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Comprehensive Income and Financial Distress Prediction An Applied Study of Egyptian Listed Companies

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Abstract

Purpose– This study investigates whether integrating comprehensive income (CI) variables into Altman's Z-score models through artificial neural networks (ANNs) improves financial distress prediction for Egyptian listed firms.

Design/methodology/approach– Using a sample of 83 Egyptian listed firms (581 firm-year observations) covering the period 2016–2022, we incorporated CI variables to Altman's original (1968) and revised (1983) Z-score models.

Findings– The proposed models improved the prediction of financial distress accuracy of Altman's models by 1.5% and 1.2%, respectively. Type I error rate is 2.45% and 3.35% lower for both Altman's models.

Practical implications– The proposed distress prediction models are effective in evaluating credit risk for stakeholders, including banks and other financial organizations. Utilizing such algorithms, they might discern enterprises having an elevated danger of default in their lending judgments.

Originality/value– This work contributes to the literature in different aspects. First, it provides the first empirical evidence in the Egyptian context for integrating CI variables with Altman's Z-score models through ANN techniques. Second, it demonstrates the impact of economic volatility on companies' performance in emerging markets.

Keywords: Bankruptcy; Financial failure; Other comprehensive income (OCI); Artificial neural networks (ANN); Altman's Z- score, Egypt.

Paper type Research paper

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الدخل الشامل والتنبؤ بالتعثر المالى: دراسة تطبيقية على الشركات المدرجة بالبورصة المصرية

ملخص البحث

هدف الدراسة: تبحث هذه الدراسة فيما إذا كان دمج متغيرات الدخل الشامل فى نماذج التنبؤ بالتعثر المالى لألتمان من خلال الشبكات العصبية الاصطناعية يُحسن من التنبؤ بالتعثر المالى للشركات غير المالية المدرجة فى البورصة المصرية.

منهجية الدراسة: باستخدام عينة من الشركات بلغت 83 شركة (581 ملاحظة) فى الفترة من 2016- 2022، تم دمج متغيرات الدخل الشامل فى نموذجى التنبؤ بالفشل المالى لألتمان Z-Score نموذج (1968) والنموذج المعدل (1983).

نتائج الدراسة: تشير نتائج الدراسة إلى أن النماذج المقترحة تُحسن دقة التنبؤ بالفشل المالى بنسبة 1.5% و1.2% على التوالى؛ وتعمل على تخفيض خطأ النوع الأول بنسبة 2.45% و3.35% لكلا النموذجين.

التطبيقات العملية للدراسة: تساهم نماذج التنبؤ بالتعثر المالى المقترحة فى تمييز الشركات التى لديها ذات خطر متزايد للتخلف عن سداد التزاماتها، كما تساعد البنوك والمؤسسات المالية الأخرى في تقييم مخاطر الائتمان.

القيمة البحثية للدراسة: تُسهم هذه الدراسة فى الأدبيات من عدة جوانب. هذه الدراسة هى الأولى فى بيئة الأعمال المصرية التى تقدم دليلاً على دور متغيرات الدخل الشامل فى تحسين التنبؤ بالتعثر المالى من خلال استخدام الشبكات العصبية الاصطناعية، كما أنها تعكس أثر التقلبات الاقتصادية على أداء الشركات فى الاقتصاديات الناشئة.

الكلمات المفتاحية: الافلاس، الفشل المالى، بنود الدخل الشامل الأخرى، الشبكات العصبية الاصطناعية، مصر.

1. Introduction

For many years, the risk of financial distress—and the potential for bankruptcy—has been a major concern for corporate stakeholders. Financial distress occurs when firms are unable to generate sufficient cash flows to cover debt commitments, despite maintaining viable strategies and operations (Altman, et al., 2019). Distress costs affect a firm's debt price and capital structure and company's restructuring choices. Scholars distinguish between direct costs (e.g., legal and administrative expenses) and indirect costs (such as reputational loss and operational disruption) when analyzing financial distress (Warner, 1977; Ang, et al., 1982; Altman, 1984; Branch, 2002), which makes accurate financial distress prediction models essential.

Although financial distress prediction has been widely studied since the foundational research of Beaver (1966) and Altman (1968), researches that considering comprehensive income (CI) on financial distress prediction-particularly in Egypt- remains scare. This gap motivates our study, which investigates whether incorporating comprehensive income (CI) variables improves the accuracy of financial distress prediction.

Altman'-score models (1986, 1983) remain widely applied because it combines multiple financial ratios to predict bankruptcy risks. However, these models rely on financial and operational measures that exclude the effect of other economic variables reflected in comprehensive income, and that combining comprehensive income with these models can enhance its prediction accuracy. The Financial Accounting Standards Board (FASB, 1985) defined comprehensive income as the total change in a company's equity during a period that comes from recognized transactions and economic events, but not from interactions with owners in their shareholder role. Dhaliwal et al. (1999) argued that CI is a broader measure of performance than net income since it reflects all non-owner related changes in net assets.

To address this, we extend Altman Z-score model (1968) and Z''-Score model (1983) by integrating CI variables and applying artificial neural networks (ANNs) to listed firms on EGX covering 2016- 2022. Egyptian firms face a volatile environment, with sharp fluctuations in inflation, exchange rates, and capital flows that make financial ratios unstable (Abdelraouf & Muharram, 2024). This in turn, makes Egyptian firms vulnerable to financial distress and in need for more sophisticated and accurate financial distress prediction models.

In developing the proposed models, 581 sample observations were divided into training and testing sampling. Variables of (Altman, 1968, 1983) and CIs variables are the input units of the neural network models. The distress prediction models are established, with one input layer containing five input nodes for Benchmark Model 1, eight input nodes for Proposed Model 1, four for Benchmark Model 2, and seven for Proposed Model 2.

For benchmark model 1, the testing data has an estimated accuracy rate of 91.3% with an 8.7% error rate. However, the accuracy rate significantly increased to 92.8%, and the error rate decreased to 7.2% when using comprehensive income variables combined with Altman, 1968 variables (Proposed model 1). Compared with the benchmark model 1, the proposed model 1's accuracy increased by 1.5%.

Additionally, for benchmark model 2, the tested data had a prediction accuracy of 92.1% with a 7.9% error rate. The accuracy rate significantly increased to 93.3%, and the error rate decreased to 6.7% by combining comprehensive income variables with Altman, 1983 variables (Proposed model 2). Compared with the benchmark model 2, the proposed model 2's accuracy increased by 1.2%.

This study contributes by introducing a more effective framework for distress prediction, offering early warning signals for corporations and regulators while supporting banks, rating agencies, and financial institutions in credit risk assessment.

To carry out our purpose, this work has the following structure: Section 2 will discuss the review of literature and hypotheses development. Section 3 will present the study methodology. Section 4 will provide the empirical analysis and discussion, while Section 5 will discuss the study's conclusion.

2. Theoretical Framework and Literature Review

2.1 Classic Models of Financial Distress Prediction

Empirical research into predicting financial distress is extensive. It has a wide range of explaining factors and methodological approaches. Because of the lack of a unifying theory, numerous models for the prediction of financial distress have been created and put to the test by researchers since Beaver's pioneering study (Beaver, 1966), which applied univariate discriminant analysis to predict credit risk.

(Altman, 1968) was the first to predict bankruptcy through the multiple discriminant analysis with its Z-score model. This model showed to obtain better prediction than Beaver,1966 model.

In the 90s, with the computer technology advancing so rapidly, some artificial intelligence methods started to be popular for prediction financial distress. (Bell, 1997) was the first applying artificial neural networks for predicting financial distress. In this study, Bell (1997) compared the obtained results with ANN and logit regression showing that ANN methodology was superior.

Another technique used to predict financial distress is the data mining. (Chen & Du, 2009) stated that data mining techniques present satisfactory results in predicting financial distress, although neural networks gets better predictions than data mining.

2.2 Comprehensive Income as financial distress predictors

CI combines net income with other comprehensive items such as unrealized securities gains, foreign currency translation adjustments, derivative valuation changes, and pension liability adjustments (Anderson, et al., 2023). According to (Larson, et al., 2018), Comprehensive income (CI) is comprised of two components: the accruals component, which represents the differences between changes in common equity and changes in cash balances; and the cash flow component, defined as the difference between earnings (calculated as the sum of comprehensive income and stock compensation expenses, less preferred dividends) and the accrual component of cash flow.

(Rahmi, et al., 2023) claim that macroeconomic conditions greatly impact the profits or losses recognized across all four categories, including variations in overall market prices and currency exchange rates. Thus, the four components provide extraneous noise to the income metric when estimating future market-adjusted company performance or evaluating managerial efficiency. However, if the aim is to forecast bankruptcy, the four items excluded from net income may have a more significant impact.

Numerous studies have examined the ability of comprehensive income to forecast future earnings. According to (Bratten, et al., 2016), fair value adjustments included in OCI can forecast profitability during the 2007–2009 financial crises, while the study of (Lee, et al., 2020) revealed that OCI is positively associated with future earnings, as net unrealized gains/losses on available for sale (AFS) investment securities are positively associated with future earnings, while other parts of OCI show insignificance. In the same context (Anderson, et al., 2023) confirm that analysts should incorporate OCI components because of their forecasting ability for core earnings.

As per (Rahmi, et al., 2023), the prediction models use a variety of OCI, accrual, and cash flow types, but none of them integrates accruals with comprehensive income and cash flow components and then incorporates them into financial ratios to predict distress.

Based on the theoretical perspective, it showed that using comprehensive income in predicting financial distress still in its early stages. In addition, no prior study has combined CI with Altman's Z-score models in the Egyptian context using ANNs.

3. Methodology

3.1 Justification for Artificial Neural Networks (ANNs) Methodology

This study applies ANNs because they do not rely on rigid statistical assumptions, can accommodate nonlinear relationships, and have been shown to deliver high predictive performance (Aydin, et al., 2022).

Additionally, ANNs work especially well in this context. According to (Lohmann & Ohliger, 2017), the relationships among distress predictors are also non-linear, and artificial neural networks (ANNs) are more adept than conventional statistical models at capturing these intricate relationships. In addition, because the Egyptian Exchange hosts a relatively small number of firms, ANNs are useful because they work well without making large-sample assumptions. Because of these characteristics, ANNs are a reliable tool for predicting Egypt's financial distress.

3.2 Models Variables Definition

The dependent variable, financial distress, is a variable with a binary value which equal 1 if the firm is financially distressed and 0 otherwise.

We compare the two benchmark models with the proposed models using the same classifier to assess the incremental power of comprehensive income variables in predicting financial distress. The benchmark model variables of the Altman Z-Score model for public firms (1968) and Altman revised Z-Score (1983), and the proposed model variables are a combination of Altman (1968) and (1983) and CIs variables are trained by artificial neural networks (ANN).

The definitions of these variables are presented in Appendix *Table AI*.

3.3 Data and Sample Selection

Our initial sample consists of all the firm-years in the fiscal year 2016-2022. The sample's financial data are obtained from the Egyptian Stock Exchange website (https://www.egx.com.eg/).

Panel A of *Table II* describes our sample selection and Panel B describes the distribution of financial distress firms in our sample by year.

The study considers the firm as "distressed" when it meets at least two of the following conditions:

(1) It has negative working capital; and/or,

(2) It has negative operating cash flow; and/or

(3) It has a negative net income in the last three years.

Table II: Sample selection and sample distribution

Panel A: Sample Selection	
Firm-year observations	
Total of firm-year observations from 2016 to 2022	1,554
Less: Companies among financial and investment companies	(329)
Less: Financial information required to perform the study period is not available	(644)
Number of selected sample	581

Panel B: Distribution of Financial Distress Firms by Year

Fiscal year	**Number of firms**		**Percentage of Distress Firms**
	Distress	**Non-Distress**	
2016	11	72	13.25%
2017	7	76	8.43%
2018	10	73	12.05%
2019	9	74	10.84%
2020	15	68	18.07%
2021	10	73	12.05%
2022	10	73	12.05%

3.4 Measurement of models' performance

The model performance was measured using a confusion matrix. A confusion matrix provided in Appendix *Table AII* gives valuable information about the performance of the classifier by comparing actual and predicted classes (Kohavi & Provost, 1998). The study also used performance measures – Appendix *Table AIII*– such as overall accuracy, error rate, sensitivity, specificity, precision, and *F*-measure (Delen, et al., 2013), to assess model efficacy.

Type I and II errors were employed to identify the misclassification errors in class prediction.

In our study, Type I error identified distress firm as non-distress, while Type II error misclassified a non-distress firm as distressed.

3.5 Descriptive Statistics

The descriptive statistics in *Table III* are employed to examine each relevant variable. We provide the sample mean, median, and standard deviation for all variables categorized by firm condition (distress or non-distress). In the univariate analysis, we illustrate the differences in means, which indicate the discriminatory power of variables. Furthermore, we illustrate the differences in standard deviation, which represents the stability of a variable; the lower the differences in standard deviation, the higher the stability of the variable. The p-value of variables indicates that distress and non-distress firms exhibit significant differences in 6 out of 9 variables.

Table III: Descriptive Statistics

Variables	Distress Firms (72 Observations)			Non-distress Firms (509 Observations)			Diff. Mean	Diff. Std.	p-value<0.05
	Mean	Median	Std.	Mean	Median	Std.			
Z_1 and Z''_1	-0.091	-0.127	0.443	0.223	0.219	0.328	0.314	-0.115	0.208
Z_2 and Z''_2	-0.021	-0.018	0.109	0.878	0.080	0.095	0.899	-0.014	0.713
Z_3 and Z''_3	6.79	1.054	28.853	11.556	0.962	100.716	4.766	71.863	0.492
Z_4	0.452	0.277	0.517	0.566	0.482	0.557	0.114	0.04	0.874
Z_5	-0.216	-0.092	0.302	0.072	0.064	0.139	0.288	-0.163	0.000
Z''_4	3.232	1.140	7.015	4.153	0.738	23.805	0.921	16.79	0.605
CI_1	-33202386	-11068520	341795204	328463697	43131061	1039546058	361666083	697750854	0.001
CI_2	-10443448	-5771935	428580125	75787921	11266126	1547223789	86231369	1118643664	0.121
CI_3	-22758938	-202887	184273686	252675775	12697759	1732258137	275434713	1547984451	0.019

4. Empirical Results and Discussion

4.1. Artificial Neural Networks (ANN) Models

To test the predictive accuracy of 4 models, each data set is split into two subsets: training set and testing (holdout) set. The training subset is used to train the prediction models. The testing (holdout) subset is used to test the model's prediction performance for data that have not been used to develop the classification models. To ensure the reliability and validity of the predictive models-for each set of data- a training subset and testing subset, consisting of 90% and 10% of the data, respectively. The training subset is used to "teach" the artificial neural network (ANN) how to recognize patterns and relationships between financial and comprehensive income variables and financial distress outcomes. By exposing the model to the majority of the data, it can optimize its parameters and minimize classification errors. The testing subset, which consists of previously unseen data (10%), is reserved to evaluate the model's predictive performance and generalizability. This separation prevents overfitting—a situation where the model performs well on the training data but fails to accurately predict new or unseen cases. Using a 90/10 split balances the need for sufficient data to train the ANN while preserving enough independent observations to objectively test its accuracy, error rates, and robustness.

We take variables from (1968, 1983) and CIs variables as input units for the neural network models. The distress prediction models are developed with a single input layer, including five input nodes for Benchmark Model 1, eight for Proposed Model 1, four for Benchmark Model 2, and seven for Proposed Model 2. Hidden layers employed the hyperbolic tangent activation, while the output layer applied a softmax function to classify firms. The architecture of the 2-layer neural network is shown in *Figure I*.

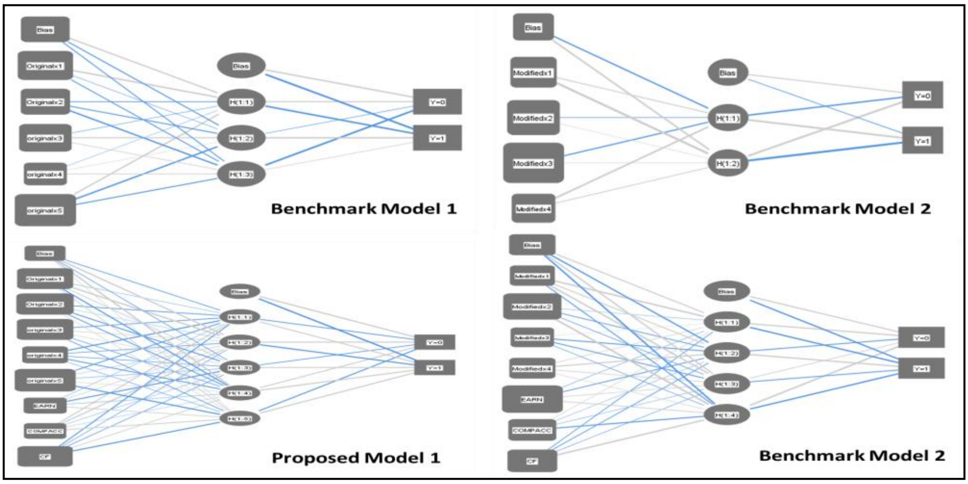

Figure I: The two-layer neural network four models

4.2. Accuracy comparison

Table IV presents the classification results of both estimated (training) samples and testing samples. Proposed Model 1 and 2 of training sample surpassed Benchmark Model 1 and 2 dues to the former models incorporating both comprehensive income variables alongside Altman's original model (1968) and his revised model (1983), whereas Benchmark Model 1 and 2 utilized only Altman's original model (1968) and his revised model (1983) alone.

We evaluated the prediction efficacy of all four models using the testing sample. Proposed Model 1 in the testing sample had an overall predictive accuracy Proposed Model 1 and 2 in the testing sample exhibited overall prediction accuracy of 92.8% and 93.3%, respectively. The overall predictive accuracy in this study improves by 1.2% to 1.5% for both proposed models, aligning with the findings of (Rahmi, et al., 2023). No prior studies have examined financial distress utilizing both comprehensive income variables alongside Altman's original model (1968) and his revised model (1983) in the Egyptian setting and, therefore, we were unable to compare our findings.

4.3. Sensitivity vs. specificity trade-off

Table V and *Figure II* provide the results different neural networks models using different performance measures. We found specificity, precision and F-measure of Proposed Model 1 and 2 to perform better than Benchmark Model 1 and 2. We also found that sensitivity ratio, which is reflects the percentage of actual distress cases correctly classified as such, fell by 0.66 to 1.98 in the Proposed Model 1 and 2 compared by Benchmark Model 1 and 2 meaning that the effectiveness of Proposed Model 1 and 2 for distress prediction might be more inadequate than Benchmark Model 1 and 2, which indicate that Proposed Model 1 and 2 performance is good.

4.4. Error analysis

Evaluating misclassification errors is critical, since incorrect predictions can impose significant financial or strategic costs on firms. *Table VI* and *Figure III* compare the performance of different neural networks models based on error rate, Type I and II errors. Our findings suggest that Proposed Model 1 and 2 outperformed Benchmark Model 1 and 2 with minimum error rate and Type 1 error but higher Type II error.

4.5. Variables Importance

According to the previous results, it is more accurate for predicting distress when comprehensive income components, such as accruals and cash flows, are combined with (Altman, 1968 and 1983) variables. We run a variable importance test to ascertain the relative importance of the variables in our model. As indicated in *Figure IV*, the cash flow component of comprehensive income (CI3) is one of the highest measures of importance (0.137) in predictive performance. Also, in *Figure V*, a proxy for comprehensive income (CI_1) has the highest measure of importance (0.227) in terms of predictive performance.

These results suggest that comprehensive income, which captures the firm's exposure to macro-risks and micro-risks, is important for predicting financial distress.

Table IV: Confusion Matrix for Neural Networks Models for Training and Testing Samples

Neural Networks Models	Type of Sample	Observed	Predicted Distress Observations	Predicted Non-Distress Observations	Overall Accuracy (%)
Benchmark Model 1	Training Sample	Distress Observations	30	37	91.3
		Non-Distress Observations	8	443	
	Testing Sample	Distress Observations	1	4	92.1
		Non-Distress Observations	57	1	
Proposed Model 1	Training Sample	Distress Observations	39	26	92.8
		Non-Distress Observations	441	11	
	Testing Sample	Distress Observations	3	4	93.8
		Non-Distress Observations	57	0	
Benchmark Model 2	Training Sample	Distress Observations	31	34	92.1
		Non-Distress Observations	458	8	
	Testing Sample	Distress Observations	4	2	93.9
		Non-Distress Observations	42	1	
Proposed Model 2	Training Sample	Distress Observations	49	18	93.3
		Non-Distress Observations	442	17	
	Testing Sample	Distress Observations	3	1	96.3
		Non-Distress Observations	49	1	

Table V: Comparison of Neural Networks Models by Using Performance Measures of Testing Samples

Performance measures	Benchmark Model 1	Proposed Model 1	Benchmark Model 2	Proposed Model 2
Sensitivity (%)	98.23	97.57	98.28	96.30
Specificity (%)	44.78	60	47.69	73.13
Precision (%)	92.29	94.43	93.09	96.09
F-measure (%)	95.17	95.97	95.61	96.19

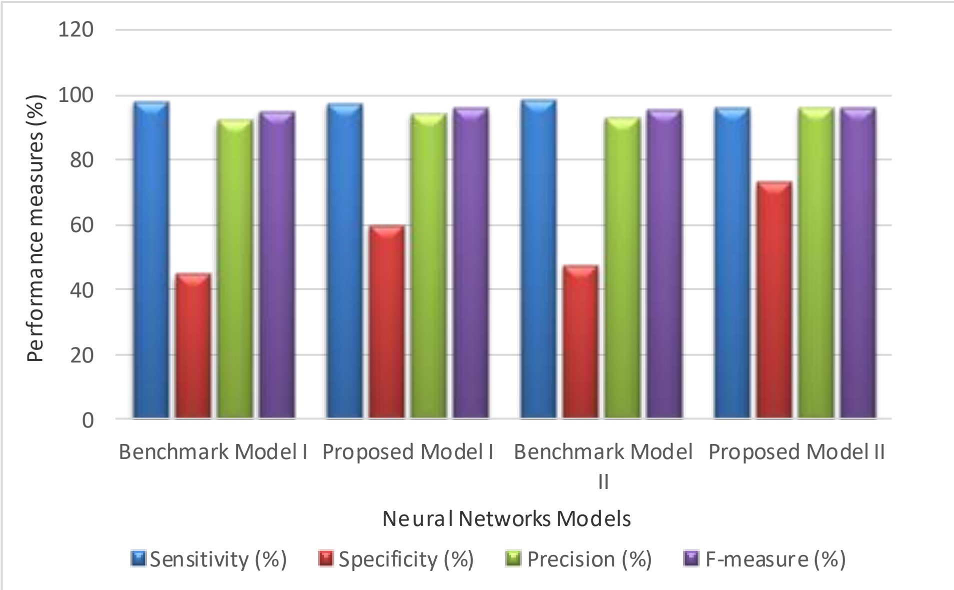

Figure II: Comparison of Neural Networks Models by Using Performance Measures

Table VI: Comparison of percentage of overall error, Type I and II error in neural networks models for testing samples

Overall, Type I and II errors in models (%)	Benchmark Model 1	Proposed Model 1	Benchmark Model 2	Proposed Model 2
Error rate	8.7	7.2	7.9	6.7
Type I error	8.35	5.90	7.42	4.07
Type II error	26.67	28.21	25.8	34.69

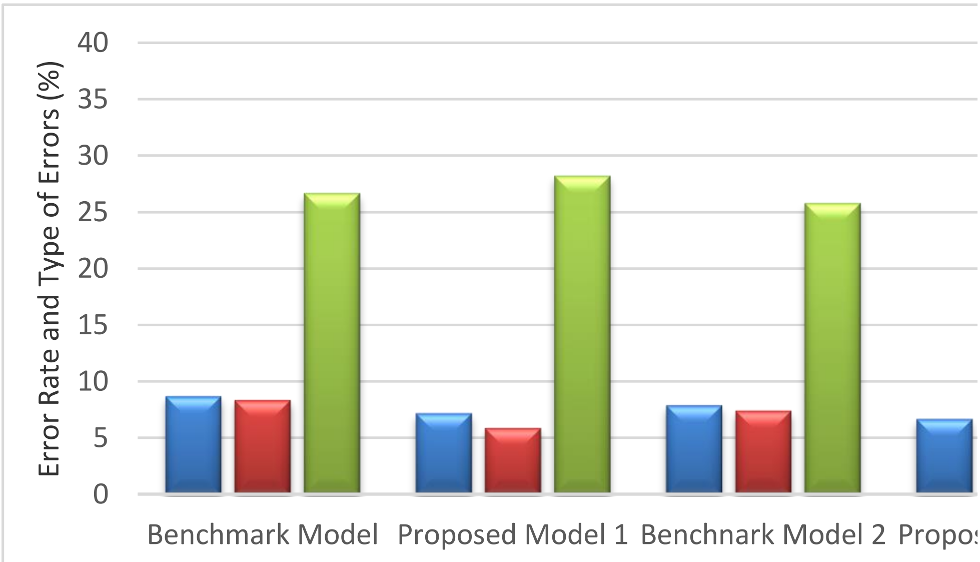

Figure III: Comparison of percentage of overall error, Type I and II error in neural networks models

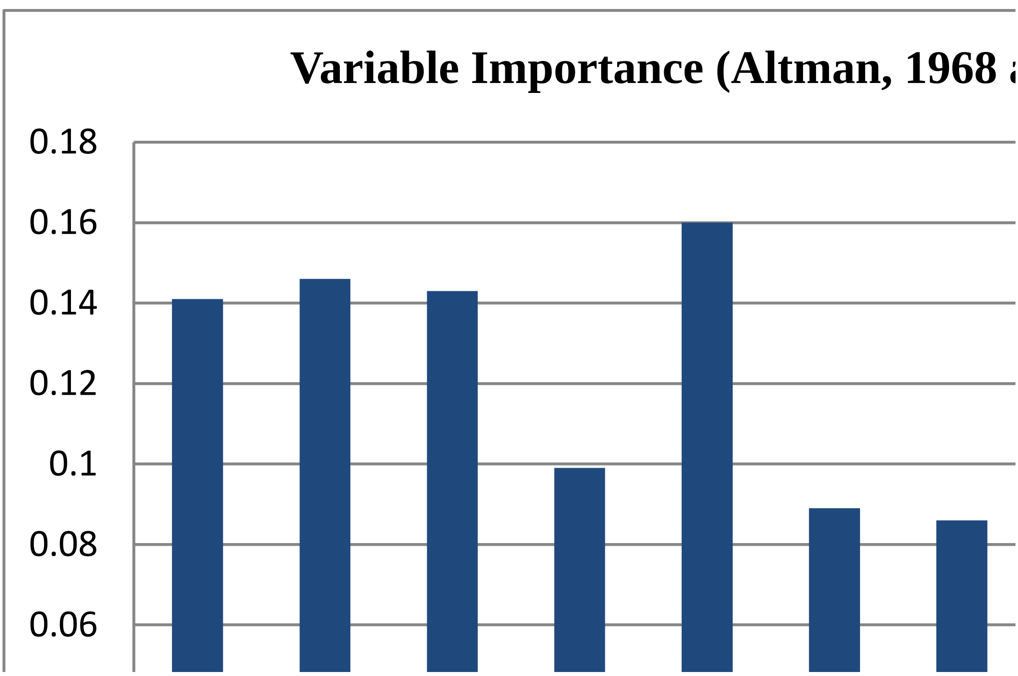

Figure V: Variables importance rank of the Altman, 1968 variables and CIs

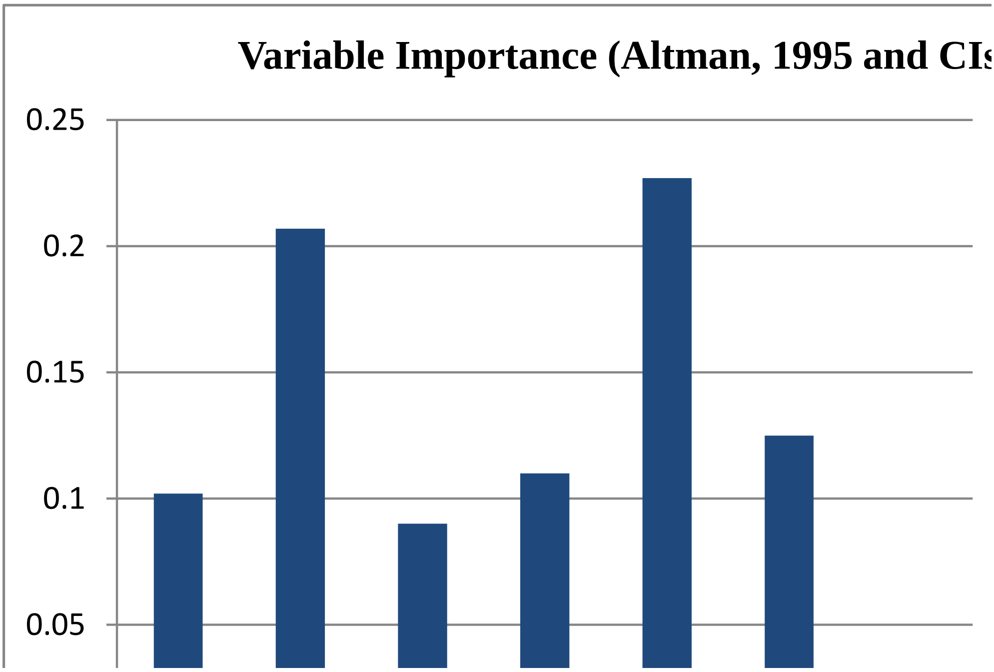

Figure IV: Variables importance rank of the Altman, 1983 variables and CIs

5. Conclusion

This study empirically provides evidence for using comprehensive income to predict financial distress among Egyptian-listed firms. Comprehensive income variables were combined with Altman's original (Altman, 1968) and revised (Altman, 1983) financial distress prediction models to examine their effect on the accuracy of distress prediction.

The proposed models improved the prediction of financial distress accuracy of Altman's models by 1.5% and 1.2%, respectively. Type I error rate is 2.45% and 3.35% lower for both Altman's models.

The study offers two primary contributions: (1) it illustrates that the incorporation of CI variables significantly enhances the predictive accuracy of financial distress models in the Egyptian context; and (2) it presents a methodological innovation by integrating CI-enhanced Z-scores into an ANN framework.

This study not only enhances the scholarly literature on distress prediction but also holds significant relevance for stakeholders, including banks and financial institutions. For banks, applying CI-enhanced ANN models strengthens credit risk management by providing earlier warning signals of borrower distress, reducing default rates, and improving loan pricing and provisioning. These models also support stress testing and portfolio monitoring under volatile economic conditions. For financial regulators -such as securities authorities, central banks, and supervisory- such models enhance early warning systems, enabling proactive supervision and timely intervention before distress escalates. By capturing broader macroeconomic risks through comprehensive income, regulators can better safeguard financial stability and maintain market confidence.

While this study provides novel insights into the role of comprehensive income in enhancing financial distress prediction, several limitations open avenues for further investigation. First, the sample size was confined to 581 firm-year observations of listed companies, which may restrict the generalizability of the findings. Future studies could expand the scope to include small and medium-sized enterprises (SMEs) and unlisted firms, as these entities are often more vulnerable to financial distress and their early detection carries significant policy and practical implications. Moreover, addressing class imbalance through paired samples or re-sampling techniques would strengthen the robustness of predictive accuracy.

Second, methodological refinements may offer richer insights. Employing panel data techniques could capture firm-level dynamics over time and account for unobserved heterogeneity. Additionally, hybrid approaches that combine artificial neural networks with alternative machine learning techniques such as random forests, gradient boosting, or support vector machines may yield stronger comparative results. Future research could also enhance interpretability by applying explainable AI methods (e.g., SHAP or

LIME) to clarify the relative influence of input variables, thus increasing the practical usefulness of these models for regulators and practitioners.

Finally, extending the variable set and context of analysis represents another promising direction. Incorporating non-financial and ESG-related measures, such as governance structures, board diversity, and environmental performance, would test whether broader sustainability indicators improve predictive accuracy beyond financial ratios. Including macroeconomic indicators—such as exchange rate fluctuations, interest rates, or inflation—would also reflect the impact of Egypt's volatile environment. Cross-country comparative studies, particularly between emerging and developed markets, could further validate the external applicability of CI-enhanced ANN models and provide valuable benchmarks for international regulators, banks, and investors.

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Appendix

Table AI: Variables Definition (Altman and Comprehensive Income Variables)

Variables	Definitions
Z_1	Working Capital to Total Assets Ratio
Z_2	Retained Earnings to Total Assets Ratio
Z_3	Earnings before Interest and Taxes to Total Assets Ratio
Z_4	Market Capitalization of Equity to Book Value of Total Liabilities
Z_5	Sales to Total Assets Ratio
Z''_1	Working Capital to Total Assets Ratio
Z''_2	Retained Earnings divided by Total Assets
Z''_3	Earnings before Interest and Taxes divided by Total Assets
Z''_4	Equity Book Value/ Total Liabilities Book Value
CI_1	Proxy of comprehensive income [(Comprehensive income + Stock compensation expenses) - Preferred dividends)]
CI_2	Accrual component of comprehensive income [Change in equity– Change in cash]
CI_3	Cash flow element of comprehensive income [C_1- C_2]

Table AII: Confusion Matrix for Predicting Financial Distress

Actual	Predicted	
	Distress Observation	Non-Distress Observation
Distress observation	True negative (TN)	False positive (FP)
Non-Distress observation	False negative (FN)	True negative (TP)

Table AIII: List of Performance Measures

Performance measures	Formula
Overall accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity	(TP)/(TP+FN)
Specificity	(TN)/(TN+FP)
Precision	(TP)/(TP+FP)
F-measure	2 × [(Precision × Sensitivity)/ (Precision + Sensitivity)]
Error rate	(1- overall accuracy)
Type I error	(Number of distress observations classified as non-distress)/ (Number of observations classified as non-distress) × 100
Type II error	(Number of non- distress observations classified as distress)/ (Number of observations classified as distress) × 100