgment of external auditors in evaluating an entity's going-concern status. The model was empirically tested on a sample of 144 non-financial firms listed on the Egyptian Stock Exchange from 2018 to 2023. The findings indicate that although the Altman Z-score provides valuable insights into assessing an entity's going-concern status, the Hybrid Model consistently outperforms the predictive performance of both the standalone Altman model and individual AI-based Big Data Analytics (BDA) techniques. The traditional Altman model achieves an accuracy of 84%. All Hybrid models exceed this baseline, with the Decision Tree (DT) model performing best at 94%, followed by the Deep Neural Network (DNN) at 92%, and the Recurrent Neural Network (RNN) at 91%, indicating that Hybrid models provide more reliable overall classifications. Also, Statistical tests, including McNemar, Phi, Cramer's V, Kappa, -2log likelihood, and Nagelkerke R Square, consistently supported the effectiveness of the Hybrid Model. These findings highlight the potential of hybrid models to significantly elevate the quality of auditors' professional judgment and decision-making in going-concern evaluations.

Keywords: Traditional Techniques; Altman's Z-Score; AI-based Big Data Analytics; Deep Neural Networks (DNN); Recurrent Neural Networks (RNN); Support Vector Machines (SVM); Random Forests (RF); Decision Trees (DT); K-Nearest Neighbors (KNN); Auditors' Professional Judgment regarding the Entity's Going Concern.

1. Introduction:

The auditing profession faces increasing pressures to enhance professional performance, improve fieldwork quality, and maximize the utility of audit reports to support the decision-making processes of financial statement users. In this context, External auditors bear increasing responsibility for evaluating an entity's ability to continue as a going concern. This issue has drawn substantial attention from both professional bodies and academic researchers (IAASB, 2018; KPMG, 2014; PCAOB, 2015; Berglund et al., 2018; Hardies et al., 2018; Brunelli, 2018). In response, Regulatory bodies have issued specific guidance to auditors, emphasizing the importance of evaluating potential financial distress and adhering to best practices in financial reporting disclosures (FRC, 2016; IASB, 2021; PCAOB, 2012; AICPA, 2021). Under both the International Standards on Auditing and the Generally Accepted Auditing Standards, auditors are required to obtain sufficient and appropriate audit evidence to evaluate management's use of the going concern basis in financial statement preparation. If substantial doubt exists, auditors must explicitly disclose this uncertainty in their reports (FASB, 2014; IAASB, 2015).

Despite regulatory guidance on assessing going concern uncertainties and best practices for financial reporting disclosures, auditors have faced criticism for failing to issue early warnings about potential business failures (FRC, 2016; IASB, 2021; PCAOB, 2012; AICPA, 2021). The financial market has witnessed numerous bankruptcies, resulting in significant losses for financial statement users and public investors. Scholars have attributed these failures, in part, to auditors' inability to fulfill their responsibilities and provide accurate professional judgments regarding an entity's going concern status (Sanoran, 2018; Balakrishnan et al., 2016). Consequently, external auditors face pressure to detect financial distress indicators, disclose risks, and issue timely warnings to safeguard stakeholders' interests (Vasarhelyi et al., 2015).

Early research regarding evaluating the entity’s going concern primarily relied on traditional models, with the Altman Z-score standing out as a foundational method. Introduced by Altman in 1968, the model employs a multivariate discriminant analysis approach, integrating multiple financial ratios to produce a single composite indicator of financial risk. Subsequent empirical studies have demonstrated that the model’s accuracy varies significantly across different geographic contexts and industry sectors, with reported rates ranging from 58% to 93% (Srour, 2021).

While these traditional techniques remain foundational, ongoing research highlights the limitations of single-method approaches, such as assumptions of linearity, normality, and independence of predictor variables, which limit their predictive accuracy, particularly in complex economic environments like emerging markets such as Egypt (Imelda & Alodia, 2017). These limitations contribute to increasing misjudgments and error rates in financial distress predictions (Yeh et al., 2014; Goo et al., 2016), which highlights a critical gap in the ability of auditors to make accurate going concern assessments using traditional techniques.

As a result of the limitations inherent in traditional techniques, there is an increasing need for more advanced methodologies capable of addressing the complexities of modern audit environments. Among these emerging solutions, AI-based Big Data Analytics (BDA) has gained substantial attention across a variety of sectors—including corporate, governmental, scientific, and academic domains—and has extended its influence into the fields of accounting and auditing (Dagilienė & Klovienė, 2019). The American Institute of Certified Public Accountants (AICPA, 2014) defines Big Data Analytics as the process of discovering and analyzing patterns, anomalies, and actionable insights through advanced analytical methods, including machine learning and deep learning techniques.

AI-based Big Data Analytics (AI-based BDA) possesses the capacity to identify non-linear relationships and hidden patterns that traditional models may fail to detect. This capability enables auditors to process large, complex datasets more accurately and precisely and extract meaningful insights from vast datasets in real time, supporting evidence-based decision-making (Elhoseny et al., 2022; Appelbaum et al., 2017a). By employing AI-based BDA, auditors can train models to autonomously detect and forecast patterns within datasets, which enhances the reliability and robustness of going concern assessments, as required under the Statement on Auditing Standards No. 59 (Chi & Shen, 2022; Saggi & Jain, 2018; Jing & Fang, 2018; Gepp et al., 2018; Barboza et al., 2017). Studies have shown that these models can achieve predictive accuracies exceeding 95% (Dolinšek & Kovač, 2024).

However, individual AI-based BDA often faces issues such as overfitting, limited interpretability, and challenges related to imbalanced datasets. To overcome these constraints, A hybrid approach, integrating traditional Altman z-score ratios with advanced AI-based BDA algorithms, has thus garnered increasing attention (Farooq & Qamar, 2019). This integrated framework benefits from the clear and understandable nature of classical models while harnessing the ability of AI-based BDA to uncover complex patterns. The outcome is a well-rounded solution that effectively balances clarity, theoretical foundations, and analytical strength.

Despite the potential of AI-based BDA to revolutionize audit practices, its integration into the profession remains in its nascent stages. Prior literature has criticized the slow adoption of AI-based BDA in auditing (Abdelwahed et al., 2023; Hezam et al., 2023; Buchheit et al., 2020; Lowe et al., 2018). Furthermore, existing research has predominantly focused on developed countries, with limited attention given to developing nations, where audit environments are less regulated (Abdelwahed et al., 2023). Additionally, many studies have relied on conceptual methodologies, leaving a gap in empirical research that explores the practical application of BDA in real-world audit scenarios (Abdelwahed et al., 2023; Lowe et al., 2018; Buchheit et al., 2020). Also, Previous studies have predominantly focused on either traditional Techniques or AI-based BDA, including Machine Learning and Deep Learning algorithms in isolation. The systematic integration of the Altman Z-score with multiple machine learning algorithms, particularly in the Egyptian market context, remains largely unexplored.

Based on the above, the research problem can be expressed in how to answer the following question practically:

- How accurate are traditional techniques (Altman Z-Score model) in supporting auditors' professional judgment in evaluating an entity's going concern for non-financial companies listed in the Egyptian Stock Exchange?
- How effective are AI-based Big Data Analytics in evaluating the entity's going-concern?
- How does the Hybrid model that integrates traditional Altman Z-score, as one of the traditional techniques, and AI-based BDA support auditors' professional judgment in evaluating an entity's ability to continue as a going concern for non-financial companies listed in the Egyptian Stock Exchange?

2. Aim and Objectives:

The primary objective of this study is to empirically evaluate the effectiveness of the Hybrid model that integrates Traditional Altman Z-score model, as one of the Traditional Techniques, and AI-based BDA to improve auditors' professional judgment in evaluating an entity's ability to continue as a going concern, with a specific focus on non-financial firms listed on the Egyptian Stock Exchange.

The main objective is further divided into the following specific sub-objectives:

- Assess the predictive accuracy of traditional statistical models (Altman Z-Score model) in supporting auditors' professional judgment in evaluating an entity's ability to continue as a going concern.
- Assess the predictive performance of AI-based BDA in supporting auditors' professional judgment in evaluating an entity's ability to continue as a going concern.
- Evaluate the effectiveness of the Hybrid model that integrates traditional techniques (Altman Z-Score model) and AI-based BDA in supporting auditors' professional judgment in evaluating an entity's ability to continue as a going concern.

3. Study Motivation:

The motivation of this study stems from its alignment with ongoing academic efforts to improve the accuracy of auditors' going concern assessments by integrating traditional statistical methods with AI-based BDA. **The motivation of this study is further emphasized by the following:**

- **Limitations of Traditional Models**: Traditional financial distress prediction models, such as the Altman Z-Score, often assume linear relationships, which may not adequately capture the complex and dynamic nature of modern business environments.
- **Filling a research gap** by providing empirical evidence on the application of AI-based BDA in auditing within a developing country, specifically Egypt, particularly in the context of going concern evaluation. Abdelwahed et al. (2023) highlight that most prior studies have concentrated on AI-based BDA implementation in developed economies,

leaving limited empirical evidence from emerging markets such as Egypt. Prior literature (e.g., Gepp et al., 2018; Appelbaum et al., 2017; Read & Yezegel, 2016) has highlighted the significant potential for AI-based Big Data Analytics (BDA) to improve auditors' ability to predict financial distress and improve going concerning judgments, aligning with the requirements of SAS No. 59 (AICPA, 1988).

- **Enhancing professional judgment** by offering insights into how advanced analytics can support evidence-based decision-making in the audit process.
- **Supporting regulatory and institutional development** by offering practical recommendations that may assist auditors, regulatory bodies, and firms in adopting more sophisticated audit approaches.

4. Literature Review and Hypotheses Development:

First: Studies focused on using traditional techniques to support auditors' professional judgment in evaluating an entity's going concern.

Traditional financial risk prediction Techniques remain fundamental tools in diverse markets, with the Altman Z-score model still regarded as a cornerstone, as confirmed by numerous studies. Empirical studies have demonstrated its strong predictive capabilities across diverse industrial contexts. Gunawan et al. (2017) established its effectiveness in manufacturing sectors. Fauzi & Saluy (2021) compared four bankruptcy prediction models—Altman, Springate, Zmijewski, and Grover—finding that the Altman model provided the most reliable and consistent results. Similar findings were reported by Supitriyani et al. (2022), who concluded that the Altman Z-Score outperformed other models when applied to transportation sector firms. These findings are corroborated by Mackevičius & Silvanavičiūtė (2006), Aminian et al. (2016), Pakdaman (2018), Prabowo (2019), Muñoz-Izquierdo et al. (2020), whose collective research confirms the model's reliability in transportation and other industrial sectors. The model's methodological robustness is further evidenced by its low standard error (Johari et al., 2019) and minimal deviation metrics (Yoewono, 2018) in comparative studies. Dolinšek and Kovač (2024) reported a reliability range of 71–80% when applying the model to Slovenian firms, Similarly, Asif et al. (2024) demonstrated its successful application to companies listed on India's National Stock Exchange (NSE).

Despite its widespread use in distinguishing between solvent and insolvent firms, the reliability of the Z-Score model has faced criticism in more recent studies. Kanapickienė and Marcinkevičius (2014) observed reduced accuracy in transitional economies like Lithuania, while Almamy et al. (2016) documented diminished predictive power during periods of macroeconomic instability.

The extant literature reveals no clear consensus regarding the accuracy of the traditional Altman Z-score for going concern assessments. As a result, the current research seeks to evaluate the contribution of the traditional Altman Z-score in assessing an entity's going concern within the Egyptian context, where unique market characteristics may influence model effectiveness differently than in previously studied contexts. To achieve this, the following research hypothesis will be tested:

H_1: Traditional Altman Z-score model, as one of the Traditional Techniques, supports auditors' professional judgment in evaluating an entity's going concern status.

Second: Studies focused on using AI-based Big Data Analytics to support auditors' professional judgment in evaluating an entity's ability to continue as a going concern.

To cater to the advent of the application of AI-based Big Data Analytics in the accounting and auditing field, many researchers adopted AI-based Big Data Analytics in their studies to develop models to classify going-concern firms.

Alles and Gray (2015) explored the use of Big Data Analytics (BDA) tools in auditing and highlighted their advantages in enhancing auditors' analytical capabilities. Their study found that BDA offers strong predictive power, supports fraud investigations, and enables the development of predictive models for assessing an entity's going concern status. Additionally, BDA helps mitigate financial statement fraud and improves the detection of red flags, as its ability to analyze vast amounts of data with 100% sampling reduces the likelihood of fraudsters manipulating all data elements.

Expanding on this, Brown-Liburd et al. (2015) explored the behavioral effects of big data on auditor judgment, discussing issues such as information overload, relevance, pattern recognition, and ambiguity. They concluded that big data techniques enhance audit value by reducing information overload and improving decision-making. Their research emphasizes selecting appropriate techniques and data for each situation, indicating the need for further studies.

Subsequent research by Brown et al. (2015), and Alles and Gray. (2016) has shown that BDA enhances audit effectiveness by improving the reliability of audit evidence and allowing auditors to conduct more comprehensive reviews, identify key risk areas, and improve judgment quality. BDA also helps reduce costs, predict future tax liabilities, detect fraud, and assess a company's going-concern status (Schneider et al., 2015; Alles, 2015).

Goo et al. (2016) employed three machine-learning techniques, namely neural network (NN), classification and regression tree (CART), and support vector machine (SVM), to develop going-concern prediction models for Taiwanese companies. They extracted twenty-two financial ratios from company financial statements for the period 2002 to 2013. Based on their empirical results, The SVM model outperformed NN and CART, achieving 89.79% accuracy and a type 1 error rate of 10%.

Barboza et al. (2017) used machine learning techniques like SVM, artificial neural networks, and random forest algorithms to predict companies' going-concern status. They found that machine learning techniques improved accuracy by about 10% compared to traditional methods, with the random forest model achieving 87% accuracy, outperforming logistic regression (69%) and discriminant analysis (50%).

Furthermore, Appelbaum et al., (2018) and Cao et al. (2015) highlighted the success of BDA in financial statement audits, particularly in detecting financial distress, fraud, and stock market trends. BDA also plays a critical role in identifying risks and irregularities, enabling auditors to gain insights that would otherwise be difficult to uncover. BDA also aids auditors in assessing the company's going-concern status by comparing the following year's forecasts with the current year's figures.

On a regional level, Nur and Panggabean (2020) aims to build Financial Distress models using Artificial Neural Network Model, Logistic Regression, and Discriminant Analysis, based on samples taken from manufacturing sectors in the Indonesia Stock Exchange in the period 2015-2018. The accuracy of the three techniques in predicting Financial Distress are compared and results indicated that ANN outperformed the other techniques in predicting financial distress, reinforcing its reliability in identifying going concern risks.

Jan (2021) developed a going concern prediction model utilizing data mining techniques to assist auditors in making informed judgments on an entity's going concern decisions. The study employed deep neural networks (DNN) and recurrent neural networks (RNN) for modeling, while CART was used to identify key variables. The dataset, sourced from the Taiwan Stock Exchange and the Taipei Exchange, included 352 companies (88 of which had going concern doubts) spanning the period 2002 to 2019. By incorporating 16 financial variables and three non-financial variables, the optimal RNN model achieved an impressive accuracy rate of 93.92%.

Corroborating Jan's findings, Chi and Shen (2022) are consistent with Jan (2021), Chi and Shen (2022) studied how artificial intelligence and machine learning can improve going-concern prediction. Their research underscores the importance of accurate auditor judgments and highlights the integration of decision tree algorithms (CART and CHAID) and machine learning models like XGB, ANN, SVM, and C5.0. Using data from Taiwanese companies (2000-2019), they found that the CHAID-C5.0 model provided the highest prediction accuracy (95.65%).

In sum, these studies provide comprehensive evidence of the critical role AI-based BDA plays in supporting auditors' professional judgment. Therefore, the following hypothesis is tested:

H_2: AI-based Big Data Analytics (DNN, RNN, SVM, RF, KNN, and DT) support auditors' professional judgment in evaluating an entity's going concern status.

This hypothesis can be divided into the following sub-hypotheses as follows:

$H_{2.1}$:"The Deep Neural Network (DNN) model supports auditors' professional judgment in evaluating an entity's going concern status."

$H_{2.2}$:"The Recurrent Neural Network (RNN) model supports auditors' professional judgment in evaluating an entity's going concern status."

$H_{2.3}$:"The Support Vector Machine (SVM) model supports auditors' professional judgment in evaluating an entity's going concern status."

$H_{2.4}$:"The Random Forest (RF) model supports auditors' professional judgment in evaluating an entity's going concern status."

$H_{2.5}$:"The K-Nearest Neighbors (KNN) model supports auditors' professional judgment in evaluating an entity's going concern status."

$H_{2.6}$:"The Decision Tree (DT) model supports auditors' professional judgment in evaluating an entity's going concern status."

Third: Studies related to the Role of a Hybrid Model in supporting Auditors' Professional Judgment in Going Concern Evaluation.

Some studies call for integrating traditional techniques with big data analytics to improve going-concern evaluations. Auditors can leverage Big Data techniques to enhance financial distress forecasting, allowing them to combine data-driven insights with professional judgment to assess a firm's future financial stability more effectively. This integration would strengthen going concern evaluations in audits, as required by the Statement on Auditing Standards No. 59 (AICPA, 1988) for public companies. Utilizing AI-based BDA could also help mitigate the costly risk of issuing unmodified audit opinions before a firm faces bankruptcy.

Zhang et al. (2015) compare the performance of financial distress prediction models based on big data analytics versus prediction models based on predetermined models from domain professionals in accounting and finance. They find that there is no significant difference in the predictions. However, a combination of both approaches performs significantly better than each on its own.

Read and Yezegel (2016) highlighted that this issue is particularly prevalent in non-Big 4 audit firms during the first five years of an audit engagement as the smaller audit firms may hesitate to issue modified going concern opinions early in an engagement due to concerns about losing clients. However, by using Big Data-driven results, these firms could better justify their modified opinions, enhancing the independence and objectivity of their evaluations. Additionally, despite the initial investment in learning Big Data techniques, these models have the potential to increase audit efficiency in assessing going concern status.

Building upon this perspective, Gepp et al. (2018) recommended that auditors incorporate BDA into financial distress predictions to improve going-concern evaluations required by the Statement on Auditing Standards No. 59 for public companies by offering more precise and detailed analyses of a company's financial stability.

Furthermore, Boztepe et al. (2025) explore the integration of artificial intelligence, particularly deep learning, into traditional bankruptcy prediction models in the banking sector. Using bank data from 2020 to 2023, the study applies established models like Altman Z, Springate, Zmijewski, and Taffler, enhanced through AI and evaluated using ensemble methods with KNN, Naive Bayes, and decision trees. The findings demonstrate that AI integration improves prediction accuracy and precision, supporting more effective financial risk assessment. The study highlights the practical benefits of risk management and emphasizes the need for further research to address inconsistencies in AI-driven models.

Collectively, these studies advocate for the development and application of a hybrid model that integrates the Traditional Altman Z-score model, as one of the Traditional Techniques, with AI-based BDA. Such an approach not only mitigates the risk of audit failure, such as issuing an unmodified opinion before a bankruptcy event—but also supports auditors in forming well-substantiated professional judgments in high-stakes decision-making contexts. Also, most previous studies have focused on developed countries (e.g., the USA, Canada, Europe, Australia, and New Zealand), which are early adopters of innovations. There is a need to explore the hybrid model in improving going-concern evaluations in developing countries like Egypt. Accordingly, the following hypotheses were developed:

H_3: The Hybrid model that integrates the traditional Altman Z-score model and AI-based Big Data Analytics (e.g., DNN, RNN, SVM, RF, DT, KNN) supports auditors' professional judgment in evaluating an entity's going-concern status more effectively than using the traditional Altman Z-score model alone.

H_4: There is no statistically significant difference in the evaluation outcomes between the hybrid model and traditional techniques in supporting auditors' going-concern judgments".

5. Theoretical background:

5.1.The Entity's Going Concern Concept in Accounting and Auditing:

The going concern assumption is a fundamental principle in both accounting and auditing. In accounting, the going concern assumption was first formally recognized in the *Framework for the Preparation and Presentation of Financial Statements* (1989) and later reaffirmed in the revised *Conceptual Framework for Financial Reporting* (2010). This assumption presumes that an entity will continue its operations for the foreseeable future unless there is evidence to the contrary, such as an intention or need to liquidate or cease operations. In such cases, financial statements may need to be prepared on a different basis, and the basis used must be disclosed (IASB, 2018; Agostini, 2018). The assumption relies on the premise that no significant indications suggest the entity will be forced or choose to discontinue operations within the standard one-year period (Chi & Shen, 2022; Goo et al., 2016; Shirata & Sakagami, 2008).

In contrast, the going concern assumption in auditing requires auditors to exercise professional judgment in evaluating the appropriateness of management's application of this assumption in preparing financial statements. Even if management has not explicitly assessed the entity's ability to continue, auditors must determine whether there is substantial doubt about the entity's ability to operate as a going concern for a reasonable period, typically not exceeding one year from the date of the financial statements (Geiger et al., 2021; Agostini, 2018).

5.2.The Entity's Going Concern under Auditing Standards:

The International Auditing and Assurance Standards Board (IAASB) outlines the auditor's responsibilities regarding an entity's going concern in *International Standard on Auditing (ISA) 570 (Revised)*. According to ISA 570, financial statements are prepared under the assumption that the entity will continue operating for the foreseeable future. Management is responsible for assessing the entity's ability to continue as a going concern, making forecasts and judgments covering at least twelve months from the financial statement preparation date. This assessment should consider all relevant information, including business size, nature of activities, market conditions, future outlooks, and transaction complexity. Forecasts are based on information, documents, and estimates available at the time of preparation (ISA 570, Para. 3–5).

The auditor's responsibility is to obtain sufficient audit evidence to evaluate the appropriateness of management's use of the going concern basis of accounting and to determine whether material uncertainty exists about the entity's ability to continue operating. This responsibility applies even if the financial reporting framework does not explicitly require a going concern assessment. However, auditors cannot predict future events or guarantee the entity's ability to continue as a going concern (ISA 570, Para. 6–7). Under ISA 570 (Revised), auditors must assess whether events or conditions raise significant doubt about the entity's ability to continue as a going concern during risk assessment procedures (ISA 315). Two scenarios may arise:

1. Management Has Conducted an Assessment: The auditor discusses management's findings and evaluates plans to address identified concerns.
2. Management Has Not Conducted an Assessment: The auditor inquires about the basis for using the going concern assumption and whether management is aware of any adverse conditions (ISA 570, Para. 10).

Auditors must remain alert for indications of going concern issues throughout the audit. If such issues are identified, they must evaluate management's assessment or request that management conduct one. Table (1) provides examples of conditions and events that could, either individually or collectively, may raise significant doubt.

Table (1): Conditions and Events that raise significant doubt regarding the entity's going concern under ISA 570

	Events or Conditions
Financial	▪ Net liability or net current liability position. ▪ Indications of withdrawal of financial support by creditors ▪ Negative operating cash flows ▪ Adverse key financial ratios. ▪ Substantial operating losses ▪ Significant deterioration in the value of assets used to generate cash flows. ▪ Arrears or discontinuance of dividends. ▪ Inability to pay creditors on due dates. ▪ Inability to comply with the terms of loan agreements.
Operating	▪ Management intentions to liquidate the entity or to cease operations. ▪ Loss of key management without replacement. ▪ Loss of a major market, key customer(s), franchise, license, or principal supplier(s). ▪ Labor difficulties. ▪ Shortages of important supplies. ▪ Emergence of a highly successful competitor.
Other	▪ Non-compliance with capital requirements ▪ Pending legal or regulatory proceedings against the entity. ▪ Changes in law or regulation or government policy are expected to adversely affect the entity. ▪ Uninsured or underinsured catastrophes occur.

In addition, the Egyptian Auditing Standard (EAS) 570, titled "Going Concern," outlines the auditor's responsibilities in evaluating an entity's ability to continue its operations for the foreseeable future. This standard, implemented in 2008, is aligned with the International Standard on Auditing (ISA) 570, which addresses the auditor's duties concerning the going concern assumption in financial statement audits.

Despite its alignment with international standards, EAS 570 has faced criticism for not providing sufficient guidance tailored to the Egyptian business environment, Researchers have noted a standards gap regarding the auditor's responsibility towards going concern assessments, suggesting that the existing standards have not provided auditors with sufficient procedural instructions to align with the evolving professional practices in Egypt. This gap has led to criticism from Egyptian auditors (Abdelrahim,2020 ؛ Elsayed, 2018).

To address these concerns, several studies have examined the challenges faced by auditors in Egypt regarding the accuracy of their judgments on going concern (Abdelrahim, 2020; Elsayed, 2018). Elsayed (2018) emphasized the need to enhance auditors' competencies by requiring the systematic use of decision aids, such as bankruptcy prediction models and data analytics tools, to improve their ability to classify firms as financially stable or bankrupt, thereby increasing the accuracy of their reporting. Similarly, Abdelrahim (2020) highlighted the urgent need to update and revise Egyptian auditing standards to align with international auditing frameworks while ensuring their relevance to the Egyptian business environment. This is seen as a crucial step toward improving audit quality.

Enhancing the precision of auditors' professional judgments on going concern in Egypt is essential for improving audit quality and ensuring reliable financial reporting. However, research on this topic remains limited, particularly in Egypt as an emerging economy. Unlike developed economies, Egypt lacks publicly available records of companies that went bankrupt after receiving a going-concern opinion, making it challenging to analyze and improve the accuracy of auditors' assessments.

5.3. Traditional Statistical Models for evaluating the entity's Going Concern:

The following section will provide a comprehensive overview of key traditional statistical models along with their applications in going concern evaluations.

(1) Traditional Altman (1968) Model:

Altman (1968) introduced a more advanced predictive model called the "Z-score" model, which incorporates multiple discriminant analysis (MDA). The MDA model not only helps predict bankruptcy but also detects earning manipulation (Parikh and Shah, 2022; Somayyeh, 2015). To this day, the Altman Z-Score is still widely used by researchers, practitioners, and academics in the accounting field compared to other prediction models (Irawan, 2023). The formula used in this calculation method is as follows:

$$\mathbf{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5}$$

Where:

X_1 = Working capital / Total assets

X_2 = Retained earnings / Total assets

X_3 = EBIT / Total assets

X_4 = Market Value of Equity / Total Liabilities

X_5 = Sales / Total assets

If a company's Z-score is greater than 2.99, it suggests a very high possibility of not going bankrupt (safe zone). On the other hand, if the Z-score is less than or equal to 1.8, it indicates a high possibility of bankruptcy (distress zone). If the Z-score falls between 1.81 and 2.67, the company is considered to be in the "grey zone" (Parikh and Shah, 2022; Somayyeh, 2015).

(2) Springate model:

The Springate model is an insolvency forecasting model that uses the multiple discriminant analysis approach (Seto, 2022). Springate model, known as the S-Score, was created in 1978 by Gordon L.V. Springate. Springate (1978) initiated the Springate model to identify financial ratios that are believed to have an impact on an event, helping the model to determine the likelihood of the event occurring (Sunaryo, 2015). The model can be used to predict bankruptcy with an accuracy rate of 92.5% (Irawan, 2023). Springate selected four key ratios to be included in the final model that he determined most effectively represented a company’s financial condition.

$$\textbf{S-Score} = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4$$

Where:

X_1 = Working capital / Total assets

X_2 = EBIT / Total assets

X_3 = Earnings before taxes / Current liabilities

X_4 = Sales / Total assets

The cut-off point for the Springate S-Score is: If the S-Score is greater than 0.862, the company is predicted to be potentially healthy and not at risk of financial distress. If the S-Score is less than 0.862, the company is classified as being in the "Bankrupt Zone" and at risk of bankruptcy.

(3) Zmijewski (1984) Model:

Zmijewski (1984) developed a prediction model using logistic regression analysis, which assesses the performance, leverage, and liquidity of a company (Fauzi & Sudjono, 2021). Known as the X-Score, the Zmijewski model applies probability analysis to distinguish between bankrupt and non-bankrupt firms, based on a sample of 40 bankrupt companies and 800 solvent companies (Irawan, 2023; Leisen & Swan, 2023). The Zmijewski model is calculated using the following formula:

$$\textbf{X- Score} = -4.3 - 4.5X_1 + 5.7X_2 + 0.004X_3$$

Where:

X_1 = Net Income / Total Assets

X_2 = Total Liabilities / Total Assets

X_3 = Current Assets / Current Liabilities

If the X-score is negative (X-Score < 0), it indicates that the possibility of not being bankrupt is very high (healthy condition), and if the x-score is positive (X-Score ≥ 0), it indicates that the possibility of being bankrupt is very high (distress zone).

6. Big Data Analytics: Theoretical Overview

6.1. Definition of Big Data Analytics:

Big Data Analytics (BDA) refers to the systematic process of managing, processing, and analyzing large and diverse datasets to uncover hidden patterns, trends, and insights that support strategic decision-making and provide a competitive advantage (Anwar et al., 2024; Alles & Gray, 2014; Udeh et al., 2024). It involves the application of advanced analytical techniques, such as predictive modeling, statistical analysis, data mining, and machine learning, to extract meaningful information from complex data sets, enabling organizations to make data-driven decisions and improve performance (Blix et al., 2021; Gepp et al., 2018; Grover et al., 2018; Salijeni et al., 2019; Saggi and Jain, 2018; Brown-Liburd et al., 2015). In the context of auditing, BDA is defined as the science and art of identifying patterns, anomalies, and useful information in data related to an audit through analysis, modeling, and visualization, aiding in audit planning and execution (AICPA, 2014, cited in Salijeni, 2019).

6.2. Types of Big Data Analytics:

Big Data analytics can be broadly divided into four categories (Jeble et al. 2017; Thirathon et al. 2017; Mohammed et al. 2014):

- **Descriptive analytics** aims to answer the question "What happened in the past?" based on the data presented through graphics and reports (Appelbaum et al., 2017b). This form of analytics focuses on understanding the gathered data and its internal structure. It involves the use of tools and algorithms to identify categorical or temporal patterns and trends within the Big Data (Saggi and Jain 2018; Thirathon et al. 2017). Descriptive analytics relies on historical data to discover models that can help managers understand what happened in the past and make informed managerial decisions.
- **Diagnostic analytics** aims to explain why a particular problem or event has occurred in the past. It relies on various techniques like data mining and data discovery to investigate the cause and effect of any past problem (Baum et al. 2018).
- **Predictive analytics** aims to answer the question "What could happen?" by using statistical models, machine learning, neural network analysis, and forecasting techniques to make predictions (Mohammed et al. 2014; Jeble et al. 2017; Thirathon et al. 2017; Baum et al. 2018). Machine learning algorithms are often utilized to detect patterns in historical data. Prior researchers have extensively explored the application of different machine-learning techniques to solve problems that are either too time-consuming or too complicated to compute for humans (Jeble et al. 2017).
- **Prescriptive analytics** uses the insights from descriptive and predictive analytics to answer the question "What should be done?" and prescribe solutions to problems (Appelbaum et al., 2017; Sheng et al. 2020). It employs techniques like simulation, optimization, and artificial intelligence to recommend future actions and guide organizations toward the best course of action (Mohammed et al. 2014; Jeble et al. 2017; Baum et al. 2018).

6.3.AI-based Big Data Analytics:

AI-based Big Data Analytics encompasses a range of sophisticated methods and tools designed to process and analyze vast and complex datasets, enabling organizations to extract valuable insights, identify patterns, and support data-driven decision-making. This research will focus exclusively on machine learning and deep learning algorithms, as they represent the most advanced and widely adopted methods within the field of Big Data Analytics.

6.3.1. Machine Learning (ML):

Machine Learning is defined as a subfield of Artificial Intelligence (AI), specializing in the development and understanding of technological models and algorithms that can learn, predict, and make decisions autonomously without explicit programming (Kelleher & Tierney, 2018). ML enables machines to "learn" from data and progressively improve their efficiency in performing specific tasks. Machine learning algorithms can be divided into two categories: supervised learning and unsupervised learning (Esther Varma, & Prasad, P. S., 2023).

Supervised learning is a popular Machine Learning paradigm in BDA, where models are trained on annotated datasets with preset outputs (Divya et al., 2018; Wu et al., 2016). For supervised approaches, the datasets contain 'labeled' examples that include target information (e.g., fraud or non-fraud, going concern or non-going concern). Supervised learning is a type of machine learning in which a labeled dataset (input) is used to train a model (algorithm) to generate predictions or decisions (output) without the need for human intervention (Divya et al., 2018; Wu et al., 2016). There are numerous supervised methods, including Support Vector Machines, K-Nearest Neighbor, Decision Trees, Random Forests, Naïve Bayes, Bayesian Belief Networks, and Artificial Neural Networks.

Unsupervised learning is a machine learning technique that differs from supervised learning by operating without labeled data. Instead of using predefined output labels, unsupervised learning identifies patterns, relationships, and structures within a dataset by grouping similar data points. This approach is commonly used for tasks such as clustering, anomaly detection, and dimensionality reduction (Gierbl, 2021).

Several studies (Chi & Shen, 2022; Jan, 2021; Goo et al., 2016) have highlighted the effectiveness of machine learning techniques in enhancing the accuracy of auditors' going concern opinions. These methods, including Support Vector Machine (SVM), Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN), have proven to be highly effective in predictive tasks such as fraud detection and bankruptcy prediction (Zhang, 2018). Consequently, the researcher will explore these techniques in greater detail.

(1) Support Vector Machine: -

Support Vector Machine (SVM) is a powerful supervised learning algorithm that operates by identifying the optimal hyperplane to maximize the separation margin between distinct classes within the feature space. Its strength lies in effectively managing non-linear patterns by employing kernel functions, which transform the input space into a higher-dimensional space where linear classification becomes feasible (Malakauskas et al., 2021). This approach has been widely applied in the context of business failure prediction, particularly due to its capability to process high-dimensional datasets and its robust performance in noisy environments (Jabeur et al., 2021; Smiti and Soui, 2020; Huang and Yen, 2019; Choi et al., 2018; Jing and Fang, 2018; Barboza et al., 2017; Fan et al., 2017.

(2) Decision Trees:

Decision Tree (DT) modeling techniques are popular machine learning methods that have been extensively utilized in applications related to business failure. DT is a non-parametric classification approach that evaluates target data based on a function of independent attributes (Tsai et al., 2014). The fundamental concept of using DT techniques in the context of business failure is to categorize businesses into a binary classification system. The process begins with a root node that encompasses both classes representing the business status, which then branches out into two nodes reflecting potential outcomes based on selected attributes, guided by a decision algorithm. In the DT framework, the leaves are designated with class labels, while the branches indicate conjunctions leading to classifications. This iterative process continues through all possible splits until an optimal decision tree is established, effectively distinguishing between going-concern and non-going-concern firms while minimizing error and misclassification rates. This classification method has been widely adopted by researchers studying business failure (Tsai and Cheng, 2012; Tsai et al., 2014; Smiti and Soui, 2020).

(3) Random forest (RF):

Random Forest is a type of supervised learning technique that builds multiple decision trees and combines their outputs to enhance prediction accuracy and reliability (Aghware et al., 2024). It constructs each tree using bootstrap samples from the training dataset and selects features randomly at each node split, which helps to minimize overfitting and improve the model's generalization. For classification tasks, the final result is based on the majority vote from all trees, while in regression, the average of all tree outputs is used. Its ability to manage high-dimensional datasets without requiring feature normalization, along with its built-in mechanism for evaluating feature importance, makes it especially useful in financial analysis contexts (Wang et al., 2023).

(4) K-Nearest Neighbour (k-NN):

K-Nearest Neighbors (KNN) is a non-parametric classification method widely used in machine learning to address classification problems (Choi et al., 2018; Smiti & Soui, 2020). The KNN algorithm analyzes all available data, classifies it, and then uses the classifications of previously established categories to determine how new cases should be classified. This algorithm is a simple yet effective approach that classifies a new sample (e.g., a firm) based on the properties of its nearest neighbors. When the properties of neighboring samples vary significantly (e.g., properties of going concern vs. non-going concern firms), the algorithm assigns the new sample to the most frequent class among its k-nearest neighbors in the training dataset (Cunningham & Delany, 2020; Choi et al., 2018). KNN is summarized in the following steps:

- Choose the number of k and a distance metric
- Find the k nearest neighbors of the sample we want to classify
- Assign the class label by majority vote.

6.3.2. Deep Learning (DL): -

The field of Big Data Analytics (BDA) has experienced a significant transformation with the advent of Deep Learning (DL) techniques, marking in a new era characterized by advanced methods and tools capable of extracting meaningful insights from vast and complex datasets (Najafabadi et al., 2015; Hordri et al., 2017). As a specialized subset of Machine Learning, DL employs neural networks with multiple layers—referred to as "deep" learning—to capture intricate patterns and relationships within large datasets. This capability has enabled groundbreaking applications in areas such as image recognition, natural language processing, and predictive analytics, revolutionizing the approach to BDA and providing powerful solutions to the complexities of big data. Deep Learning techniques encompass a variety of architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GANs), Deep Belief Networks (DBNs), Deep Reinforcement Learning (DRL), and Graph Neural Networks (GNNs). However, this research will focus specifically on Deep Neural Networks (DNNs) and Recurrent Neural Networks (RNNs), as these architectures hold significant potential for enhancing the accuracy of going concern evaluations in auditing.

(1) Deep Neural Networks:

Deep Neural Networks (DNN) are an advanced model derived from Artificial Neural Networks (ANN) designed to simulate how the human brain learns new information, making it a fundamental deep learning model. Unlike traditional artificial neural networks, DNNs have many hidden layers. This layered structure enables DNNs to deal with more complex problems and effectively process large, big data. In an ANN, data is fed into the hidden layer for computation by the neurons, and the results are then sent to the output layer, while in a DNN, additional hidden layers are incorporated into this framework.

According to how it works, an artificial neural network inputs data to the output layer for processing by the neurons in the hidden layer, then outputs the results. The equation displays the computation of the hidden layer (1). The activation function (AF) nonlinearly transforms the outputs processed by neurons after the data in the input layer have been multiplied by weights, added up with biases, and input into the subsequent layer until the desired results are obtained, and then the results are returned to adjust the weights (Jan, C. L.,2021). The equation can be expressed as:

$$Y = AF\ (X_1W_1 + X_2W_2 + X_3W_3 + \cdot\cdot\cdot + X_nW_n + \text{bias})$$

(2) Recurrent Neural Network:

Recurrent Neural Networks (RNN) are a widely used sequence model in deep learning, designed to handle ordered data and effectively capture the temporal dependencies in sequential information. This capability enables RNNs to achieve high accuracy in predicting time series data. The RNN architecture allows for the processing of different data at each time step while retaining essential information. The output from Phase t is fed into a hidden state within the hidden layer, along with the data from Phase t + 1 for further computation (Bianchi and Suganthan, 2020; Bianchi et al., 2017). The activation function employed by the recurrent neural network is the hyperbolic tangent function (tanh), leading to the following equation:

$$y_t = tanh\ (wt\ (state_{t\text{-}1} + x_t) + b_h)$$

6.4. Advantages of using AI-based BDA in external audits:

There are multiple advantages to using Big Data Analytics techniques in an external audit. The most common ones are explained in this section.

- **Larger populations:** By using data analytics, auditors can examine larger datasets and concentrate on testing only the outliers or anomalies. This approach enhances the collection of audit evidence and allows for the selection of more relevant samples (Cao et al., 2015; CFRR, 2017; IAASB, 2015a; IFAC, 2016; O'Donnell, 2015; Ramlukan, 2015).
- **Improves auditors' performance & focus on risky areas:** Using data analytics significantly enhances auditors' performance by allowing them to concentrate on high-risk areas. By automating manual and repetitive tasks, auditors can allocate more effort to more judgmental tasks, focusing on outliers and complex aspects of the audit (Appelbaum et al., 2017a; Cao et al., 2015; IFAC, 2016; IRE, 2018).
- **Enhanced Understanding of the Client's Business and Environment:** By assessing larger datasets efficiently, auditors can gain a deeper understanding of their clients' businesses and the environment in which they operate. This improved insight into client operations, risks, and controls allows auditors to identify issues more quickly, enabling timely and responsive actions (AICPA, 2018; Cao et al., 2015; CFRR, 2017; IFAC, 2016; O'Donnell, 2015).
- **Enhances the Client Relationship:** The incorporation of big data and data analytics positively influences client relationships by improving communication with those in governance roles and providing more reliable information (AICPA, 2018; IRE, 2018).
- **Enhances Auditor Credibility:** The credibility of the audit is bolstered through the added value provided, improved services, and strengthened client relationships (IRE, 2018).

- **Enhanced Audit Quality:** Utilizing Big Data Analytics can significantly improve audit quality. Analyzing client data at an earlier stage enables auditors to identify and assess risky areas sooner. This proactive approach allows for a more tailored audit plan that addresses specific client risks, making it more relevant (CFRR, 2017).
- **Improved Accuracy and Reliability in Accounting Information:** Big Data technologies play a crucial role in enhancing the accuracy and reliability of accounting information. Advanced techniques such as data cleansing, data integration, and data validation help organizations identify and rectify errors, inconsistencies, and outliers in financial data.

7. Research Methodology:

7.1. Population and Sample Selection:

The population of the study includes all the companies listed on the Egyptian Stock Exchange during the period from 2018 to 2023. The number of these companies reached 225. The criteria for the sample selection used in this study are as follows:

- Including all non-financial firms listed in the Egyptian Stock Exchange during the period from 2018 to 2023.
- Excluding Banks, insurance companies, and companies operating in the field of financial securities due to their special nature.
- Excluding firms listed in the Egyptian Stock Exchange after the year of 2018.
- Excluding Firms with incomplete financial reports.
- Excluding Firms whose financial reports were prepared in foreign currency.

As a result, the number of companies included in the study is 144 companies, with a total of 864 observations over the period from 2018 to 2023.

Table (2): Sample Size and Industry Representation

Panel A: Description of the final data set	**No. of firms**	**Percentage**
Population	225	100%
(-) Financial firms	(49)	(21.8%)
(-) Firms listed after the year of 2018	(9)	(4%)
(-) Firms with incomplete financial reports	(16)	(7.1%)
(-) Firms with financial reports prepared in foreign currency	(7)	(3.1%)
Final data set	**144**	**64%**

7.2. Research Model:

The hybrid model for integrating Altman z-score as one of the traditional techniques and AI-based Big Data Analytics can be presented as shown in Figure (1) as follows:

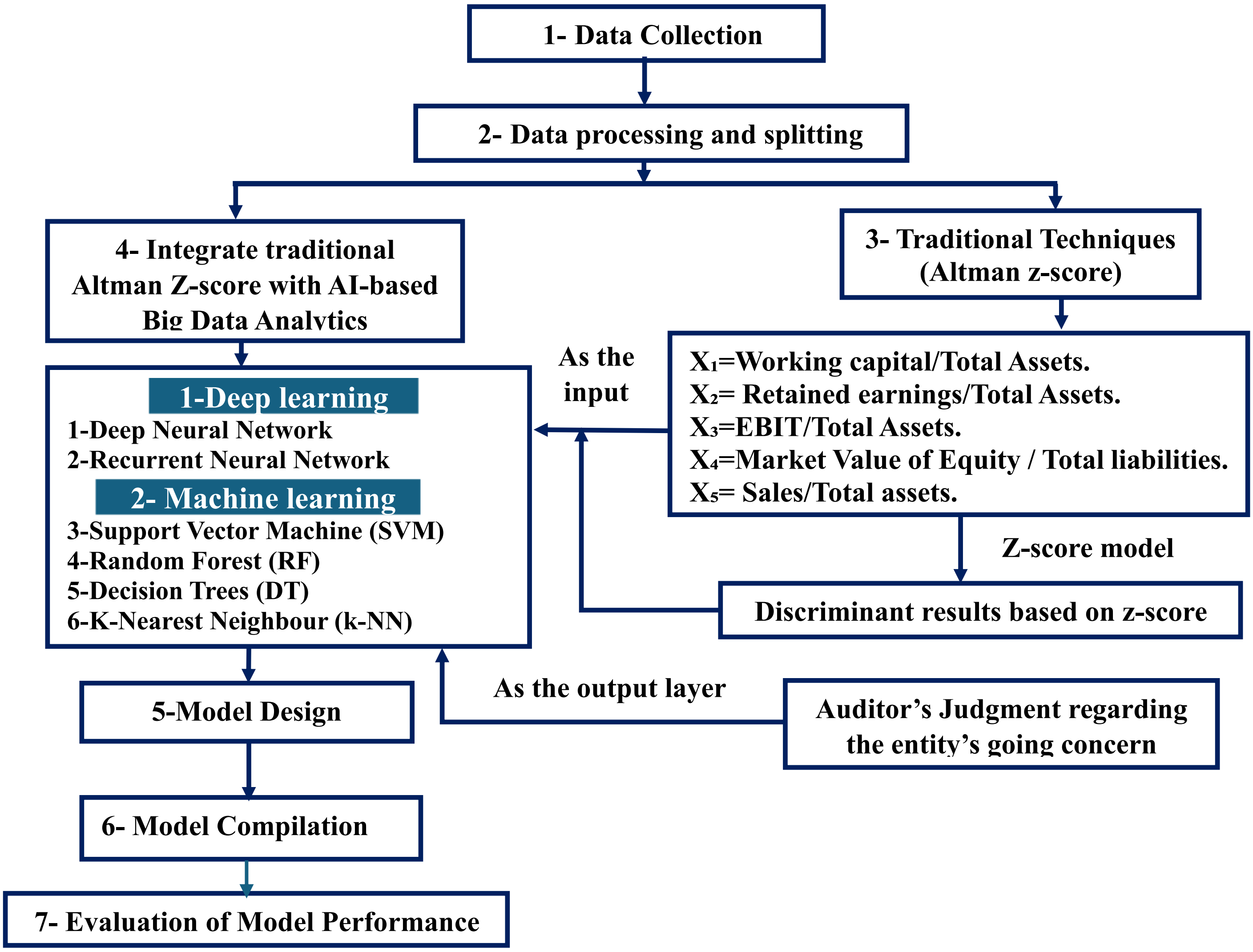

Figure (1): Hybrid Model

Source: by the researcher

The steps of the hybrid model are as follows:

Step 1: Data Collection:

Regarding data collection, this study relies on secondary data extracted from the financial reports of the firms included in the analysis. The researcher obtained the required data to operationalize the model and measure both dependent and independent variables from multiple sources, notably Misr Information Publishing Company, the Mubasher website (https://www.mubasher.info), the Investing website (https://www.investing.com), as well as information available on the companies' official websites and the Egyptian Stock Exchange website (https://www.egx.com.eg).

Step 2: Data Pre-Processing and Splitting:

Data pre-processing is a critical step to ensure the dataset is clean, consistent, and suitable for analysis. This involves cleaning the data by removing outliers, handling missing values, and addressing inconsistencies, as well as selecting relevant features and normalizing the data to ensure consistency. Once pre-processed, the dataset is split into a training set (e.g., 80% of the data) for model development and a testing set (e.g., 20% of the data) for validation.

Step 3: Computing Classification Scores for Traditional Techniques:

In this step, traditional financial models are applied to compute classification scores that assess the entity's financial health models using the Altman z-score model as one of the Traditional Techniques (as shown in Table 6).

Table (6): Traditional Altman Z_score formula

Formula	Score
Z- Score =1.2X_1**+1.4**X_2**+3.3**X_3**+0.6**X_4**+1.0**X_5 X_1=Working Capital/Total Assets. X_2 = Retained Earnings/Total Assets. X_3 =Ebit/Total Assets. X_4 = Market value of Equity/Total Liabilities. X_5 = Sales/Total Assets	B: <1.81 G: 1.81–2.99 H: >2.99

Step 4: Integrate traditional Altman Z-score with AI-based BDA:

Although traditional models offer valuable insights, they often fall short in capturing the complex, non-linear relationships inherent in financial data. To address these limitations, this stage integrates AI-based BDA specifically, machine learning algorithms (e.g., Support Vector Machines, Random Forests, Decision Trees) and deep learning architectures (e.g., Deep Neural Networks, Recurrent Neural Networks)—to enhance predictive accuracy. Within this Hybrid model, the inputs consist of the individual variables derived from traditional Altman z-score model, along with its respective Z-score classification results. These inputs are then fed into the AI-based BDA, which processes them to uncover complex patterns and interrelationships within the data, ultimately generating an output that reflects the external auditor's professional judgment. To achieve this integration, a hybrid approach combining deep learning and machine learning techniques is employed.

Step 5: Model Design:

Each AI-based BDA is structured according to its unique architecture:

- **Deep Neural Networks (DNN):** Construct a deep neural network with input, multiple hidden layers, and an output layer using non-linear activation functions (e.g., ReLU, Softmax).
- **Recurrent Neural Networks (RNN):** Design a sequential model to capture temporal patterns, especially useful for multi-period financial data.
- **Random Forest (RF) and Decision Trees (DT):** Configure decision trees or an ensemble of randomized decision trees for classification.
- **Support Vector Machine (SVM):** Implement a support vector classifier with kernel functions to separate non-linear data distributions.
- **K-Nearest Neighbors (k-NN):** Select an appropriate value of k to classify a firm based on the majority class of its nearest neighbors.

Step 6: Model Compilation:

- **Loss Function:** Define an appropriate loss function (e.g., binary cross-entropy) depending on the classification task.
- **Optimizer:** Choose optimization algorithms such as Adam to minimize the loss function.

Step 7: Evaluation of Model Performance:

In AI-based BDA models, algorithms are primarily evaluated using the confusion matrix. Table (7) presents the confusion matrix which comprises four key elements:

Table (7): Confusion Matrix Table

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="2">Predicted classifier (%)</th></tr>
<tr><th>Non-Going concern</th><th>Going concern</th></tr>
<tr><th rowspan="2">Actual class (%)</th><th>Non-Going concern (positive)</th><td>True Positive (TP) (Sensitivity)</td><td>False Negative (FN) (Type II Error)</td></tr>
<tr><th>Going concern (Negative)</th><td>False Positive (FP) (Type I Error)</td><td>True Negative (TN) (Specificity)</td></tr>
</table>

- **True Positives (TP):** occurs when the auditor's professional judgment identifies an entity as a non-going concern (distressed) entity, and the model also correctly as a non-going concern (distressed) entity.
- **True Negative (TN):** occurs when the auditor's professional judgment identifies an entity as a going concern (healthy) entity, and the model is correctly classified as a going concern (healthy) entity.
- **False positives (FP),** also called **Type I errors**, is the number of instances incorrectly predicted as positive. It happens when the auditor's professional judgment identifies an entity as a going concern (healthy) entity, and the model is incorrectly classified as a non-going concern (distressed) entity.
- **False negatives (FN),** also called **Type II errors**, is the number of instances incorrectly predicted as negative. It happens when the auditor's professional judgment identifies an entity as a non-going concern (distressed) entity, and the model is incorrectly classified as a going concern (healthy) entity.

To validate and evaluate the prediction performance of the models used in this study and to derive robust conclusions regarding their predictive accuracy, seven performance metrics were selected:

1. **Average Accuracy Rate:** measures the percentage of correctly classified instances across the dataset. The accuracy rate is calculated using the following formula (Chi and Shen, 2022):

$$\textbf{Average accuracy rate} = \frac{TP+TN}{TP+TN+FN+FP}$$

2.Type I and Type II Errors: -

Based on confusion matrix data, Type I Error is associated with false positives (FP), while Type II Error is associated with false negatives (FN). A Type I Error occurs when a going concern entity is incorrectly classified as a non-going concern entity, whereas a Type II Error occurs when a non-going concern entity is misclassified as a going concern entity. These error types are commonly analyzed in studies on business failure (Barboza et al., 2017; Fan et al., 2017; Huang & Yen, 2019; Du Jardin, 2021). The formulas for these errors are:

$$\textbf{Type I Error} = \frac{FP}{TN+FP} \qquad \textbf{Type II Error} = \frac{FN}{TP+FN}$$

3.Sensitivity and Specificity:

Sensitivity, as defined by Chi and Shen (2022), indicates how well a classifier identifies the positive class. It calculates the percentage of correctly classified non-going concern entities as a non-going concern entity, which is referred to as true positive (TP) predictions based on the confusion matrix. **Specificity**, also defined by Chi and Shen (2022), measures how effectively a classifier identifies firms with a negative class. It determines the proportion of correctly classified going concerning entities, known as true negative (TN) predictions. The formulas for sensitivity and specificity are as follows:

$$\textbf{Sensitivity} = \frac{TP}{TP+FN} \qquad \textbf{Specificity} = \frac{TN}{TN+FP}$$

4. **Precision:** is a metric that assesses the accuracy of positive predictions by determining the proportion of true positives among all positive predictions. This is calculated using the following equation (Chi and Shen, 2022):

$$\textbf{Precision} = \frac{TP}{TP+FP}$$

5. **F1-score:** is the average of precision and recall, providing a balanced measure of both metrics. It is calculated as follows (Chi and Shen, 2022):

$$\textbf{F1-score} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

7.3. Data Analysis:

The study utilized the Python programming language, an open-source platform that incorporates artificial intelligence and machine learning techniques. Python was used through the Anaconda distribution and executed via Jupyter Notebook, a widely adopted environment for data analysis and model development in academic and professional contexts. Python is extensively used in commercial applications, research, education, and training. Furthermore, the SPSS software was employed to compare the predicted classifications produced by the algorithms with the actual financial conditions of the companies during the practical testing phase of the model.

7.4. Measurement of Variables:

- **Dependent variable:**

The professional judgment of the auditor regarding the entity's going concern is measured by a dummy variable equal to (0) if the firm received the audit opinion of going concern doubt and (1) if the firm did not receive the audit opinion of going concern doubt, based on the indicators of ISA 570. Studies conducted by Bava and Trana (2019), Desai et al. (2017), Geiger et al. (2019), and Mai et al. (2019) identify the following top five financial distress indicators (Table 8).

Table (8): Indicators for Measuring the Dependent Variable

Variable	Measure	References
Net liability (Negative working capital)	**Working capital = Current assets - current liabilities** [0, if the firm had negative working capital (non-going concern); 1, otherwise (going concern)]	ISA 570; EAS 570; Desai et al. (2017); Kozjak (2020); Bava and Trana (2019)
Negative operating cash flows	[0, if the firm had negative operating cash flows (non-going concern); 1, otherwise (going concern)]	ISA 570; Carson et al. 2013; Geiger et al. 2019; Mai et al. 2019; Bava and Trava, 2019; Desai et al. (2017)
Recurring operating losses	[0, if the firm had a loss from operation for two consecutive years (non-going concern); 1, otherwise (going-concern)]	ISA 570; Altman, et al., (2016); Agostini, 2018), Desai, V., (2017).
Adverse key financial ratios	**Losses to Equity ratio = Losses ÷ Total Equity** [0, If accumulated losses exceed half of the entity's equity (non-going concern); 1, otherwise (going concern)]	Aslamiah, S. et al., (2023); Purwanto & Pardistya (2021); Purnomo, A. (2018); Desai et al. (2017)
	Debt ratio = total liabilities ÷ total assets. [0, if debt ratio near or above one (non-going concern); 1, otherwise (going concern)]	
	Cash to current liabilities ratio = Cash ÷ Current liabilities [0, if the ratio is less than one (non-going concern); 1, otherwise (going concern)]	
Inability to pay creditors when due	**Current Ratio = Current Liabilities ÷ Current Assets** [0, if current ratio is less than one (non-going concern); 1, otherwise (going concern)]	Purnomo, A. (2018); Aslamiah, S. et al., (2023); Purwanto& Pardistya (2021)

When three factors or more of the above indicators are present, then the entity will receive a going concerning opinion (Geiger et al., 2024). Based on these criteria, the observations are categorized across the study years, including 250 company samples with going concern doubt and 614 company samples with no going concern doubt, as shown in Table (9).

Table (9): Results of Auditors' Professional Judgment regarding the Entity's Going Concern

	Firms received the audit opinion of going concern doubt	Firms did not receive the audit opinion of going concern doubt	Total
2018	38	106	**144**
2019	42	102	**144**
2020	46	98	**144**
2021	45	99	**144**
2022	41	103	**144**
2023	38	106	**144**
Total	**250**	**614**	**864**

- **Independent variables:**

The independent variables in the present research involve traditional techniques and big data analytics.

First: Traditional techniques:

The Traditional Altman Z-score is used as one of the Traditional Techniques used for evaluating the entity's going concern in this study:

$$\text{Z- Score} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

X_1=Working Capital/Total Assets.

X_2 = Retained Earnings/Total Assets. B: <1.81

X_3 =Ebit/Total Assets. G: 1.81–2.99

X_4 = Market value of Equity/Total Liabilities. H: >2.99

X_5 = Sales/Total Assets

Second: AI based Big Data Analytics: -

For using AI- based Big Data Analytics in evaluating the entity's going concern, Previous studies (Chi and Shen, 2022; Jan, 2021; Goo et al., 2016) have used machine learning techniques like artificial neural networks (ANN), decision trees (DT), and support vector machines (SVM) to evaluate the entity's going concern.

In the present study, the researcher will employ the following machine learning techniques to evaluate an entity's going concern status: Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbor, and Random Forest (RF). These supervised learning algorithms have demonstrated high effectiveness in predictive tasks, such as fraud detection and bankruptcy prediction (Zhang, 2018). Additionally, this study will incorporate deep learning techniques, specifically Deep Neural Networks (DNN) and Recurrent Neural Networks (RNN), to further enhance the accuracy of going concern evaluations.

8. Statistical Analysis for Study Variables:

8.1. Descriptive Statistics:

According to Table 10, the descriptive statistics table provides an overview of the dataset used in the study, which includes 864 valid observations with no missing data across all variables. The dependent variable, judgment, appears to be binary, ranging from 0 to 1, with a mean of 0.7106. This indicates that approximately 71.1% of the cases were classified as a going concern (value = 1), suggesting a relatively high level of concern among auditors. The Altman Z-score, representing the traditional model, has a wide range from -30.58 to 421.17, a mean of 4.93, and a high standard deviation of 17.40, reflecting considerable variation and the presence of potential outliers.

The additional variables (X_1 to X_5) likely represent financial indicators used in the integrated model. Variable x1 has a narrow range and low variability, while x2 shows a negative mean and higher variability, suggesting that it may reflect a distress-related metric. Notably, x4 exhibits an extremely high maximum value (701.31) and a large standard deviation (28.59), indicating possible outliers or a highly skewed distribution. Variable x5 appears more normally distributed, with a mean of 0.6963 and a moderate standard deviation. These findings suggest that before applying machine learning models, standardization or normalization of the variables may be necessary due to the differing scales and presence of outliers. Additionally, given the imbalance in the judgment variable, care should be taken when evaluating classification model performance to avoid biased outcomes.

Table (10): Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
judgment	864	.00	1.00	.7106	.45372
Altman z_score	864	-30.58	421.17	4.9281	17.40432
X_1	864	-2.10	.98	.1716	.31392
X_2	864	-18.90	.52	-.1250	1.38231
X_3	864	-1.44	1.73	.0631	.18019
X_4	864	-1.20	701.31	6.6536	28.59386
X_5	864	-.01	9.96	.6963	.88405
Valid N (listwise)	864				

8.2.Multicollinearity and Variation Inflation Factor:

The dependent variable should have a strong relationship with independent variables. However, any independent variables should not have a strong correlation among other independent variables. Multicollinearity is an incident where one or more of the independent variables are strongly correlated with each other. In such an incident, we should use only one among correlated independent variables.

Variance Inflation Factor (VIF) statistics were used to assess multicollinearity in the indicators (Fornell & Larcker, 1981). According to (Hair et al., 2019), VIF values higher than 10 indicate that independent variables have serious multicollinearity issues. Table (11) shows the VIF values for the study's indicators and demonstrates that each indicator's VIF is below the suggested level.

Table (11): VIF for Independent Variables in Hybrid model

Coefficients[a]			
Model		Collinearity Statistics	
		Tolerance	VIF
1	**Z score**	.839	1.192
	x_1	.689	1.452
	x_2	.628	1.593
	x_3	.547	1.829
	x_4	.962	1.040
	x_5	.937	1.067
a. Dependent Variable: judgment			

8.3. Hypotheses Tests and Experimental Results:

This section presents a comprehensive analysis of the performance of individual traditional classifiers, as well as their integration with big data analytics, across two datasets of Egyptian companies. The evaluation is structured through a series of tables that document and compare classifier performance based on seven selected performance metrics. These metrics serve to assess and compare the classifiers, facilitating the identification of the most effective model for classifying an entity's going concern.

Testing the First Hypothesis:

H_1: Traditional Altman Z-score model, as one of the Traditional Techniques, supports external auditors' professional judgment in evaluating an entity's going concern status."

The results presented in Table 12 illustrate the performance of the Traditional Altman Z-Score model in evaluating an entity's going concern status from 2018 to 2022. The Traditional Altman Z-Score exhibits consistent accuracy throughout the years, ranging from 81.25% in 2018 to 86.11% in 2022, with an overall accuracy of 83.61%. Precision improves over time, peaking at 71.19% in 2021 before slightly declining to 68.42% in 2022, indicating enhanced identification of at-risk entities despite minor fluctuations. Furthermore, Specificity, which indicates the model's ability to correctly classify going concern entities, remains stable at an average of

81.10%, while the Type I error rate (misclassification of going concern entities as non-going concern) remains moderate, decreasing slightly from 19.81% in 2018 to 17.48% in 2022. Meanwhile, Recall shows significant improvement, reaching 95.12% in 2022, accompanied by a notable decline in the Type II error rate from 15.79% in 2018 to 4.88% in 2022, signifying better classification of non-going concern entities. Finally, the F1-score, which balances precision and recall, follows an upward trend, peaking at 80.77% in 2021, confirming a balanced performance. Overall, the model exhibits strong predictive capability, though minor variations in precision and recall should be considered.

Table (12): Results of the performance of Traditional Altman Z-Score model

	2018	2019	2020	2021	2022	Average
Accuracy	81.25%	81.94%	82.64%	86.11%	86.11%	83.61%
Precision	60.38%	63.33%	68.42%	71.19%	68.42%	66.43%
Specificity	80.19%	78.43%	81.63%	82.83%	82.52%	81.10%
Recall	84.21%	90.48%	84.78%	93.33%	95.12%	89.62%
Type I error	19.81%	21.57%	18.37%	17.17%	17.48%	18.90%
Type II error	15.79%	9.52%	15.22%	6.67%	4.88%	10.38%
F-1	70.33%	74.51%	75.73%	80.77%	79.59%	76.31%

Given these strong indicators, it is evident that the Traditional Altman Z-score model provides valuable insights and enhances auditors' professional judgment. Therefore, $H_{1.1}$ is accepted, confirming that the Traditional Altman Z-score model supports external auditors' professional judgment in evaluating an entity's going concern status.

Testing the Second Hypothesis:

H_2:"AI-based Big Data Analytics (DNN, RNN, SVM, RF, KNN, and DT) support external auditors' professional judgment in evaluating an entity's going concern status."

Tables (13) to (18) present the performance results of AI-based BDA in enhancing auditors' professional judgment regarding an entity's going-concern status. The researcher employed a range of AI-based BDA techniques, including Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN). The performance of each model will be presented in detail in the following sections.

$H_{2.1}$:"The Deep Neural Network (DNN) model supports external auditors' professional judgment in evaluating an entity's going concern status."

Table 13 presents the annual performance metrics of the Deep Neural Network (DNN) model for the years 2018 to 2022, as well as for the overall dataset. The DNN consistently demonstrates high classification performance across all years, with an overall accuracy of 94.03%, indicating strong predictive capability in evaluating going-concern status. Precision and recall values remain high, averaging 90.05% and 89.62% respectively, which reflects the model's ability to correctly identify both distressed and non-distressed companies. The F1-score, a harmonic means of precision and recall, further confirms the model's balanced performance with a strong overall score of 89.83%.

Importantly, specificity is consistently high (average of 95.87%), suggesting the model is effective in correctly identifying non-distressed companies. Type I errors (false positives) are relatively low, especially in earlier years, with a slight increase in 2022. Type II errors (false negatives) show a similar trend but are somewhat higher, particularly in 2021 (17.78%), indicating that the model was more likely to miss distressed companies that year. The decline in performance in 2022 (e.g., lower precision and F1-score) may suggest changes in economic conditions or data patterns that slightly affected the model's robustness.

The empirical results strongly support the acceptance of hypothesis ($H_{2.1}$), showing that the DNN model achieves high predictive accuracy, precision, and recall. This indicates that DNN effectively supports external auditors' professional judgment in assessing an entity's going-concern status.

Table (13): Results of the performance of DNN

	2018	2019	2020	2021	2022	Average
Accuracy	95.83%	95.83%	95.14%	93.06%	90.28%	94.03%
Precision	88.10%	95.00%	95.35%	94.87%	78.72%	90.05%
Specificity	95.28%	98.04%	97.96%	97.98%	90.29%	95.87%
Recall	97.37%	90.48%	89.13%	82.22%	90.24%	89.62%
Type I error	4.72%	1.96%	2.04%	2.02%	9.71%	4.13%
Type II error	2.63%	9.52%	10.87%	17.78%	9.76%	10.38%
F-1	92.50%	92.68%	92.13%	88.10%	84.09%	89.83%

$H_{2.2}$:"The Recurrent Neural Network (RNN) model supports external auditors' professional judgment in evaluating an entity's going concern status."

Table 14 illustrates the performance of the Recurrent Neural Network (RNN) model in predicting going-concern status over the period from 2018 to 2022, along with aggregated results for the average dataset. The overall accuracy of 90.42% indicates strong predictive capabilities, with the highest accuracy recorded in 2022 (95.14%). Precision is also high (86.67% overall), suggesting that the model effectively identifies distressed firms. Specificity (94.88%) further supports the model's strength in correctly classifying non-distressed firms. However, recall fluctuates significantly across the years, reaching a low of 73.33% in 2021 before improving to 92.68% in 2022. This inconsistency is reflected in the Type II error rate, which is relatively high (20.28% overall). In contrast, the Type I error remains low (5.12%), meaning that fewer non-distressed firms are incorrectly classified as distressed. The F1-score of 83.05% suggests a balanced trade-off between precision and recall, though improvements in recall stability would enhance overall reliability.

Overall, the empirical results support the acceptance of Hypothesis $H_{2.2}$, indicating that RNN models can support auditors' professional judgment by providing consistent and accurate predictions.

Table (14): Results of the performance of RNN

	2018	2019	2020	2021	2022	Average
Accuracy	88.89%	88.36%	89.58%	88.89%	95.14%	90.42%
Precision	77.50%	82.05%	89.74%	89.19%	90.48%	86.67%
Specificity	91.51%	93.27%	95.92%	95.96%	96.12%	94.88%
Recall	81.58%	76.19%	76.09%	73.33%	92.68%	79.72%
Type I error	8.49%	6.73%	4.08%	4.04%	3.88%	5.12%
Type II error	18.42%	23.81%	23.91%	26.67%	7.32%	20.28%
F-1	79.49%	79.01%	82.35%	80.49%	91.57%	83.05%

$H_{2.3}$:"The Random Forest (RF) model supports external auditors' professional judgment in evaluating an entity's going concern status."

Table 15 presents the performance metrics of the Random Forest (RF) model from 2018 to 2022, showing moderate improvements compared to the traditional model with an overall accuracy of 88.33 and an F1-score of 79.41%. The model demonstrates a specificity of 93.31%, suggesting strong capability in correctly identifying non-distressed firms. However, precision is slightly lower at 82.65%, indicating some misclassification of distressed entities. The recall values fluctuate significantly, ranging from 71.43% in 2019 to 82.93% in 2022, resulting in an overall recall of 76.42%. The high Type II error rate (23.58% overall) suggests that the model struggles with correctly identifying all non-going concern entities, particularly in 2019 (28.57%) and 2021 (26.67%). In contrast, the Type I error remains relatively low at 6.69%, reflecting a lower likelihood of misclassifying going-concern entities as non-going concern entities.

Overall, the results suggest that the RF model supports external auditors' professional judgment in evaluating an entity's going concern status. Therefore, hypothesis ($H_{2.3}$) is accepted.

Table (15): Results of the performance of Random Forest (RF)

	2018	2019	2020	2021	2022	Average
Accuracy	87.50%	88.19%	88.89%	86.81%	90.28%	88.33%
Precision	75.00%	85.71%	87.50%	82.50%	82.93%	82.65%
Specificity	90.57%	95.10%	94.90%	92.93%	93.20%	93.31%
Recall	78.95%	71.43%	76.09%	73.33%	82.93%	76.42%
Type I error	9.43%	4.90%	5.10%	7.07%	6.80%	6.69%
Type II error	21.05%	28.57%	23.91%	26.67%	17.07%	23.58%
F-1	76.92%	77.92%	81.40%	77.65%	82.93%	79.41%

$H_{2.4}$:"The K-Nearest Neighbors (KNN) model supports external auditors' professional judgment in evaluating an entity's going concern status."

As evidenced by the results in Table 16, the KNN model shows an accuracy of 89.86%, ranging from 88.19% to 93.06%, with the highest recorded in 2022, making it another viable alternative for financial distress prediction. The Type I error drops to 3.94%, meaning it correctly classifies most stable companies. However, its Type II error remains at 25%. The model also achieves high specificity (96.06%), indicating its strong ability to correctly classify going-concern entities. Precision is notably high at 88.83% overall, reaching its peak at 96.97% in 2022. The F1-score remains solid at 81.33%, balancing precision and recall effectively.

While KNN shows improvements over the traditional model, it does not outperform deep learning techniques. Therefore, Hypothesis $H_{2.4}$ is accepted, as the KNN model effectively aids auditors in evaluating going concern status. However, it should be used as a supplementary tool rather than a standalone decision-making mechanism, with further validation recommended in real-world audit scenarios to ensure practical applicability.

Table (16): Results of the performance of the K-Nearest Neighbors

	2018	2019	2020	2021	2022	Average
Accuracy	88.19%	90.97%	88.19%	88.89%	93.06%	89.86%
Precision	78.38%	91.43%	91.43%	87.18%	96.97%	88.83%
Specificity	92.45%	97.06%	96.94%	94.95%	99.03%	96.06%
Recall	76.32%	76.19%	69.57%	75.56%	78.05%	75.00%
Type I error	7.55%	2.94%	3.06%	5.05%	0.97%	3.94%
Type II error	23.68%	23.81%	30.43%	24.44%	21.95%	25.00%
F-1	77.33%	83.12%	79.01%	80.95%	86.49%	81.33%

$H_{2.5}$:"The Decision Tree (DT) model supports external auditors' professional judgment in evaluating an entity's going concern status."

According to Table 17, the DT Altman model delivers 93.19% accuracy, with an exceptional precision of 98.80%, reaching 100% in multiple years, indicating that when it predicts financial distress, it is almost always correct—the highest among all techniques. The Type I error is reduced to just 0.39%, ensuring almost no false positives. Additionally, specificity is extremely high at 99.61%, showing the model's effectiveness in correctly identifying going concern entities. However, its recall is slightly lower at 77.83%, meaning it has a higher tendency to misclassify distressed firms as financially stable. The F1-score of 87.07% balances the trade-off between precision and recall, reinforcing the model's strong performance overall.

Overall, these results demonstrate that the DT model offers strong classification capabilities, making it a valuable tool for supporting external auditors' professional judgment in assessing an entity's going concern status. Therefore, Hypothesis $H_{2.5}$ is accepted.

Table (17): Results of the performance of Decision Tree (DT)

	2018	2019	2020	2021	2022	Average
Accuracy	93.75%	93.06%	91.67%	92.36%	95.14%	93.19%
Precision	96.77%	100.00%	97.22%	100.00%	100%	98.80%
Specificity	99.06%	100.00%	98.98%	100.00%	100%	99.61%
Recall	78.95%	76.19%	76.09%	75.56%	82.93%	77.83%
Type I error	0.94%	0.00%	1.02%	0.00%	0.00%	0.39%
Type II error	21.05%	23.81%	23.91%	24.44%	17.07%	22.17%
F-1	86.96%	86.49%	85.37%	86.08%	90.67%	87.07%

$H_{2.6}$:"The Support Vector Machine (SVM) model supports external auditors' professional judgment in evaluating an entity's going concern status."

According to Table 18, the results indicate a strong predictive performance of Support Vector Machine (SVM) with an overall accuracy of 94.03% and an F1-score of 89.83%. The Type I error drops significantly to 4.13%, ensuring that financially stable entities are correctly identified. The precision score of 90.05% suggests that the model is highly effective at correctly identifying distressed firms, while the specificity of 95.87% indicates strong capability in classifying non-distressed firms accurately. However, the recall values exhibit noticeable fluctuations, with a low of 68.89% in 2021 and a high of 78.57% in 2019, leading to an overall recall of 89.62%.

The strong performance of SVM in line with DNN further confirms that the use of AI-based Big Data Analytics optimizes the professional judgment of auditors in evaluating an entity's going-concern status, supporting the acceptance of hypothesis ($H_{2.6}$).

Table (18): Results of the performance of SVM

	2018	2019	2020	2021	2022	Average
Accuracy	87.50%	91.67%	88.19%	87.50%	90.28%	89.03%
Precision	76.32%	91.67%	89.19%	88.57%	86.49%	86.34%
Specificity	91.51%	97.06%	95.92%	95.96%	95.15%	95.08%
Recall	76.32%	78.57%	71.74%	68.89%	78.05%	74.53%
Type I error	8.49%	2.94%	4.08%	4.04%	4.85%	4.92%
Type II error	23.68%	21.43%	28.26%	31.11%	21.95%	25.47%
F-1	76.32%	84.62%	79.52%	77.50%	82.05%	80.00%

In conclusion, the findings consistently demonstrate that all AI-based BDA models support external auditors' professional judgment in evaluating an entity's going concern status and outperform the Traditional Altman Z-score model in terms of accuracy, precision, recall, and error reduction. The machine learning models (DNN, RNN, and SVM) show the highest improvements, while RF, DT, and KNN also contribute positively. Given this strong empirical evidence, hypothesis (H_2) is accepted

Testing the Third Hypothesis:

H_3:"The Hybrid model that integrates the traditional Altman Z-score model and AI-based Big Data Analytics (e.g., DNN, RNN, SVM, RF, DT, KNN) supports auditors' professional judgment in evaluating an entity's going-concern status more effectively than using the traditional Altman Z-score model alone."

Table 19 presents a comparative performance analysis of the Traditional Altman Z-score Model and a Hybrid model that incorporates Big Data Analytics techniques, including DNN, RNN, SVM, RF, DT, and KNN. The results indicate that the integrated models consistently outperform the traditional model across multiple performance metrics, including accuracy, precision, specificity, recall, and F-1 score, while also reducing Type I and Type II errors.

Notably, the Traditional Altman Model achieves an accuracy of 84%, whereas all integrated models demonstrate higher accuracy, with Decision Tree (DT) achieving the highest at 94%, followed by DNN at 92%. Furthermore, the precision and specificity of the integrated models are substantially higher than those of the traditional model, indicating a more effective classification of entities' going-concern status. Additionally, the Type I and Type II error rates, which are critical in assessing the reliability of predictions, are significantly reduced in the hybrid models. For instance, DT exhibits a Type I error rate of only 2% compared to 19% in the Traditional Altman Model, reinforcing its superior predictive capability.

The F-1 score, which balances precision and recall, further supports these findings. The integrated models consistently yield higher F-1 scores than the traditional model, with DT achieving the highest at 89%, followed closely by DNN at 87%. These improvements suggest that integrating Big Data Analytics techniques enhances external auditors' ability to assess an entity's going-concern status with greater accuracy and reliability.

Table (19): Comparative Performance Analysis of a Hybrid Model and the Traditional Altman Model

	Accuracy	Precision	Specificity	Recall	Type I error	Type II error	F-1
Altman model	84%	66%	81%	80%	19%	20%	76%
Altman with DNN	92%	88%	95%	85%	5%	15%	87%
Altman with RF	89%	82%	93%	80%	7%	20%	81%
Altman with DT	94%	94%	98%	84%	2%	16%	89%
Altman with KNN	88%	82%	94%	81%	6%	19%	78%
Altman with SVM	89%	81%	92%	82%	8%	18%	81%
Altman with RNN	91%	85%	94%	83%	6%	17%	84%

Given these findings, Hypothesis (H_3) is accepted, as the results provide strong empirical support for the claim that the integration of the Altman Z-score model and AI-based Big Data Analytics enhances external auditors' professional judgment more effectively than the traditional model alone.

Testing the Fourth Hypothesis:

H_4:"There is no statistically significant difference in the evaluation outcomes between the Hybrid model and traditional Altman z score in supporting auditors' going-concern judgments".

To statistically test this hypothesis, the researcher relied on the following tests: Kolmogorov-Smirnov test -and Shapiro-Wilk to test the normality. The McNemar test was used to compare the predictive performance of the two models on the same dataset. Phi and Cramer's V measures indicate the strength of association between the models and classification outcomes. Kappa measure evaluates agreement beyond chance. -2 Log Likelihood measure evaluates the fitness of model. Nagelkerke R Square measure indicates the explanatory power of the model. The statistical analyses yielded the following results:

The results of the normality tests (Kolmogorov-Smirnov and Shapiro-Wilk) indicate that none of the variables in the dataset follow a normal distribution. This conclusion is based on the p-values for all variables being less than 0.001 (Sig. < 0.001), which is significantly below the common alpha level of 0.05. Both tests agree in their findings, as the Shapiro-Wilk test (more suitable for smaller sample sizes) and the Kolmogorov-Smirnov test (better for larger sample sizes) consistently reject the null hypothesis of normality. Since both tests reject the null hypothesis of normality at a 0.05 significance level, parametric tests may not be appropriate for comparing model performances. Instead, non-parametric alternatives such as the McNemar test (for paired comparisons) should be considered.

The results in Table 20 highlight the significant improvements achieved by integrating the traditional Altman Z-score with various Big Data Analytics models. Panel A, based on the McNemar test, shows that all integrated models produce statistically significant differences (p < .001) compared to the standalone traditional Altman Z-score. The highest Chi-Square value (96.01) is observed for KNN, followed by Decision Tree (71.44) and RNN (63.68), indicating that these models contribute the most substantial changes in classification performance. The results suggest that integrating machine learning enhances the Altman Z-score's predictive ability, making it more effective for financial distress evaluation.

Panel B further confirms these findings through key performance metrics:

- **Phi and Cramer's V**: The values increase with model integration, indicating stronger associations than the traditional model (0.66). The highest associations are observed in the Decision Tree (DT) and Deep Neural Network (DNN) models (both 0.847), while the Random Forest (RF) and Support Vector Machine (SVM) models also show strong results (0.735 and 0.734, respectively).
- **Kappa**: The traditional model shows moderate agreement (0.399), while all integrated models demonstrate significantly improved values. The highest agreement levels are seen with DT and DNN models (0.845), closely followed by RNN (0.778) and SVM (0.734).
- **-2 Log Likelihood**: A lower value indicates a better model fit. The integrated models demonstrate improved fit compared to the traditional Altman Z-score (539.08), with the best reduction observed for RF (0) and Decision Tree (288.07).
- **Nagelkerke R Square**: This metric assesses the explanatory power of the model. The traditional Altman Z-score explains 52.8% of the variance, while integrated models provide enhanced predictive power. RF and DT lead with values of 0.630 and 0.792, respectively, confirming a substantial increase in explanatory strength.

Overall, the Hybrid model that integrates the Altman Z-score with AI-based BDA models significantly improves the strength of association, classification agreement, model fit, and explanatory power. Among all models, Decision Tree (DT) and Random Forest (RF) consistently deliver the most substantial improvements across all performance indicators.

Table (20): Results of the significant difference tests between the traditional Altman model and the Hybrid model.

Panel (A)

Test Statistics[a]						
	Z-score& integrated Z-score and KNN	Z-score& integrated Z-score and SVM	Z-score& integrated Z-score and RF	Z-score& integrated Z-score and DT	Z-score& integrated Z-score and RNN	Z-score& integrated Z-score and DNN
N	720	720	720	720	720	720
Chi-Square[b]	96.010	59.513	45.161	71.442	63.684	58.877
Asymp. Sig.	<.001	<.001	<.001	<.001	<.001	<.001
a. McNemar Test						
b. Continuity Corrected						

Panel (B)

Variable	Test				
	Phi	Cramer's V	Kappa	-2log likelihood	Nagelkerke R Square
Traditional Altman Z-score	0.66	0.66	0.399	539.08	0.528
Sig.	<.001	<.001	<.001		
Integrated Z-score and KNN	0.691	0.691	0.689	476.49	0.603
Sig.	<.001	<.001	<.001		
Integrated Z-score and SVM	0.734	0.734	0.734	453.06	0.629
Sig.	<.001	<.001	<.001		
Integrated Z-score and RF	0.735	0.735	0.735	452.032	0.630
Sig.	<.001	<.001	<.001		
Variable	Test				
	Phi	Cramer's V	Kappa	-2log likelihood	Nagelkerke R Square
Integrated Z-score and DT	0.847	0.847	0.845	288.07	0.792
Sig.	<.001	<.001	<.001		
Integrated Z-score and RNN	0.778	0.778	0.778	401.2	0.684
Sig.	<.001	<.001	<.001		
Integrated Z-score and DNN	0.847	0.847	0.845	405.077	0.680
Sig.	<.001	<.001	<.001		

In conclusion, the findings consistently demonstrate that all Big Data-enhanced models outperform the Traditional Altman Z-score model alone in terms of accuracy, precision, recall, and error reduction. The deep learning models (DNN, RNN, and SVM) show the highest improvements, while RF, DT, and KNN also contribute positively.

Given this strong empirical evidence, hypothesis ($H_{2.1}$) is accepted, confirming that "a Hybrid model using Traditional Altman Z-score model and AI-based BDA improves auditors' professional judgment in evaluating an entity's going-concern status."

8.4.Testing the Performance of a Hybrid Model supporting the professional judgment of the auditor in Going Concern Evaluation:

Table 21 presents a comparative analysis between the standalone traditional Altman model and Hybrid model using test dataset. The results indicate that incorporating AI-based BDA significantly enhances model performance across all evaluation metrics. The traditional Altman model achieves 84% accuracy, 69% precision, and an F1-score of 70%, which, while respectable, reveals limitations in recall (71%) and a relatively high Type II error (29%), potentially leading to the misclassification of distressed firms.

When integrated with Deep Neural Networks (DNN), the model's performance improves dramatically, reaching 96% accuracy, 94% precision, 89% recall, and an F1-score of 92%, alongside a very low Type I error (2%) and Type II error (11%). This suggests a highly reliable predictive capability and enhanced auditor support. Similarly, Recurrent Neural Networks (RNN) integration yields strong performance (95% accuracy, 92% recall, and 91% F1-score), with balanced error rates, showing the strength of time-dependent pattern recognition in financial distress prediction.

The Random Forest (RF) and Support Vector Machine (SVM) integrations also offer significant enhancements with accuracy values of 94% and 93%, respectively, and F1-scores near 88%, reflecting both robustness and consistency. Although Decision Tree (DT) and K-Nearest Neighbors (KNN) also improve on the base Altman model, their performance is relatively lower compared to DNN and RNN combinations, particularly evident in the higher Type II error rates of 26% in both cases.

Table (21): Comparative Performance Analysis of a Hybrid Model and the Traditional Altman Model on Test Data

	Accuracy	**Precision**	**Specificity**	**Recall**	**Type I error**	**Type II error**	**F-1**
Traditional Altman	84%	69%	89%	71%	11%	29%	70%
Traditional Altman with DNN	96%	94%	98%	89%	2%	11%	92%
Traditional Altman with RF	94%	89%	96%	87%	4%	13%	88%
Traditional Altman with DT	87%	76%	92%	74%	8%	26%	75%
Traditional Altman with KNN	90%	88%	96%	74%	4%	26%	80%
Traditional Altman with SVM	93%	87%	95%	87%	5%	13%	87%
Traditional Altman with RNN	95%	90%	96%	92%	4%	8%	91%

8.5. Conclusion:

The results of the hypothesis testing revealed several key findings:

1. **Traditional Altman Z-Score demonstrated high accuracy (83.61%) and improved recall (95.12% in 2022), confirming its effectiveness in identifying distressed entities.**
2. **AI-based Big Data Analytics support the external auditors' professional judgment when evaluating an entity's going concern. These results align with prior research by Appelbaum et al. (2018), Cao et al. (2015), Jan (2021), and Chi and Shen (2022), which collectively affirm that BDA provides more reliable, accurate, and balanced predictions.**

- **DNN (Deep Neural Network)** consistently demonstrates high classification accuracy (94.03%), with robust precision (90.05%) and recall (89.62%). Its balanced performance is reinforced by an F1-score of 89.83%, indicating its effectiveness in identifying both distressed and non-distressed firms.
- **RNN (Recurrent Neural Network)** achieves an overall accuracy of 90.42%, with peak performance in 2022 (95.14%). High precision (86.67%) and excellent specificity (94.88%) confirm its reliability in classifying both types of entities.
- **RF (Random Forest)** shows moderate improvement over traditional methods, achieving 88.33% accuracy and an F1-score of 79.41%. While its specificity is strong (93.31%), its precision (82.65%) and fluctuating recall (overall 76.42%) suggest occasional misclassifications of distressed companies.
- **KNN (K-Nearest Neighbors)** records an overall accuracy of 89.86%, with a maximum of 93.06% in 2022. It excels in minimizing Type I errors (3.94%) and offers high specificity (96.06%), though its Type II error remains elevated at 25%, indicating weaker sensitivity to distressed cases.
- **DT (Decision Tree)** achieves high accuracy (93.19%) and exceptional precision (98.80%), with values reaching 100% in several years. It boasts the lowest Type I error (0.39%) and highest specificity (99.61%), reflecting near-perfect classification of stable firms. However, its recall (77.83%) is comparatively lower, indicating some under-detection of distressed entities.

- **SVM (Support Vector Machine)** delivers strong predictive performance, matching DNN in accuracy (94.03%) and F1-score (89.83%). Its low Type I error (4.13%), high precision (90.05%), and specificity (95.87%) emphasize its balanced and reliable performance in identifying both categories.

3. **The results reveal that all Hybrid models significantly outperform the traditional Altman model across key classification metrics, demonstrating the value of combining traditional statistical methods with AI-based BDA in enhancing going-concern evaluation. These results agree with Zhou et al. (2015); Read and Yezegel (2016); and Boztepe et al. (2025).**

- **Accuracy**: The traditional Altman model achieves an accuracy of 84%. All Hybrid models exceed this baseline, with the Decision Tree (DT) model performing best at **94%**, followed by the Deep Neural Network (DNN) at **92%**, and the Recurrent Neural Network (RNN) at **91%**. This indicates that integrated models provide more reliable overall classifications.
- **Precision**: The Altman model yields a precision of 66%, whereas Hybrid models show marked improvement. The DT model achieves the highest precision at **94%**, followed by DNN at **88%** and RNN at **85%**, signifying better positive predictive value in identifying companies at risk.
- **Specificity**: The traditional model's specificity stands at 81%, while Hybrid models perform better across the board. DT again leads with **98%**, suggesting superior ability to correctly identify healthy firms, followed closely by DNN (**95%**) and KNN (**94%**).
- **Recall (Sensitivity)**: While the traditional model performs well in recall at **90%**, DNN and DT maintain relatively high recall levels at **85%** and **84%**, respectively. Although a slight decline is observed in recall, this is offset by significant gains in precision and specificity, resulting in a better overall balance.
- **Type I Error**: The Type I error rate is a critical concern in going-concern assessments. The traditional model records a high Type I error of **19%**, while the DT model reduces this rate drastically to **2%**, followed by DNN at **5%** and RNN at **6%**, highlighting enhanced reliability in avoiding false negatives.

- **Type II Error**: Type II errors are also notably reduced in Hybrid models. The traditional model has a Type II error rate of **10%**, compared to **15%** in DNN and **16%** in DT—though these are slightly higher, the overall performance (particularly precision and specificity) still marks substantial improvement.
- **F-1 Score**: The F-1 score, balancing both precision and recall, further confirms the superiority of Hybrid models. The DT model achieves the highest F-1 score at **89%**, followed by DNN at **87%** and RNN at **84%**, compared to **76%** in the traditional Altman model.

4. **The integration of AI based Big Data Analytics with the traditional Altman Z-score demonstrated statistically significant improvements ($p<0.001$) across all machine learning methods, with Decision Trees (DT) and Deep Neural Networks (DNN) showing the most substantial enhancements in association (Phi/Cramer's V=0.847), classification agreement (Kappa=0.845), model fit (-2LL=288.07), and explanatory power (Nagelkerke R^2=0.792), while Random Forest (RF) and Support Vector Machines (SVM) also showed significant but comparatively weaker improvements over the standalone model.**

8.6. Recommendations:

Considering the research objectives, its problem, and the general findings, the most important implications and recommendations of the research can be presented as follows:

1. Adoption of Hybrid Predictive Models:

- Audit firms should transition from traditional financial distress models to hybrid models integrating BDA techniques such as Deep Neural Networks (DNN), Random Forest (RF), and Decision Trees (DT).
- Standardized methodologies should be developed to incorporate AI-based predictions in financial audits.

2. Auditor Training and Technological Competency:

- Professional training programs should focus on machine learning applications in auditing, big data analytics, and predictive modeling.
- Auditors should receive hands-on experience with AI tools to interpret model outputs effectively.

3. Regulatory and Policy Enhancements:

- Standard-setting bodies (e.g., IAASB, PCAOB) should provide guidelines on AI integration in audit procedures.
- Audit standards should incorporate thresholds for predictive accuracy and misclassification rates when using AI in going-concern evaluations.

8.7. Future Research Directions:

Based on the findings of the research, both theoretical and applied, the researcher suggests the following areas for further accounting research:

- Use another deep learning algorithm, such as deep belief networks (DBN), convolutional neural networks (CNN), convolutional deep belief networks (CDBN), and long short-term memory (LSTM).
- Explore the potential of emerging machine learning techniques, such as reinforcement learning, natural language processing (NLP), and generative adversarial networks (GANs), in enhancing going-concern evaluations.
- Investigate the use of unstructured data (e.g., textual data from financial reports, news articles, and social media) to improve predictive accuracy.
- Explore the integration of natural language processing (NLP) with financial statement analysis to detect financial anomalies and risks.

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نموذج هجين لدعم الحكم المهني للمراجع عند تقييم الاستمرارية باستخدام الأساليب التقليدية وتحليلات البيانات الضخمة القائمة على الذكاء الاصطناعي

المستخلص:

تقترح هذه الدراسة نموذجًا هجينًا يدمج بين نموذج ألتمان – (Altman Z-score) وهو إحدى الاساليب التقليدية للتنبؤ بالتعثر المالي – وستة تقنيات من تحليلات البيانات الضخمة القائمة على الذكاء الاصطناعي، وهي الشبكات العصبية العميقة(Deep Neural Networks (DNN ، والشبكات العصبية المتكررة(Recurrent Neural Networks (RNN ، ومتجهات الدعم الآلي (Support Vector Machines (SVM، والغابات العشوائية (Random Forest (RF ، وأشجار القرارات(Decision Trees (DT ، والجار الأقرب (K-Nearest Neighbors (KNN، وذلك بهدف تعزيز الحكم المهني للمراجع عند تقييم قدرة المنشأة على الاستمرارية.

وقد تم اختبار النموذج تطبيقيا على عينة مكونة من ١٤٤ شركة غير مالية مدرجة في البورصة المصرية خلال الفترة من ٢٠١٨ إلى ٢٠٢٣. وأشارت النتائج إلى أن نموذج ألتمان Altman Z-score يوفر رؤى مهمة في تقييم استمرارية المنشأة، إلا أن النموذج الهجين يتفوق باستمرار على كل من نموذج ألتمان Altman Z-score وتحليلات البيانات الضخمة القائمة على الذكاء الاصطناعي من حيث الأداء التنبؤي.

وقد حقق النموذج ألتمان Altman Z-score دقة بلغت ٨٤٪، بينما تجاوزت جميع النماذج الهجينة هذا المعدل، حيث سجل نموذج شجرة القرار (DT) أفضل أداء بنسبة دقة بلغت ٩٤٪، تلاه نموذج الشبكة العصبية العميقة (DNN) بنسبة ٩٢٪، ثم الشبكة العصبية المتكررة (RNN) بنسبة ٩١٪، مما يشير إلى أن النماذج الهجينة توفر تصنيفات أكثر موثوقية بوجه عام.

كما دعمت الاختبارات الإحصائية – مثل اختبار مكنيمارMcNemar، ومعامل فاي(Phi)، ومعامل كريمر(Cramer's V) ، وكابا(Kappa) ، و2log likelihood-، و Nagelkerke R Squareفعالية النموذج الهجين بشكل متسق .وتبرز هذه النتائج الإمكانات الكبيرة للنماذج الهجينة في الارتقاء بجودة الحكم المهني وفعالية اتخاذ القرار لدى المراجعين في تقييم استمرارية المنشآت.

الكلمات المفتاحية:

الأساليب التقليدية؛ نموذج ألتمان (Altman's Z-Score) ؛ تحليلات البيانات الضخمة القائمة على الذكاء الاصطناعي؛ الشبكات العصبية العميقة (DNN) ؛ الشبكات العصبية المتكررة (RNN) ؛ متجهات الدعم الآلي (SVM)؛ الغابات العشوائية(RF) ؛ أشجار القرارات (DT) ؛ الجار الأقرب (KNN)؛ الحكم المهني للمراجع الخارجي بشأن استمرارية المنشأة.