



مجلة الشروق للعلوم التجارية
ISSN: 1687/8523
Online :2682-356X
2007/12870
sjcs@sha.edu.eg
<https://sjcs.sha.edu.eg/index.php>
موقع المجلة : <https://sjcs.sha.edu.eg/index.php>



Predicting a Going-Concern Auditor's Opinion: ANN Approach

Manar saad Mohamed Hassan

Assistant Lecturer in Accounting Dept, Faculty of Commerce, Menoufia University

Mohamed Aly Wahdan

Professor of Auditing- Faculty of Commerce, Menoufia University

Mohamed Saber Elsayed

Assistant Professor of Accounting, Faculty of Commerce, Menoufia University

Mahmoud Abdel-Wahab Mostafa

Accounting Professor in Accounting Dept, Faculty of Commerce, Menoufia University

Keywords:

ANN, Going Concern Opinion, Financial Ratios, Board of Director, Earning quality, Big 4, Auditor-client relationship

التوثيق المقترح وفقا لنظام APA :

Hassan, Manar,et al (2025), Predicting a Going-Concern Auditor's Opinion: ANN Approach, Al-shorouk Journal of Commercial Sciences, volume 17, The Higher institute for computers and Information Technology, Al-Shorouk Academy, Page 341-391.

Predicting a Going-Concern Auditor's Opinion: ANN Approach

Abstract

Purpose: The objective of this research is to employ neural network techniques that can screen out the most important variables when predicting GCOs. These factors include financial and non-financial variables related to both auditor and auditee.

Design/methodology: The study was conducted on a sample consisting of 61 firms listed in the Egyptian Stock Exchange (ESE) belonging to seven sectors which are Food, Beverage & Tobacco, Industrial & automotive Services, Healthcare & Pharmaceuticals, Tourism & Leisure, Properties, Contracting & Engineering Construction, and Building materials during the period from 2018-2021 with a total of (244) observations. The study adopts two stages to construct going concern prediction models. In the first stage, ANN is used to screen out the most important variables. A total of 9 variables are selected based on their importance value (importance value ≥ 0.05), including CATA, Predictive ability of earnings, Return on assets, Current liabilities/ total assets, Audit lag, Profit ratio, Sales revenue growth rate, and Managerial ownership. In the second stage, the proposed model is constructed for predicting going concern uncertainties.

Findings: The results reject the study hypothesis and prove that ANN can be used in predicting GCO with high accuracy. The research depended on contingency table to testing the accuracy of ANN model through comparing the predicted results of 61 observations with the actual values. The significant value is 0.000 which is less than (.05). It gains confidence that the variables are independent and, in some way, related. Moreover, behind that, the Wilcoxon test is used to ensure that there is no difference between the actual and predicted opinion by ANN. Result indicate that the p-value equal (0.157) which is more than 0.05, which point out that the two groups aren't different.

Originality/value: The study makes a contribution to the existing literature and helps future researchers by combining some of financial and non-financial variables related to auditor and auditee and analyzing their importance on going concern opinion because it may help auditors in evaluating the company's ability to continue., and assist investors such as creditors, suppliers, banks, and shareholders in better understanding the going concern uncertainties effects on their investment behavior.

Keywords: ANN, Going Concern Opinion, Financial Ratios, Board of Director, Earning quality, Big 4, Auditor-client relationship

التنبؤ برأي مراجع الحسابات حول الاستمرارية: مدخل الشبكات العصبية

ملخص البحث:

الهدف: يتمثل الهدف الرئيسى للدراسة فى صياغة نموذج يساعد المراجع للتنبؤ بشأن استمرارية الشركات عن طريق الاستفادة من الشبكات العصبية لتحديد أهم المتغيرات التى يمكن أن يعتمد عليها المراجع عند إبداء رأيه المهنى بشأن الاستمرارية.

التصميم / المنهجية: أجريت الدراسة على عينة مكونة من (61) شركة مدرجة فى البورصة المصرية تنتمى الى (7) قطاعات هى الموارد الأساسية، والرعاية صحية و الأدوية، وخدمات و منتجات صناعية و سيارات، والعقارات، والسياحة و الترفيه، الأغذية والمشروبات والتبغ، والمقاولات والإنشاءات هندسية خلال الفترة من 2018- 2021 باجمالى عدد مشاهدات 244 مشاهدة، وقد تمت الدراسة التطبيقية على مرحلتين، المرحلة الأولى تضمنت اختيار أهم العوامل التى يمكن أن تساعد المراجع فى إبداء رأيه بشأن الاستمرارية، وقد تم تحديد 9 متغيرات وفقا قيمه أهميتها فى نتائج الشبكات العصبية (الأهمية $\leq 0,05$) و هم إجمالى الأصول المتداولة / إجمالى الأصول، والقدرة التنبؤية بالأرباح المحاسبية، ومعدل العائد على الأصول، وإجمالى الخصوم/ إجمالى الأصول، وفترة تأخير تقرير المراجع، ومعدل نمو الإيرادات و الملكية الإدارية، وتضمنت المرحلة الثانية بناء نموذج يساعد المراجع فى التنبؤ بقرار المراجع بشأن الاستمرارية باستخدام الشبكات العصبية.

النتائج: توصلت الدراسة الى رفض الفرض القائل بانه لا توجد دقة للنموذج المقترح للتنبؤ برأى المراجع بشأن الإستمرارية، حيث أثبتت الدراسة أنه يمكن الاعتماد على النموذج المقترح استنادا على نتائج جدول الاحتمالات حيث بلغت المعنوية (0,000)

و هي أقل من (0,05) بالإضافة إلى نتائج اختبار Wilcoxon test و الذى أكد على أنه لا يوجد اختلاف بين نتائج النموذج المقترح و القيم الفعلية لرأى المراجع.

الأصالة / القيمة: تساهم الدراسة فى الأدبيات الموجودة بالإضافة الى مساعدة الباحثين المستقبليين من خلال الجمع بين المتغيرات المالية و غير المالية المتعلقة بمكتب المراجع والشركة محل المراجعة و تحديد مدى أهمية تلك المتغيرات و إمكانية الاعتماد عليها عند إبداء الرأى بشأن الاستمرارية بالإضافة إلى مساعدة أصحاب المصالح مثل المستثمرين و الموردين و البنوك و المساهمين فى فهم تأثير الشكوك بشأن استمرارية المنشأة على قراراتهم الاستثمارية.

الكلمات المفتاحية: الشبكات العصبية، رأى المراجع بشأن الاستمرارية، النسب المالية، خصائص مجلس الإدارة، جودة الأرباح، العلاقة بين مكتب المراجعة و الشركة محل المراجعة

Predicting a Going-Concern Auditor's Opinion: ANN Approach

1. Introduction

Financial statements are organized representation of the financial performance, cash flows and financial position of an entity (Gkouma, et al., 2018). The quality of information in the financial statements is closely associated with the added credibility from the external auditor. This credibility has been questioned and raises many doubts after several corporate scandals such as Enron 2001, WorldCom 2002, Arthur Andersen, XEROX, and others (Carson et al., 2013; Zureigat, 2015; Carlino, 2020). These scandals as well as the pandemic COVID-19 crisis alerted the attention on the quality of financial reporting, and the application of accounting assumptions such as going concern assumption (GC). In addition, the prediction of firms' going concern become the focus of attention of the accounting, auditing, and financial research (Fernández et al., 2018). It presents a framework about the entity's operational stability and helps users to make informed business decisions (Proho, 2023).

The preparation of the financial statements is based on the going-concern assumption, which is the responsibility of the management. However, Auditor's responsibilities are to obtain sufficient appropriate audit evidence regarding the appropriateness of management's use of the going concern basis of accounting in the preparation of the financial statements, and to conclude whether a material uncertainty exists about the entity's ability to continue as a going concern (ISA, 570).

The overall frequency of going concern opinion (GCOs) increases after the passage of Sarbanes- Oxley Act (SOX) (Carson et al., 2013) As strengthening auditors' independence

was achieved, for example, through restrictions on providing non-audit services to reduce the conflict of interests and audit partner rotation every five years (Carlino, 2020). In addition, it generates a growing tide of criticism on auditors' role and behavior due to their collusion with managers (Chen, 2019). If auditors fail to put forward the audit opinion of going concern prior to a business's bankruptcy or financial crisis, it harms stakeholders and capital market as well as this harm will result in audit failure from the prospective of the users of financial statements (Chen, 2019).

Issuing GCO is a difficult decision for the auditor because this opinion gives a negative signal to the company's business continuity and issuing this opinion will also have a negative impact on the company, such as decreasing the level of confidence of investors or shareholders to invest in the company, stock valuation and credit challenges (Islami et al., 2022; Zdolsek, et al., 2022; Kausar & Ilennox, 2017). GCO has potential consequences for lenders. Moreover, it is considered as a red flag to lenders and users of financial statements about the possible effect that a firm failure will have on the asset book values (Carson et al., 2013). Going concern doubt will seriously damage the sustainability of companies and capital market development and will increase the risks of shareholders and creditors in the agency relationship (KPMG, 2020).

If the auditor does not issue a GCO on the financial statements of distressed firms, it leads to an obvious increase in the probability of type II error and that increases litigation risk. type II error arises when the auditor does not issue a GCO and the client (auditee) fails in the following year (Etheridge et al., 2000). Therefore, GCO has been an object for academic research for the last decade (Laitinen & Laitinen, 2020).

Information in the accounting systems has two major characteristics: firstly, information is dependent on many variables. Secondly, accounting data have very complex

relationships among their components that make them very difficult to analyze. For example, earnings are commonly deemed to be the status of an enterprise's past business performance (Chen et al., 2015). Once the financial statements are manipulated, it is hard for the users of financial statements to evaluate the financial position, the operating performance, and to detect earnings manipulation.

This problem has caused an issue in the accuracy of prediction of the conventional analysis. Managers and auditors require the use of information technology (IT) techniques that enable to predict or structure raw data (Mirzaey et al., 2017). It is difficult for traditional auditing technologies to identify abnormal behavior in complex information, requiring research to explore other techniques. The purpose of this study is to employ artificial neural networks (ANN) in determining the most important factors auditors can rely on when predicting GCO that may help auditors to void audit failure.

2. Research Problem

Users of financial statements expect the auditor to inform them of a real situation and the company's fair view. To date, predicting GCO is noted as one of the most difficult and complex decisions faced by the auditing profession (Carson et al., 2013; Guo et al., 2020). Problems may arise when auditors issue an inappropriate audit opinion (type I error & type II error). Type I error arises if the auditor issues a GCO and the client does not fail in the following year. While type II error arises when the auditor does not issue a GCO, and the client fails in the following year.

Despite the issuance of going concern standards began with SAS No.2 in 1981, followed by SAS No. 34 in 1988 and SAS No.59, SAS No. 126, then ISA 570 in 2007. where auditors' disclosure consists of an explanatory paragraph in the audit report if there's any doubt about the entity ability to continue. ISA No. 570 "Going Concern" was revised in line with

accounting standards states that “the financial statements are prepared on the assumption that the entity is a going concern and will continue its operations for the foreseeable future.” ISA 570 specifies that auditors have the responsibility “to obtain sufficient appropriate audit evidence regarding, and conclude on, the appropriateness of management’s use of the going concern basis of accounting in the preparation of the financial statements, and to conclude, based on the audit evidence obtained, whether a material uncertainty exists about the entity’s ability to continue as a going concern.” Moreover, it provides a series of conditions or events that, considered separately or as a whole, may cast significant doubt on the entity’s ability to continue as a GC. The standard shows three categories of events (financial, operating, and others). Furthermore, the pandemics have raised concerns about the ability of companies to continue and going concern is considered a key audit matter that may be significant in the auditor’s professional judgment especially in sectors such as hospitality and travel (Carlino, 2020; Elmarzouky et al., 2023). Questions have been raised about using professional judgment in accumulating and evaluating evidence to determine whether going concern status is questionable or not. Furthermore, whether there is a material uncertainty about management use of going concern assumption. As the auditor’s responsibility is to evaluate the appropriateness of management’s use of the going concern assumption in the preparation of the financial statements and conclude whether there is a material uncertainty about the entity’s ability to continue as a going concern (Gkouma et al., 2018). Auditors’ evaluations are made based on knowledge obtained from audit procedures, knowledge existing at or prior to the completion of fieldwork that relates to the validity of the going-concern assumption, and the use of the going-concern basis for preparing the financial statements (Carson et al., 2013; Barr-Pulliam et al., 2024).

The main reason for audit failure lies in the complicated decision-making process auditors make, which is based on auditor's professional judgment (Chen, 2019). Personal judgements may lead to different auditors reaching different decisions even in GCO or other aspects require professional judgements. Moreover, this approach sometimes leads to a bias/ misleading judgement (Wahdan, 2006).

Therefore, auditors are sometimes cautious about doubting the continuity of the company, as the declaration can bring negative consequences for both the auditor and the company being audited. It would bring auditor's consideration into a question (litigation risk) and harm their reputation. In addition, GCO could accelerate the company's bankruptcy. The appearance of going concern prediction studies synchronized with financial crises. The critical issue in such scandals is that it is too late for stakeholders to take corrective actions to avoid loss and damage (e.g., creditors or shareholders cannot return their loans or sale their stocks).

Recent literature has focused when issuing a GCO on traditional approach of predictive models using different set of variables that vary from study to study. These variables include auditor/ client attributes, the client financial condition, going bankruptcy models, financial distress models, and earning quality etc. It is therefore helpful to learn which variables auditors can rely on in addition to update evidence using the advantage of ANN.

ANN has major advantages compared to linear regression (Tsai & Chiou, 2009; Mahmoudi et al., 2017), as it can learn any complicated design and nonlinear mapping. It does not consider any default in data distribution; ANN does not make a prior assumption about the distribution of data and multi-collinearity, and is very flexible against incomplete, missing, and caustic data.

The research monitors indicators about the continuity of the firm that contribute to taking the necessary corrective actions on time. In addition to examine whether alternatives to a linear approach in the form of neural network techniques can predict GCOs. research questions are formulated to summarize and elaborate the study

- To what extent is it possible to employ neural network techniques that can be used in predicting GCO?

3. Research objective

The objective of this research is to:

- Examine the accuracy of the proposed ANN model of predicting GCOs.

4. Literature Review & Hypothesis Development

3.1 Literature Review

4.1.1 Neural network in accounting and auditing

Throughout the last few decades, artificial intelligence has been a hot topic in science fiction and news stories. Today, many algorithms in this category are used in daily life by people with self-driving cars, automatically generated image captions on search engines, recommendation algorithms, and even hiring processes. Despite being widely used, this term has no exact definition other than "a program that does something smart," with the concept of "smart" evolving over time. Recently, this word has primarily been used to describe data-driven algorithms, also known as machine learning algorithms. One of these algorithms is neural networks (Guilhoto, 2018).

Neural network development began in the early 1940s. It became quite popular in the latter part of the 1980s. The field of ANN has been largely driven by the goal of creating artificial systems that are able to perform complex, potentially "intelligent," computations that are like the human brain. ANN aims to mimic how the human brain solves problems by

acquiring the skills in processing data and finding solutions through training.

There are many previous literatures that define ANN. It can be defined as a data-driven method that falls within the Artificial Intelligence (AI) umbrella. It is a tool for clustering, nonlinear estimating, data sorting, optimization, and pattern recognition. It is also a highly powerful modeling and simulation tool (Gupta, et al., 2019). While Caldeira et al. (2015) describes Neural networks as a non-linear data modelling system that were developed based on the concepts of how the human brain functions. When stimuli are received by these models' neurons, they propagate to other neurons until the final layer is reached, at which point the model responds (Caldeira et al., 2015). Likewise, Aryadoust & Goh (2014) use the term "ANN" to refer to mathematical nonparametric models made up of a set of connected "neurons," or processing units, that are capable of adaptation, training, and experience. Like the brain, ANNs are made up of interconnected neurons that can recognize patterns, make predictions, classify data, and learn new things. The networks learn from the data and store that knowledge in a system of synaptic strengths, also known as weights, which are the strengths of connections between neurons (Aryadoust & Goh, 2014).

The area of intelligent techniques has expanded phenomenally over the last years since 1940s, both in terms of the range techniques and number of applications where they have provided a competitive edge (Pardo et al., 2008). Researchers investigate ANN techniques' advantages in specific tasks in accounting, auditing, and finance such as for investment decisions (Rai, 2006; Azarova et al., 2020), for predicting stock price index (Sinai et al., 2005; Akinrinola et al., 2024), for predicting fair value of option contracts (El-sayed, 2012; Zouaoui & Nadjat Naas, 2023), for predicting financial solvency (Kumar & Bhattacharya, 2006; Abdullah, 2021), and for

predicting the amount of transactions with related party (Vaez & Banafi, 2017; Mao et al., 2022)

Moreover, ANN techniques have been applied to an abundance of decision problems in auditing domain in general, such as for formulating the auditors' opinion (Pourheydari & Azami, 2010) for going-concern opinion (Etheridge et al., 2000; Koh & Low, 2004; chen 2019; El-Gawad, 2023), for helping to review analytical procedures (Koskivaara, 2004). In addition, it can help in estimating the final cost (Wang, 2007), for predicting accrual earnings management (Tsai & Chiou, 2009; Hoglund, 2010; Chen et al., 2015; Mahmoudi et al., 2017; Li & Sun, 2023), and for predicting real earnings management (Haga et al., 2014).

The study of Etheridge et al. (2000) compared the performance of three ANN- backpropagation, categorical learning, probabilistic neural network as a classification tool to support auditors' judgement on going concern. Using a set of financial ratios, performance is compared on the basis of overall rates. Results indicate that when overall error rate is considered, the probabilistic ANN is the most reliable in classification, however when the estimated relative costs of misclassification are considered, the categorical learning network is the least costly.

However, Koh & Low (2004) explored the usefulness of neural networks, decision trees and logistic regression in predicting a firm's going concern status using six financial ratios. The study indicated that neural network and decision trees in going concern prediction is powerful alternative or complement to the more commonly used statistical methods. The GCO prediction model has been constrained to only the six financial ratios: market value of equity to total assets (MVTA), total liabilities to total assets (TLTA), interest payments to earnings before interest and tax (IEBT), net income to total assets (NITA), retained earnings to total assets (RETA), and

quick assets to current liabilities (QACL). GCO prediction can be considered as an extension of bankruptcy prediction.

Recently, in 2019, the study of Chen constructed four going-concern prediction models using traditional statistical method which is stepwise regression (SR) and ANN to screen out the most important variable in addition to data mining techniques such as classification and regression trees (CART) and C5.0 to establish the prediction models. Sample of the study was companies listed in Taiwan stock exchange, a sample of 196 companies including 49 companies with going concern doubt. The accuracy rates of models using CART show good performance than the other; SR +CART (87.42%) > ANN +CART (86.23%) while SR +C5.0 (85.52%) > ANN +C5.0 (77.32%).

4.1.2 Going concern opinion

Going concern opinion means that auditors make evaluation regarding whether entities have doubts concerning their ability to continue in business for at least 12 months. Over the past decades, most research show ancient origins of going concern in an attempt to analyze the trend of going concern supported by international institutions to harmonize the standards. The findings of Provasi and Riva (2015), and Triani et al. (2017) indicated that the application of ISA 570 gives facilities for the auditors in publishing a GCO. The auditor will use financial indicators, operational indicators, and others. In addition, they exercise professional judgments in their work. Recently, Abdel-Rehim (2020) explored the modification in the form and the content of the auditor's report on going-concern. The study found that there is a significant impact of the amendments involved in the revised ISA 570 (for the year 2015) on investment and credit granting decision in Egypt.

A considerable amount of literature highlights the relation between going concern and investor decisions, aiming at discovering factors associated with predicting going concern

opinion. In most studies, client (auditee) characteristics are important factors associated with the auditor decision to issue a GCO. Client characteristics are divided into financial and non-financial variables. Financial variables (liquidity ratio, profitability ratio, and leverage ratio) are one of the ranking methods used in predicting GCO (Carson, et al., 2013; Gallizo & Saladrighes, 2016; Triani, et al., 2017; Mukhtarudin, et al., 2018;). A large and growing body of literature has focused on using models of financial distress and bankruptcy such as Altman Z-Score (Altman, 1996), KIDA (Kida, 1980) and others as a proxy in measuring going concern doubts. However, the set of independent variables varies from study to study, it is therefore helpful to learn which variable auditors actually should rely on in practice.

The study of Gallizo & Saladrighes (2016) went in depth into the relationship between going concern opinion and certain characteristics of the company (auditee) and the auditor. The study concluded that the most important indicator that the auditor has to bear in mind for including a GCO is the continued existence of losses.

Other studies such as Etheridge et al. (2000), Koh & Low (2004), and Chen (2019) considered the impact of financial variables on GCO using other techniques as ANN and decision tree (DT). The objective is to maximize the model's predictive accuracy. The results of Chen (2019) indicated the most important variables when predicting GCO, which are pre-tax profit ratio, current ratio, net income/ total assets, sales revenue growth rate, inventory / total assets, accounts receivables turnover, operating cash flow ratio, and quick ratio. Several studies highlight the importance of client attributes such as company size, debt defaults, prior GCO, and ownership structure (Altman, 1968; Kida, 1980; Triani, et al., 2017; Chen, 2019; Carson, et al., 2013; Gallizo & Saladrighes, 2016).

Besides financial variables, literature documents other non-financial variables that are associated with the issuance of

GCO. Non-financial variables also include market variables such as industry-adjusted return and return volatility (Carson, et al.,2013). The general findings are that auditors are more likely to issue a GCO when a company has a lower industry- adjusted return and higher return of volatility, strategic initiatives, and governance characteristics. Several Studies conducted to investigate the impact of client attributes on GCOs. The study of Dewi & Dewi (2017) determines the effect of corporate social responsibility on GCO. Moreover, changing audit firm or not is the most important non-financial variables affect the prediction of GCO (Chen, 2019).

More recent attention has focused on the effect of ownership structure on company going concern. Agency theory argues that concentrated ownership may reduce the interests' conflicts between the managers as agent and shareholders as principal. Ownership concentration refers to the proportion of firm's stock owned by a certain number of institutions, individuals or families (Makhlouf & Al-Sufy, 2018). In 2018, Makhlouf & Al-Sufy investigated whether ownership concentration affects the going concern. The study examined whether the ownership concentration leads to improve the firm performance and provides great benefits to firms' continuity. Going concern was measured using Altman's Z-Score Model. The outcomes report that the family ownership and directors' ownership are positively associated with going concern and enhancing investors' confidence in financial reporting. This study only investigated two types of ownership structure namely family ownership and directors' ownership.

The study of (Yulfa & Fitriany, 2018) examined whether GCO and institutional ownership measured affect the cost of equity. The study found a positive relationship between GCO and the cost of equity which satisfies signaling theory, firms can signal investors through audit practices. Moreover, the study concluded that institutional ownership weakens the positive influence of GCO on cost of equity.

Archival studies have investigated the association between GCO and audit quality. Audit quality proxies are divided into two categories: Firstly, input-based audit quality measures: auditor characteristics and auditor-client contracting features (auditor size, audit fees, and industry specialization). Secondly, output-based audit quality: it means the aftermath findings of the audit process including issue GCO, discretionary accruals, meet or beat earnings target, earning quality (Defond and Zhang, 2014).

Auditing experts expect that larger auditors will be more likely to issue a going concern opinion to distressed client. Berglund et al. (2018) found that the big 4 are more than mid-tier auditors to issue a GCO. However other studies Mukhtarudin et al. (2018), and Foster & Shastri (2016) considered Big 4 firms and non-Big 4 firms has no effect in issuing an audit opinion. Mukhtarudin, et al. (2018) examined the effect of the company's financial condition measured by Altman Z-Score, company's growth that was proxy by the ratio of sales growth, and the audit quality represented in being audited by big four or not on acceptance of going concern opinion. The research uses 252 sample of manufacturing companies listed in Indonesia stock exchange in 2010-2012. The study found that companies' financial condition influences the acceptance of the GC audit opinion, while company's growth and audit quality do not influence the acceptance of GC audit opinion.

There is mixed evidence on the relation between audit fees and auditor tendency to issue a GCO (Carson et al., 2013; Defond & Zhang, 2014). The study of Blay & Geiger (2013) indicated that the magnitude of audit fees is negatively related with issuing GCO. However, Foster & Shastri (2016) concluded that there is a significant relation between audit fees and the type of audit report (GCO or not).

Numerous studies have used auditors' tendency to issue going concern opinion as a measure of audit quality. The study of Guo et al. (2020) examined whether audit quality influences the probability of financially distressed firms and the issuance of

GCOs. The results indicate that financially distressed firms are more likely to receive GCOs. However, financially distressed firms that receive GCOs from their auditors, are limited to firms that have higher-quality audits. However, the study of Defond and Zhang (2014) criticizes the use of GCO as audit quality proxy.

In 2017, Ittonen et al. reported a new and convenient procedure to evaluate the informational value of going concern audit reports at various hypothetical bankruptcy probability thresholds that auditors could use to evaluate the “substantial doubt” of an entity’s ability to continue as a going concern.

Recent evidence suggests that earning quality (EQ) has a significant impact in enhancing the GC of the company. The study of Ali et al. (2019) explored the effect of the quality of accounting earnings in improving a company’s ongoing concerns. Figure 1 clarifies the relationship between EQ and GC.



Figure 1: Impact of EQ on firm's GC
Source: (Ali, et al., 2019)

Disclosure of accounting earnings is tied to responses from investors and usually leads to positive feedback from investors. Investor response to earnings is directly reflected in the enhancement of the market value of the company that leads to a good and stable rate of return.

Therefore, high quality accounting profit reflects a stable financial ability now and in the future. The study used Miller 2009 model to measure earning quality and Altman Z score for measuring GC, and considered three control variables which are age, size, and liquidity. The results indicated that EQ has a positive and significant impact on enhancing the GC of the company.

5. Hypothesis development

The accuracy of auditors' opinion on going concern affects decision makers. Inaccuracy of the auditor's judgment regarding going concern led to two types of error (type 1 error and type 2 error). Type 1 error, (false rejection) arises if the auditor issues a GCO and the client does not go bankrupt in the subsequent year. While type 2 error (false acceptance) refers that the auditor does not issue a GCO, and the company went bankrupt in the subsequent year (Etheridge et al., 2000). Numerous prior studies have investigated the impact of using bankruptcy prediction models such as Altman (1968), Sprinate (1978), Kida (1980), Sherrod (1987), and others in predicting going concern opinion. In addition, prior studies indicate that a neural network can recognize patterns more than traditional auditing techniques, therefore the neural network is used to explain significant factors that may affect the auditors' going concern opinion. the research hypothesis is formulated as follows:

H₀₁: There is no significant accuracy of the proposed ANN model to predict GCO.

6. Empirical Methodology

6.1 Sample Selection

The population consists of all Egyptian listed firms reached 184 firms, during the period from 2018-2021. It uses a total of 61 listed companies distributed into 18 sectors, totaling 244 observations.

Sample is selected based on the following conditions:

- 1- They have been active in the stock exchange throughout the study period.
- 2- Financial statements and information required for this research are available.
- 3- Financial statements amounts are in the Egyptian pound.
- 4- Their financial statements date is 31/12.
- 5- Every sector must contain firms that receive GCO and other firms that don't receive GCO.
- 6- Banks and financial institutions are excluded, due to their different nature. (This exclusion is in line with the literature of GCO prediction as the majority studies relied on non-financial firms).

6.2 Variables Measurement

The dependent variable of the current study is auditor's opinion regarding going concern uncertainties. GCO is extracted from the audit report of listed companies; (0) if the firm receive unqualified opinion; (1) whether the audit report include any information that doubt the going concern of the firm whether the auditor's opinion was unqualified or qualified.

There are 30 independent variables used and examined to ensure their strength and judging ability in determining the entity going concern uncertainties. These variables include 15 financial variables and 11 non- financial variables related to the auditee. It particularly includes liquidity variables, for they were

considered to be determinant on the decision of reporting going concern audit opinions. Profitability variables, activity variables and leverage variables are also included. Moreover, the study has included other variables to capture the corporate governance effect and ownership structure effect as a risk factor of financial information. In addition, three variables that may give an idea about the auditor-client relationship and one variable that reflect if the auditor is classified as big 4 or not. Table (1) shows the variables description and its measures.

Table (1) Variables description and measures.

Category	Symbol	Variable	Measurement method	References
Financial ratios (the auditee)				
Liquidity ratio	X1	Current ratio	Current assets/ Current liabilities	Gallizo & Saladrighes, 2016
	X2	Current assets to total assets (CATA)	Current assets/total assets	Chen, 2019
	X3	Operating cash flow ratio	operating cash flow/average current liabilities	Etheridge et al.,2000; Chen, 2019
Profitability ratio	X4	Profit ratio	Net profit / net sales	Arens et al., 2014
	X5	Operating cash flow	cash flow from operating activities	Chen, 2019
	X6	Sales revenue growth rate	Δ sales revenue/sales revenue prior year	Chen, 2019
	X7	Return on Assets (ROA)	Net income/average total assets	Etheridge et al.,2000; Koh& Low, 2004
Activity ratio	X8	Inventory/total assets	Inventory/total assets	Chen, 2019
	X9	Inventory turnover	COGS/average inventory	Junaidi, et al., 2012;
	X10	Total assets turnover	net sales/average total assets	Junaidi, et al., 2012;
Leverage ratio	X11	Current liabilities/ total assets	Current liabilities/ total assets	Bellovary et al., 2007

Category	Symbol	Variable	Measurement method	References
	X12	Debt ratio	total liabilities/ total assets	Etheridge et al.,2000; Koh& Low, 2004
	X13	Debt-to-equity ratio	total liabilities/ total equity	Chen, 2019
Internal firm characteristics				
Firm size	X14	Firm size	Natural logarithm of total assets	Gallizo & Saladrignes, 2016
Firm age	X15	Firm age	Natural logarithm of firm age	Makhlof, 2017
Ownership structure	X16	Managerial ownership	Managerial ownership ratio	Elsayed, 2020 ; Ibrahim & Yahaya, 2023; Zureigat, 2015)
	X17	Family ownership	Family ownership ratio	Elsayed, et al., 2023; Ibrahim & Yahaya, 2023; Zureigat, 2015
	X18	Foreign ownership	Foreign ownership ratio	Elsayed, et al., 2023; Ibrahim & Yahaya, 2023; Zureigat, 2015
Governance (Board of director)	X19	BOD independence	The proportion of the number of independent directors to the total number of board members.	Almaleeh, 2022; Hashad, 2023; Zureigat, 2015
	X20	Duality	A dummy variable equal to 1 if the CEO is also the Chairman of the board whereby 0 signifies that the positions of CEO and chairman of the board are occupied by different directors.	Hashad, 2023
	X21	No. of meeting	No. of meeting	Li, et al., 2021
	X22	Gender	A dummy variable equal 1 if the BOD includes women, 0 otherwise.	Liu et al., 2014
	X23	Gender2	The proportion of the number of females in the board of directors to the total number of board members.	Ishak, 2016; Elsayed, et al., 2023
	X24	Board size	Natural logarithm of the total number of board directors in the firm.	Hashad, 2023
Earning Quality	X25	Conservatism	Market value of equity/ book value of equity	Wahdan, 2019; Almaleeh, 2022

Category	Symbol	Variable	Measurement method	References
	X26	Predictive ability of earnings	$\text{Earnings}_{t+1} / \text{Total Assets}_t = B_0 + B_1(\text{Earnings}_t / \text{Total Assets}_t) + \text{error}_t$	Elsayed, 2020
Auditor-client relationship				
Auditor-client relationship	X27	Change audit firm or not	1 if auditor in the current year is different from auditors in the prior year; 0 if auditor as previous year.	Foster & Shastri, 2016
	X28	Audit lag	Period between date of financial statements and issuing an audit opinion	Averio, 2021
	X29	Audit lag2	Ln (no. of days)	Munsif et al., 2012
Related to auditor				
Related to auditor	X30	Audited by BIG 4 or not	1 for companies audited by BIG 4; otherwise, 0	Berglund, 2018; Chen, 2019

6.3 Data source and analytic methods

The current study employs quantitative research method based on secondary data. Data for all required variables are obtained from the financial disclosure which includes annual financial statements of Egyptian-listed firms, and non-financial disclosure such as information about the board characteristics, ownership structure, and during the period from 2018 to 2021 which was the latest data available at the time of the study. The required data were extracted directly from firms' websites, the Mubasher website, and Egyptian Company for Information Dissemination.

- 1- Descriptive statistics:** refers to a set of methods used to provide a brief description of the features of study data using some measures of central tendency and measures of dispersion.
- 2- ANN:** is a computational technique in artificial intelligence which uses as a powerful learning method for solving complex problems in the field of machine learning, market forecast, optimization, nonlinear systems, financial analysis ...etc.

3- Wilcoxon signed rank test: a nonparametric statistical test that compares two paired groups. The tests essentially calculate the difference between sets of pairs and analyze these differences to establish if they are statistically significantly different from one another.

6.4 Descriptive Statistics

Descriptive statistics provide a brief description of the features of study data using some measures of central tendency and measures of dispersion. Table (2) presents some descriptive statistics of the continuous of the study. Whereas Table (3) presents some descriptive statistics of the discrete variables in the study.

Table (2): descriptive statistics of variables

Panel A: Continuous variables					
No.	Variable	Mean	Standard deviation	Minimum	Maximum
x1	Current ratio	9.3404	29.87653	-3.93	236.40
x2	Current assets to total assets (CATA)	0.7851	0.33720	-3.16	1.00
x3	Operating cash flow ratio	-0.0794	3.97220	-48.50	13.15
x4	Profit ratio	-0.2765	3.31923	-39.24	6.21
x5	Operating cash flow	1512278 32.8552	902959653.155 65	(537252 2663)	5368360 310.00
x6	Sales revenue growth rate	0.2784	1.90149	-1.00	24.75
x7	Return on Assets (ROA)	0.0281	0.11815	-1.32	0.25
x8	Inventory/total assets	0.1547	0.19692	0.00	1.49
x9	Inventory turnover	26.9996	84.98832	0.00	635.36
x10	Total assets turnover	0.7671	0.85518	0.00	4.78
x11	Curr. liabilities/ total assets	0.3913	0.39035	0.00	3.09

Panel A: Continuous variables					
No.	Variable	Mean	Standard deviation	Minimum	Maximum
x1	Debt ratio	0.4523	0.32053	0.00	3.18
2					
x13	Debt-to equity ratio	0.6400	9.27159	-109.80	71.72
x14	Firm size	20.9875	2.09533	17.23	26.20
x15	Firm age	3.4189	0.48942	2.08	4.74
x16	Managerial ownership	0.1465	0.21057	0.00	0.98
x17	Family ownership	0.0677	0.15603	0.00	0.81
x18	Foreign ownership	0.1806	0.23180	0.00	0.86
X19	BOD independence	0.2085	0.18311	0	1
x21	No. of meeting	7.8971	3.94928	4.00	21.00
x23	Gender2	0.0925	0.10672	0.00	0.50
x24	Board size	8.0492	2.53487	3.00	15.00
x25	Conservatism	1.1399	2.74448	-27.36	10.83
x26	Predictive ability of earnings	0.0608	0.10119	0.00	1.34
x28	Audit lag	66.3893	21.30264	15.00	175.00
X29	Audit lag2	4.1488	0.30825	2.71	5.16

The above table represents the mean value of the research variables that reflect the center of each variable data. In addition to the minimum and maximum value. Moreover, it shows how the data are spread from the mean through the value of the standard deviation.

Table (3) shows the mean value of liquidity ratio that are represented in current ratio, CATA, and operating cash flow ratio. As for the second category of financial ratios, which is profitability ratio. Profitability ratio is represented in profit ratio, operating cash flows, sales revenue growth rate, and ROA. The mean value of sales revenue growth rate is 0.2784 with minimum and maximum values of -1 and 24.75, respectively.

This result is consistent with the results of Wahdan (2019), As for the other measure of profitability which is ROA. It showed a mean value of 0.0281 with minimum and maximum values of -1.32 and 0.25, respectively. This result goes in the same vein as Almaleeh (2022) which showed a mean value of 0.0363.

Activities ratios are inventory to total assets, inventory turnover, and total assets turnover. The mean value of total assets turnover is 0.767 with minimum and maximum values of 0 and 4.78, respectively. This result is consistent with Goe, et al. (2016) which showed a mean value of 0.859.

The leverage ratio in the study is reflected in current liabilities to total assets, debit ratio, and debt-to-equity ratio. As for current liabilities to total assets, its mean value is 0.391 with minimum and maximum values of 0 and 3.09, respectively. It agrees with Li, et al. (2021) which showed mean value of (0.347). Moreover, the mean value of debt ratio is 0.452 that is consistent with Hashad (2023) with mean value of 0.493. debt to equity ratio shows a minimum and maximum value of (-109.8, 71.72) respectively. a negative minimum value is because the liabilities of some of the firms in the study sample are more than their assets. Its mean value is 0.64 which is consistent with Elsayed (2021) with mean value of 0.68. in addition, a moderate values of leverage ratio indicate that most firms in the sample depend on both inside and outside source of financing.

The mean value of the firm size is 20.987 which goes in the same vein as Elsayed (2021) and Hashad (2023) where the mean values of firm size were (20.49, 21.28) respectively. However, it is higher than the reported value of Wahdan (2019) and Ibrahim & Yahaya (2023) where the mean values of firm size were (4.33, 8.95) respectively. Firm age has a mean value of 3.4 years with minimum and maximum values of 2.08 and 4.74 respectively which is less than other previous studies such as (Kusumaningrum et al., 2022) and (Hashad, 2023) with mean value of 29.73, 34.23 years. Their mean values differ from this study due to different measures employed for firm age.

In terms of ownership structure variables, managerial ownership keeps an average of 14.6% with a minimum of 0% and maximum 98%, which is consistent with Elsayed et al, (2023) with mean value of 15.7%. Moreover, family ownership displayed a mean of 6.7% and the minimum and maximum levels of 0.00% and 81%. This finding is close to Elsayed et al. (2023) with a mean value of 7.5%.

Furthermore, foreign investors own 18.06% of total outstanding shares, which range from 0.00% to 86%. This result is close to Elsayed et al. (2023) with a mean value of 16.8%. In addition, this finding is slightly above the result of Garba (2018) who reported a mean of 11.78%.

With respect to board of director characteristics variables, the average number of directors on the board is 8 with a minimum of 3 and maximum of 15, which goes in the same vein as Li (2021) and Zureigat (2015) where the mean values of directors were (8, 7) respectively. This result means that the Egyptian listed firm in the sample have an acceptable commitment with the requirements of Corporate Governance Code. The proportion of independent directors has an average of 0.2085 with a minimum of 0 and maximum of 1. This finding is slightly above the result of Hashaad (2023) who reported a mean of 0.122.

As for the No. of meetings, the result shows that the mean of board meeting measured by the number of board meetings in a year is around 8 meetings, whereas the minimum and maximum values are 4 and 21 meetings respectively. This result is consistent with Zureigat (2015) which showed a mean value of 7 meetings. In addition, the result indicates that the listed companies in Egypt have complied with the Corporate Governance Code, which mandates that there should be four board meetings annually at minimum. The result also reveals that the boards of directors meet regularly, indicating that they discuss significant concerns within their companies.

In terms of earning quality proxies, the mean conservatism variable is 1.13 with a minimum and maximum value of (-27.36, 10.83). This result is consistent with the results of Wahdan (2019). An increase in the average accounting conservatism above one indicates that firms in the study sample apply conservatism policies in financial reports during the study period (Wahdan, 2019).

As for the predictive ability of earnings, the mean value is 0.06 with a minimum and maximum value of (0, 1.34) respectively. A small value of in predictive ability of earnings in this sample is consistent with previous studies such as (Elsayed, 2020). Finally, the mean value of audit lag is about 66 days with a minimum of 15 days and a maximum of 175 days. This result is close to the result of Shofiyah & Suryani (2020) with a mean value of 71 days. It means that Egyptian listed firm are very timely in presenting financial statements.

Table (3): descriptive statistics of discrete variables

Panel B: Discrete variables				
Variables	1		0	
	Frequency	%	Frequency	%
Going concern opinion (Y)	72	29.5	172	70.5
Duality (x20)	100	41	144	59
Board of director, gender (x22)	126	51.6	118	48.4
Change audit firm (x27)	41	16.8	203	83.2
Audited by big 4 or not (x30)	85	34.8	159	65.2

The descriptive statistics for the discrete variable reported that the dependent variable (GCO) is paired into 2 groups, for a total of 244 observation, among which 72 (30%) observation represent GC doubts and 172 (70%) observations are normal (have no GC doubts) which is consistent with Chen (2019) sample distribution (25% have GC doubt, 75% normal).

The proportion of CEO that serve as the chairperson of the BOD is 41%, which is lower than the portion in Hashad (2023) which is 55.4%. Finally, BIG4 variable indicates that around 34.8 % of the study sample is being audited by a big 4 firm. Which is close to Hidayat & Setiyawati (2022) with 42.6% audited by a big 4 firm.

7. ANN model procedures

This section consists of two stages. Stage one illustrates screening out the most important factors that can be used in predicting GCO. in addition, ANN IS used to establish the prediction model.

7.1 Stage one: screen out the most important variables (ANN).

This study adopts ANN to screen out the more important variables. It uses a total of 61 listed companies, 30 research variables, 4 years of data (2018-2021), totaling 244 observations. Of the 244 observations, 183 (75%) were used to train the network, 61 (25%) were used to test the network. The NN model is set as follow:

Input layer: it refers to the first layer of nodes in ANN that receives the input data and passes it directly to the first hidden layer. It consists of 30 input variables. **Hidden layer:** Consists of 2 hidden layers. The 1st hidden layer contains 4 neurons whereas the 2nd hidden layer contains 3 neurons. **Output layer:** The output layer generates post-processing prediction results. It contains two output levels (0/1) that represent the predicted auditor GCO.

Figure (2) presents an ANN where the input layer is connected to the hidden layers via weights. Each weight represents the strength of the connection between the two nodes it connects.

Table (4) presents the ANN classification results for the learning and testing samples. The accuracy of classification of

class1 was higher than the accuracy of class 2 for both the training (n = 128 out of 133 or 96.2%) and testing subsamples (n= 38 out of 39 or 97.4%). The accuracy of classification of class 2 for the training subsample was 51.8 % (n = 29 out of 50 or 58%) and the accuracy level of the testing subsample (n = 11 out of 22 or 50%). The overall accuracy of classification in the learning and testing samples was 85.8% and 80.3%. Overall, the network had a fairly high accuracy, evidenced by the percentage of incorrect classifications in the training and testing stages which were about 14% and 20% respectively.

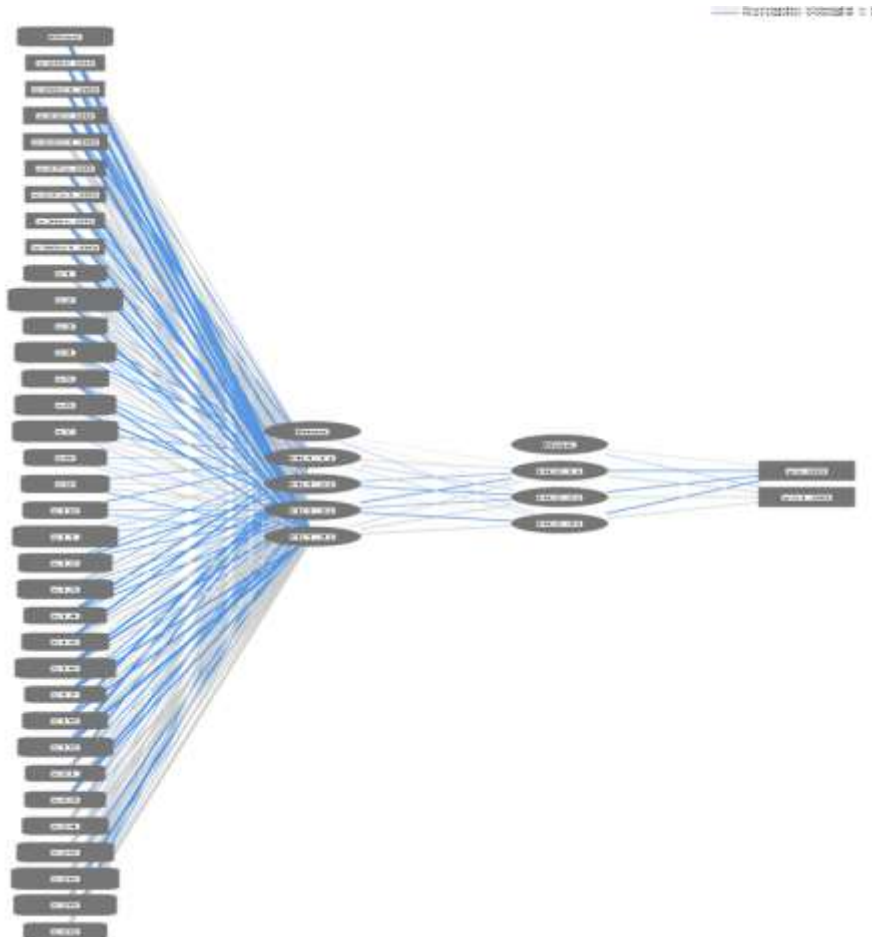


Figure (2): An artificial neural network with three layers, 30 inputs (X1, X2,...,x30), three bias terms, and two outputs (Y1 & Y2).

Table (4): ANN classification results for the training and testing subsamples-step1

Classification					
Sample	Observed	No. of cases	Predicted		
			.00	1.00	Percent Correct
Training	Class 1 (.00)	133	128	5	96.2%
	Class2 (1.00)	50	21	29	58%
	Overall	183	149	34	85.8%
Testing	Class1 (.00)	39	38	1	97.4%
	Class2 (1.00)	22	11	11	50%
	Overall	61	49	12	80.3%

Finally, the Normalized Importance Index was estimated for the input variables. Table (5) presents the 30 variables which influenced the auditor opinion regarding GCO.

Table (5): The ANN-estimated variable importance

Variables	Importance	Normalized Importance
Current ratio	0.015	15.9%
Current assets to total assets(CATA)	0.092	100.0%
Operating cash flow ratio	0.019	20.4%
Profit ratio	0.059	64.4%
Operating cash flow	0.024	26.5%
Sales revenue growth rate	0.059	64.3%
Return on Assets (ROA)	0.069	74.6%
Inventory/total assets	0.015	15.8%
Inventory turnover	0.027	29.5%
Total assets turnover	0.019	20.5%
Current liabilities/ total assets	0.068	74.1%
Debt ratio	0.040	43.7%
Debt-to equity ratio	0.046	49.7%
Firm size	0.014	15.4%
Firm age	0.025	26.9%
Managerial ownership	0.057	61.8%
Family ownership	0.011	11.7%
Foreign ownership	0.020	21.5%
BOD independence	0.045	48.5%
Duality	0.005	5.6%
No. of meeting	0.007	7.3%
Board of director, gender	0.016	17.7%
Gender2	0.011	11.4%
Board size	0.022	24.3%
Conservatism	0.048	52.3%
Predictive ability of earnings	0.074	80.5%
Change audit firm	0.009	10.1%
Audit lag	0.062	67.5%
Audit lag2	0.015	16.0%
Audited by big 4 or not	0.004	4.6%

Total of 9 variables were selected based on their importance value (importance value ≥ 0.05) (Chen, 2019). The order of the importance of the variables is CATA, Predictive ability of earnings, Return on assets, Current liabilities/ total assets, Audit lag, Profit ratio, Sales revenue growth rate, Managerial ownership, and conservatism. Table (6) illustrates the screened variables with their importance.

Table (6): ANN- selection results

Independent Variable Importance			
NO.	Variable	Importance	Normalized Importance
x2	CATA	0.092	100.0%
X26	Predictive ability of earnings	0.074	80.5%
x7	Return on assets	0.069	74.6%
x11	Current liabilities/ total assets	0.068	74.1%
x28	Audit lag	0.062	67.5%
x4	Profit ratio	0.059	64.4%
x6	Sales revenue growth rate	0.059	64.3%
x16	Managerial ownership	0.057	61.8%
X25	Conservatism	0.048	52.3%

It is accepted that liquidity management is very important for financial management, as control over liquidity can ensure the running of a firm's business. CATA ratio reflects both liquidity and profitability. A higher investment in current assets may indicate higher liquidity and decrease profitability.

Therefore, CATA ratio is very important as it is a very important ratio that can be used in determining the optimal level of current assets that should be maintained. This interpretation is consistent with the findings of prior studies such as (Averio, 2021; Fernández, et al., 2018). The prior studies suggested that liquidity has a negative effect on receiving a going concern opinion, while the study of (Masyitoh & Ardhariana, 2010; Arum, et al., 2022; Anggarini & Zulfikar, 2022) indicated that liquidity has no effect on receiving a going concern opinion.

Auditors are less likely to issue GCO when firms are more profitable. Return on assets is a very important ratio auditors

can rely on as it indicates how much profit a company is able to generate from its assets and auditors can evaluate management's ability to generate earnings from economic resources. Moreover, profit ratio and sales revenue growth rate are considered meaningful. Profit ratio measures the operating efficiency, whereas sales revenue growth rate indicates the increase or decrease in a company's sales between periods (growth/ shrunk). These results support the results of Hasanuddin et al. (2019) who stated that company growth has a positive effect on GC audit opinion.

The leverage ratios show the extent of the use of debt in financing a company. If the leverage ratio is too high, it may indicate that the company has used up its borrowing capacity and the source of funding is mainly from loans. If it is too low, it means that available leverage is not used to maximize the owner's benefit. Therefore, it's a very important indicator for auditors to understand the financial structure of the company and understand the company's ability to repay its loans. This interpretation is consistent with the results of (Ibrahim et al. 2023; Averio , 2021).

Earning information is one of the major and important items of the financial statements and is often used as the measurement of company performance (Pagalung & Sudibyo, 2012). Earnings quality can be defined through specific attributes of earnings such as predictability and conservatism. (Dechow et al., 2010). The predictive ability of accounting profits is one of the measures of sustainability of accounting profits that helps to rationalize stakeholders' Decisions. Therefore, high quality accounting profit reflects a stable financial ability now and in the future this interpretation is consistent with Ali, et al. (2019).

Financial information must be disclosed as early as possible to be used as a basis for decision making and avoid delays in decision making (Mukhtarudin et al., 2018). Therefore, the longer the audit report lag, the more likely the company face

problems and receive GCO. This result was not consistent with the results of Meidawati & Dwitama (2023), which proved that audit lag has no influence on the issuance of GCO.

7.2 Stage two: Models of ANN

The study initially tested an ANN with two hidden layers. It achieved excellent classification accuracy and precision in both the learning and testing subsamples. Total of 9 variables are selected based on their importance value (importance value ≥ 0.05). Figure (3) presents the 2nd ANN which is set as follows Input layer refers to the first layer of nodes in ANN that receives the input data and passes it directly to the first hidden layer. It consists of nine input variables. Hidden layers Consist of two hidden layers. The 1st hidden layer contains seven neurons whereas the 2nd hidden layer contains five neurons. The output layer generates post-processing prediction results. It contains two output levels (0/1) that represent the predicted auditor GCO. Appendix 1 gives the weight indices of the input and output variables. Unlike the β coefficients of the regression models.

The ANN classification results for the training and testing subsamples were summarized in table (7).

Table (7): ANN classification results for the training and testing subsamples-step2

Classification					
Sample	Observed	No. of cases	Predicted		
			.00	1.00	Percent Correct
Training	Class 1 (.00) No	133	131	2	98.5%
	Class2 (1.00) Yes	50	31	19	38%
	Overall	183	162	21	82%
Testing	Class1 (.00)	39	39	0	100%
	Class2 (1.00)	22	14	8	36.4%
	Overall	61	53	8	77%

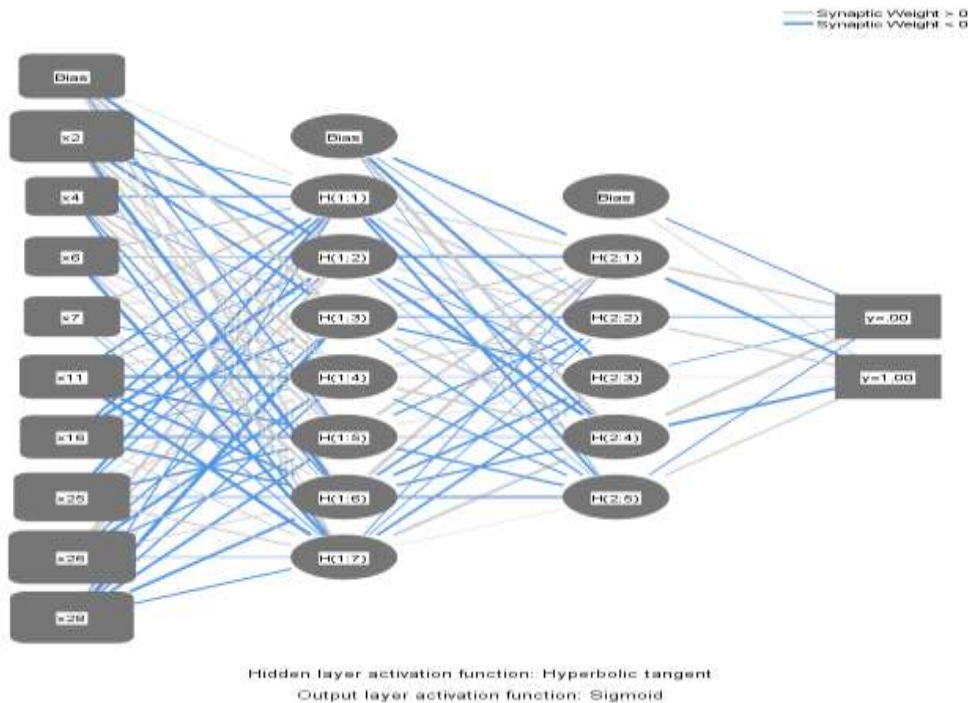


Figure (3): ANN of the most important variables

The accuracy of classification of class1 was higher than the accuracy of class 2 for both the training (n = 131 out of 133 or 98.5%) and testing subsamples (n = 39 out of 39 or 100%). The accuracy of classification of class 2 for the training subsample was 51 % (n = 19 out of 50 or 38%) and the accuracy level of the testing subsample (n = 8 out of 22 or 36.4%). The overall accuracy of classification in the learning and testing samples was 82% and 77% respectively. Overall, the network had a fairly high accuracy, evidenced by the percentage of incorrect classifications in the training and testing stages which were about 18% and 23% respectively.

8. Testing Hypotheses and Results Discussion

In this section, the findings of testing hypotheses and results discussion are presented.

8.1 Testing the Accuracy of ANN Model

After the training process of the neural network model, the testing set is used to evaluate the model's accuracy. The study uses new data to evaluate the model and sees how accurate it is. The predicted results of 61 observations (61 different companies in 7 sectors in the same year) are compared with the actual values to determine the accuracy of ANN model. The study tests the hypothesis which is concerned with **“There is no significant accuracy of the proposed ANN model to predict GCO”** through the comparison between the predicted results of 61 observation and the actual values.

The research depended on contingency table of the observed and predicted observation to determine how accurate the ANN model is in predicting GCO. The analytical results were illustrated in table (8) as follows:

Table (8): Results of assessing the accuracy of predicting GCO using ANN.

Measurements to assess the accuracy of predicting GCO		
Chi square tests	Test Statistics	p-value
Pearson Chi square	16.322	0.000
Continuity Correction	13.287	0.000
Likelihood Ratio	18.563	0.000

Pearson's chi-square test examines whether there is an association between two categorical variables. It tests whether the two variables are independent. If the significance value is small enough (conventionally Sig. must be less than .05) then the null hypothesis will be rejected that the variables are independent and gain confidence in the hypothesis that they are in some way related.

Table (9) illustrates the chi-square value of the ANN model, which indicates the overall fit of the model, and a higher value suggests a better fit between the predicted values and the actual values of the dependent variable. In this case, the chi-square value of 16.322 with 1 degree of freedom, the two-tailed

P value is less than 0.0001. Therefore, the association between predicted and observed in testing set is statistically significant.

For testing whether the research variables follow the normal distribution, Kolmogorov-Smirnov and Shapiro-Wilk tests were used to determine if the distribution of the research variables complied with the normal distribution or not. When the test is non-significant ($p > 0.05$), it means that the distribution of the sample is not significantly different from a normal distribution (it is probably normal) and significance ($P < 0.05$) indicates a deviation from normality.

Table (9) illustrates that the p-value for the test statistics in Kolmogorov-Smirnov test and Shapiro-Wilk test are less than 0.05, therefore the data doesn't follow the normal distribution.

Table (9): Normality test

Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df.	Sig.	Statistic	df.	Sig.
Y	0.411	61	0.000	0.608	61	0.000
Predicted Value for y	0.519	61	0.000	0.398	61	0.000

Moreover, the study attempts to examine that there is no difference between the actual and predicted opinion using Wilcoxon Signed Ranks Test statistic as the assumption of normality is not met. The logic behind the Wilcoxon test is that there is no difference between the actual and predicted opinion by ANN. Look at the row labelled Asymp. Sig. (2-tailed). If the value is less than .05 then the two groups are significantly different. Table (10) illustrates the result of Wilcoxon test.

Table (10): Wilcoxon Signed Ranks Test

Wilcoxon Signed Ranks Test statistic	-1.414
Asymp. Sig. (2-tailed)	0.157

The value of Asymp. Sig. (2-tailed) equal (0.157) which is more than 0.05. Therefore, there is no difference between actual and predicted opinion by ANN. As a result of the

research findings, there is a strong indication to reject the first research hypothesis which indicates that “There is no significant accuracy of the proposed ANN model to predict GCO”. This is because the study proves that ANN can be used in predicting GCO with high accuracy.

9. Conclusion

The conclusion of the study can be summarized as follows:

The consequences of several corporate scandals (Enron 2001, WorldCom 2002, Arthur Andersen, XEROX, and others) alerted the attention on the quality of financial reporting. It generates a growing tide of criticism on auditors' role and behavior due to their collusion with managers. Therefore, the issue of whether a firm has going concern doubt attracts attention. The study explores the most important factors (financial and non-financial variables/related to auditor – auditee, and EQ) that may affect predicting going concern uncertainties. Researcher found from the theoretical study of auditing profession that this environment is very typical for ANN to be used in. As auditing profession needs expertise and quickly response decisions with professional judgments in many points during the auditing process especially for predicting going concern uncertainties. The purpose of this study is to construct effective GCO prediction models using ANN and logistic regression.

Sampling is taken from 4 years of data (from 2018 to 2021). The study adopts two stages to construct going concern prediction models. In the first stage, ANN is used to screen out the most important variables. In the second stage, a proposed model is constructed for predicting going concern uncertainties. The ANN model consists of 9 input variables, 2 hidden layers, and 2 neurons in the output layer. The 1st hidden layer contains 7 neurons whereas the 2nd hidden layer contains 5 neurons. The output layer generates post-processing prediction results. It contains two output levels (0/1). The overall accuracy of

classification in the learning and testing samples were 82% and 77%, respectively. Overall, the network had a high accuracy, evidenced by the percentage of incorrect classifications in the training and testing stages which were about 18% and 23% respectively.

The study rejects the hypothesis and proves that ANN can be used in predicting GCO with high accuracy. The research depended on contingency table to test the accuracy of ANN model through comparing the predicted results of 61 observations with the actual values. The significant value is 0.000 which is less than (.05). It gains confidence that the variables are independent and, in some way, related. Moreover, behind that, the Wilcoxon test is used to ensure that there is no difference between the actual and predicted opinion by ANN. Result indicate that the p-value equal (0.157) which is more than 0.05, which point out that the two groups aren't different.

10. Recommendation

As stated in the previous sections that the ANN prediction model is accurate in predicting GCO. This study has some limitations. Overcoming these limitations will be an opportunity for future researches.

10.1 Study Limitation

This study is only concerned with predicting GCO. Sample will be selected based on certain conditions mentioned in sample selection and data collection method section. In addition, predictive ability of earnings and conservatism are used as a proxy for measuring Earnings quality. Board of director characteristics and ownership structure are used as a proxy for governance.

10.2 Suggestions for Future Researches

Based on the study limitations, many thoughts for the future study can be as follows:

- 1- In depth assessment: use larger study sample to include financial institutions and help auditors in predicting GCO in this sector.
- 2- Compare the accuracy of ANN and the traditional regression model in predicting GCO.
- 3- Further studies that may apply another models and techniques in assessing going concern uncertainties.
- 4- Subsequent research can consider the effect of other variables that don't exist in the current study such as opinion shopping, implementation of management strategies, governance mechanisms other than board of directors and ownership structures, and implementation of management strategies.

References

- Abd-El-Rhim, R. (2020). The modification in the form and the content of the auditor's report according to revised ISA 570 about going concern on investment and credit granting decision in Egypt: an experimental study, **Alexandria Journal of Accounting Research**, Vol. 4, No. 2, pp. 1-94.
- Abdullah, M. (2021), "The implication of machine learning for financial solvency prediction: an empirical analysis on public listed companies of Bangladesh", **Journal of Asian Business and Economic Studies**, Vol. 28, No. 4, pp. 303-320. <https://doi.org/10.1108/JABES-11-2020-0128>.
- Ahmed, A. (2023). The Impact of The Characteristics of The Board of Directors on The Volatility of Stock Returns and Its Reflection on The Going Concern of The Companies in The Light of The Russian Ukrainian Crisis: An Applied Study, **Alexandria Journal of Accounting Research**, Vol.7, No. 1, pp. 517-600.
- Akinrinola, O., Afua Addy, W., Ajayi-Nifise, A., Odeyemi, O., and Falaiye, T. (2024). Predicting stock market movements using neural networks: A review and application study, **GSC Advanced Research and Reviews**, Vol.18, No. 2, pp. 297–311.
- Ali, G. (2021). The Predictive Role of Auditor Going Concern Opinion and Auditor Characteristics in Corporate Bankruptcy: Evidence From Firms Listed on the Egyptian Stock Exchange, **Alexandria Journal of Accounting Research**, Vol.5, No.2, pp.1-33.
- Ali, M., Almagtome, A., Hameedi, K. (2019). Impact of Accounting Earnings Quality on the Going Concern in the Iraqi Tourism Firms, **African Journal of Hospitality, Tourism and Leisure**, Vol.8, No. 5, pp.1-19.
- Almaleeh, N. (2022). Audit committee characteristics and accounting conservatism: An empirical investigation, *Scientific Journal for Financial and Commercial Studies and Research*, Faculty of Commerce, Damietta University, Vol3, No. 1, pp. 1-33.
- Altawalbeh, M. A., & Alroud, L. (2023). Going Concern Audit Opinion and Market's Reaction, **International Journal of Academic Research in Accounting Finance and Management Sciences**, Vol.13, No.2, pp. 650– 664

- Altman, E. (1968). Financial ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, **Journal of Finance**, Vol. 23, No.4, pp. 589-609.
- Andriana, T. , Handokob, B. , Wijaya, Z. (2019). The Acceptance of Going Concern: Does Audit Opinion Matter?, **International Journal of Innovation, Creativity and Change**, Vol. 9, No. 10, pp. 1-13.
- Anggarini, D & Zulfikar, Z. (2022). Factors Affecting Audit Opinion Going Concern, *Advances in Economics, Business and Management Research*, Vol, 218, pp. 8-14.
- Arens, A., Elder, R., & Beasley, M. (2014). **Auditing and Assurance Services: An Integrated Approach**, Global Edition, Pearson, England.
- Arum, G., Hastuti, A., Suprayitno, A. (2022). Effect of Financial Performance on Going Concern Audit Opinion, **International Journal of Research in Social Science and Humanities (IJRSS)**, Vol. 3, No. 8, pp. 36-45.
- Aryadoust, V. & Goh, C. (2014). Predicting Listening Item Difficulty with Language Complexity Measures: A Comparative Data Mining Study, **CaMLA Working Papers** 2014- 02, www.CambridgeMichigan.org
- Averio, T. (2021). The Analysis of Influencing Factors on the Going Concern Audit Opinion- A Study in Manufacturing Firms in Indonesia, **Asian Journal of Accounting Research**, Vol 6, No. 2. available at: <https://doi.org/10.1108/AJAR-09-2020-0078>
- Azarova, A., Azarova, L., Nikiforova, L., Azarova, V., Teplova, O., Kryvinska, N. (2020). Neural Network Technologies of Investment Risk Estimation Taking into Account the Legislative Aspect, **CEUR Workshop Proceedings**, pp. 308–323. <http://ceur-ws.org/Vol2805/paper23.pdf>
- Barr-Pulliam, D., Calvin, C., Eulerich, M., & Maghakyan, A. (2024). Audit evidence, technology, and judgement: A review of the literature in response to ED-500. **Journal of International Financial Management & Accounting**, 35, 36–67. <https://doi.org/10.1111/jifm.12192>
- Bellovary, J., Giacomino, D., Akers, M. (2007). A Review of Going Concern Prediction Studies: 1976 To Present, **Journal of Business & Economics Research**, Vol., No. 5, pp. 9-28.
- Berglund, N., Eshleman, J., Guo, P. (2018). Auditor Size and Going Concern Reporting, *Auditing: A Journal of Practice*, Vol. 37, No. 2, pp. 1-25.

- Blay, A., and Geiger, M. (2013). Auditor Fees and Auditor Independence: Evidence from Going Reporting Decision, **Contemporary Accountig Research**, Vol. 30, No. 2, pp. 579-606.
- Caldeiraa, A., Gassenferthb, W., Machadoc, M. & Santosd, D. (2015). Auditing Vehicles Claims using Neural Networks, **Procedia Computer Science**, Vol. 55, pp. 62 – 71.
- Carlino, C. (2020). The Role of Auditors to Improve Sustainability in Financial Reporting, Accountability, **Ethics and Sustainability of Organizations**, pp.111-129: Springer
- Carson, E., Fargher, N., Geiger, M., Lennox, C. (2013). Audit Reporting for Going-concern Uncertainty: A Research Synthesis, **Auditing: A Journal of practice & Theory**, Vol. 32, No.1, pp. 353-384.
- Chen, S. (2019). An Effective Going Concern Prediction Model for the Sustainability of Enterprises and Capital Market Development, **Applied Economics**, Vol. 51, No. 31 <https://doi.org/10.1080/00036846.20191578855>
- Chen. F., Chi. D., & Wang, Y., (2015). Detecting Biotechnology Industry's Earnings Management using Bayesian Network, Principal Component Analysis, Back Propagation Neural Network, an Decision Tree. **Economic modelling**, Vol. 23, pp.461-510.
- Dechow, P., Ge, W., Schrand, C. (2010). Understanding Earnings Quality: A Review of the Proxies, Their Determinants and Their Consequences, **Journal of Accounting and Economics**, Vol. 50, PP 344-401
- Defond, M., Zhang, J. (2014). A Review of Archival Auditing Research, **Journal of Accounting and Economics**, Vol, 58, No. 2, pp. 275-326.
- Dewi, O., Dewi., P. (2017). Corporate Social Responsibility, Green Banking, and Going Concern on Banking Company in Indonesia Stock Exchange, **International Journal of Social Sciences and Humanities**, Vol. 1, No. 3, pp. 118-134.
- Effiong, S., & Ekpoese, J. (2020) Firms' Characteristics and Going Concern Status: A Diagnostic Spectrum Analysis, **Journal of Critical Reviews**, Vol. 7, No. 11, pp. 4591-4600
- El-Gawad, S. (2023). The Effect of Using Machine Learning Algorithms Alternatives on the Prediction Accuracy of Going Concern Opinion, **Scientific Journal, Financial and Administrative Research**, Sadat University, Special Issue.

- Elmarzouky, M., Hussainey, K., Abdelfattah, T. and Karim, A.E. (2022). Corporate risk disclosure and key audit matters: the egocentric theory, **International Journal of Accounting & Information Management**, Vol. 30, No. 2, pp. 230-251. <https://doi.org/10.1108/IJAIM-10-2021-0213>
- El-sayed, M. s. (2012). **A Sugested Model to Predict of the Fair Value of Option Contracts in Terms of the Accounting Standards: An Application Study on Egyptian Commercial Banks**, PHD Thesis, Menoufia University.
- Elsayed, M., Elgendy, k., Eid, E. (2023). The Impact of Corporate Governance Quality and Operating Cash Flow on Capital Structure Adjustment Speed: An Empirical Study, Vol. 43, No. 1, pp. 52-104.
- Elsayed, M., Srour, A. and Elsayed, M. (2023). How Does Gender Diversity Moderate the Relationship between Income Smoothing and Stock Liquidity? Evidence from Egypt, **Scientific Journal for Financial and Commercial Studies and Research**, Faculty of Commerce, Damietta University, Vol. 4, No. 2, pp.717- 743.
- Etheridge, H., Sriram R., & Kathy-Hsu, H. (2000). A Comparison of Selected artificial neural Networks That Help Auditors Evaluate Client Financial Viability. **Decision Sciences**, Vol. 31, No. 2, pp. 531-549.
- Fernández, M., Sánchez, J., Alaminos, D., & Casado, G. 2018. Predicting Going Concern Opinion for Hotels Industry Using Classifiers Combination. **International Journal of Scientific Management and Tourism**, Vol. 4, pp. 91–106.
- Foster, B., Shastri, T. (2016). Determinants of Going Concern Opinions and Audit Fees for Development Stage Enterprises, **Advances in Accounting, Incorporating Advances in International Accounting**, Vol. 33, pp. 68-84.
- Gabra, S. (2018). Ownership Structure and Going-Concern of Listed Nigerian Financial Institution: The Moderating Effect of Audit Committee's Characteristics, Ph. D Thesis, Utara Malaysia University.
- Gallizo, J., and Saladrighes, J. (2016). An Analysis of Determinants of Going Concern Audit Opinion: Evidence from Spain Stock Exchange, **Intangible Capital**, Vol. 12, No. 1, pp. 1-16. <http://dx.doi.org/10.3926/ic.683>
- Geiger, M. A., Gold, A., & Wallage, P. (2019). A Synthesis of Research on Auditor Reporting on Going-Concern Uncertainty: An Update and Extension. FAR Report.

- Gkouma O, Filos, J., and Chytis, E. (2018). Financial crisis and corporate failure: The going concern assumption Findings from Athens stock exchange, **Journal of Risk & Control**, Vol. 5, No.1, pp. 141-170
- Goo, Y., Chi, D. and Shen, Z. (2016). Improving the prediction of going concern of Taiwanese listed companies using a hybrid of LASSO with data mining techniques, **SpringerPlus**, Vol.5, No.539, pp. 1-18
- Guilhoto, L. (2018). An Overview of Artificial Neural Networks for Mathematicians, **Mathematics, Computer Science**
- Guo, Y., Delaney, D., & Ahmed, A. (2020). Is an auditor's propensity to issue going concern opinions a valid measure of audit quality? **Australian Accounting Review**, Vol. 30, No. 2, pp.144- 153. <https://doi.org/10.1111/auar.12300>
- Gupta, A., Akinola, S. Salau, A., Nwulu, N., Chaturvedi, P. (2019). Artificial Neural Networks: Its Techniques and Applications to Forecasting, **International Conference on Automation, Computational and Technology Management (ICACTM)**, Amity University, pp.320-324.
- Haga, J., Siekkinen, J., Sundvik, D. (2014). A Neural Network Approach to Measure Real Activities Manipulation, **Expert system with applications**.
- Hashad, T. (2023). The Impact of the Board Characteristics on Sustainability Performance Disclosure and Its Reflection on the Firm Value: An Applied Study on Companies Included in the S&P/EGX ESG Index, **Alexandria Journal of Accounting Research**, Vol.7, No. 2, pp. 125-221.
- Hidayat, A. H., & Setiyawati, H. (2022). Impact of Pandemic Financial Crisis to the Going Concern Audit Opinion Factors. **Advances in Social Sciences Research Journal**, Vol. 9, No.5, pp. 147-158.
- Hoglund, H. (2010). **Detecting Earnings Management Using Neural Networks, PHD. Thesis**, Hanken School of Economics, Department of Accounting and Commercial Law, Vassa, Finland.
- Ibrahim, M. and Yahaya, O. (2023). Do Board Characteristics Matter for Growth Firms, **Australasian Accounting Business and Finance Journal (AABFJ)**, Vol. 17, No.4, pp. 239-258
- Ibrahim, M.; Azzam, M. and Elbasuony, H. (2023). The Impact of Earnings Quality on the Corporate Financial Distress: Empirical Evidence from Egypt, **Scientific Journal for Financial and Commercial Studies and Research**, Faculty of Commerce, Damietta University, Vol.4, No. 1, pp. 37- 67.

- Ishak, S. (2016). Going-Concern Audit Report: The Role of Audit Committee, **International Journal of Economics and Financial issues**, Vol. 6, No. 56, pp. 36-39.
- Islami, A., Mukhtaruddin, Dewi, K. , Nurullah,A. (2022). Audit Going Concern Opinion: The Effect of Company Growth, Audit Tenure and Audit Delay as Moderating Variable, **AKUNTABILITAS**, Vol.16, No.2, 2022.
- Ittonen, K., Tronnes, P., Wong, L. (2017). Substantial Doubt and the Entropy of Auditors' Going Concern Modifications, **Journal of Contemporary Accounting & Economics**, Vol. 13, pp. 134-147.
- Junaidi, J., Triyatmi, c.s. & Nurdiono, N. (2012). Financial and Non-Financial Factors on Going-Concern Opinion. **The Winners**, Vol. 13, No. 2, pp. 135-146
- Kausar, A., & Lennox, C. (2017). Balance Sheet Conservatism and Audit Reporting Consevatism, **Journal of Business Finance & Accounting**, Vol. 44, No. 7, pp. 1-50.
- Kida, T. (1980). An Investigation into Auditors' Continuity and Related Qualification Judgements, **Journal of Accounting Research**, Vol. 18, No. 2, pp. 506-523.
- Koh, H., and Low, C. (2004). Going Concern Prediction using Data Mining Techniques, **Managerial Auditing Journal**, Vol. 19, No.3, pp. 462-476.
- Koskivaara, E. (2004). Artificial Neural Networks in Analytical Review Procedures. **Managerial Auditing Journal**, Vol. 19, No.2, pp. 191-223.
- KPMG. (2020). Guidance on Going Concern Assessment amid COVID-19, available at: https://assets.kpmg/content/dam/kpmg/in/pdf/2020/05/guidance-on-going-concern-assessment-amid-covid-19.pdf?fbclid=IwAR0t-8_jKr2y9ePBiPqnRSPspfUlu9gD9VToMrq5MVUdINEhfNLalHk8toc
- Kumar, K. & Bhattacharya, S. (2006). Artificial Neural Network vs. Linear Discriminant Analysis in Credit Ratings Forecast: A Comparative Study of Prediction Performances. **Review of Accounting & Finance**, Vol. 5, No. 3, pp. 198-216.
- Kusumaningrum, F., Astuti, S. and Sutoyo, S. (2022). The Effect of Firm Age, Profitability, Audit Opinion, and Solvency on Audit Report Lag Empirical Studies: Non-Financial and Banking Sector Companies, **Journal of International Conference Proceedings**, Vol. 5, No. 5

- Laitinen, E. K., & Laitinen, T. (2020). Why does an auditor not issue a going concern opinion for a failing company? Impact of financial risk, time to bankruptcy, and cognitive style, **Theoretical Economics Letters**, Vol. 10, No.1, pp. 131–153.
- Li, J. & Sun, Z. (2023). Application of Deep Learning in Recognition of Accrued Earnings Management, **Heliyon**, Vol.9, pp.1-11, <https://doi.org/10.1016/j.heliyon.2023.e13664>
- Li, Q, Wei Z., Hui, Z., and Jiaxuan, C. (2021). Do Board Characteristics Matter for Growth Firms? Evidence from China. **Journal of Risk and Financial Management**, Vol.14, No. 380, pp.1-9. <https://doi.org/10.3390/jrfm14080380>.
- Liu, W., Wei, Z., & Xie, F. (2014). Do Women Directors Improve Firm Performance in China? *Journal of Corporate Finance*, Vol. 28, pp. 169-184. [10.1016/j.jcorpfin.2013.11.016](https://doi.org/10.1016/j.jcorpfin.2013.11.016)
- Mahmoudi, S., Mahmoudi, S., Mahmoudi, A. (2017). Prediction of Earnings Management by Use of Multilayer Perceptron Neural Network with two Hidden Layers in Various Industries, **Journal of Entrepreneurship, Business and Economics**, Vol.5, No. 1, pp. 216-236.
- Makhlouf, M., AL-sufy, F. (2018). Ownership Concentration and Going Concern: Evidence from Jordanian Listed Firms, **International Journal of Business and Management**, Vol, 13, No. 9, pp. 139-147
- Mao, X., Liu, M., Wang, Y., (2022). Using GNN to detect financial fraud based on the related party transactions network, **Procedia Computer Science**, Vol. 214, pp. 351-358, <https://doi.org/10.1016/j.procs.2022.11.185>.
- Masyitoh, O. & Ardhariana, D. (2010). The Analysis of Determinants of Going Concern Audit Report, **Journal of Modern Accounting and Auditing**, Vol. 6, No. 1, pp. 26-37.
- Meidawati, N. & Dwitama, D. (2023). Determinants of going-concern audit opinion, **International Journal of Research in Business & Social Science**, Vol.12, No. 7, pp. 345-357
- Mirzzaey, M., Jamshidi M., & Hojatpour, Y. (2017). Application of Artificial Neural Networks in Information System of Management Accounting. **International Journal of Mechatronics, Electrical and Computer Technology**, Vol. 7, No. 2, pp. 3523-3530.
- Mukhtarudin, M., Pratama, H., Meutia, I. (2018). Financial Condition, Growth, Audit Quality and Going Concern opinion: Study on Manufacturing

- Companies Listed on Indonesia Stock Exchange, **Journal of Accounting, Business and Finance**, Vol. 2, No. 1, pp. 16-25.
- Munsif, V., Raghunandan, K. & Rama, D. (2012). Internal Control Reporting and Audit Report Lags: Further Evidence. **Auditing: A Journal of Practice & Theory**. Vol. 31, pp. 203-218.
- Pardo, M., Llobet, E., Iliescu, D., & Yang, J., 2008. Intelligent Systems: Techniques and Applications.
- Pourheydari, O. & Azami, Z (2010). Identification of the Type of Comments put by Auditors using Neural Networks. **Accounting Knowledge**, Vol. 3, pp. 77-79.
- Proho, M. (2023). Going Concern Assessment: A Literature Review, **Journal of Forensic Accounting Profession**, Vol.3, No.2, pp.48- 62.
- Provasi, R., Riva, P. (2015). Assessment of Going Concern for the Italian Listed Companies: An Empirical Study, **Review of Business and Finance Studies**, Vol. 6, No.1, pp. 27-34.
- Qamar, R. & Zardari, B. (2023). Artificial Neural Networks: An Overview, **Mesopotamian journal of Computer Science**, Vol. 2023, pp. 130–139
- Rai, R. (2006). Choosing Risky Portfolio using Neural Networks. **Investigations in Accounting and Auditing**, Vol. 46, pp. 71-83.
- Sinai, H., Mortazavi, S., & Teymouri (2005). Predicting the Indicators in TSE using Artificial Neural Networks. **Investigations in Accounting and Auditing**, Vol. 41, pp.59-83.
- Suryani, I., Yuniarti, R., & Syahrudin, M. (2023). Effect of Financial Distress, liquidity, and Leverage on the Audit Opinion Going Concern on companies listed on IDXESGL During the Pandemic Period (2019-2021), **International Journal of Business, Economics and Social Development**, Vol. 4, No. 1, pp. 1-11.
- Triani, N. (2017). Determining the Effectiveness of Going Concern Audit Opinion by ISA 570, **Asian Journal of Accounting Research**, Vol.2, pp.29-35.
- Tsai, C., Chiou, Y.J., (2009) Earnings Management Prediction: A Pilot Study of Combining Neural Networks and Decision Trees. **Expert Systems with Applications**, Vol. 36, pp. 7138-7191.
- Vaez, S., Banafi, M., (2017). Prediction of Related Party Transactions Using Artificial Neural Network, **International Journal of Economics and Financial Issues**, Vol. 7, No. 4, pp. 207-213.

- Wahdan, M. (2006), **Automatic Formulation of the Auditor's Opinion**, PHD. Thesis, Maastricht University, Maastricht, The Netherland.
- Wahdan, M., (2019). "Evaluating the Impact of Joint Audit on Accounting Conservatism in the Light of the Auditor Industry Specialization: An Applied Study", *Scientific Journal of Trade searches*, Menoufia University, 34(3), PP.9- 96.
- Wang Q., (2007). Artificial Neural Network as Cost Engineering methods in Collaborative Manufacturing Environment. **International Journal of Production Economics**, Vol. 109, pp. 53-64
- Yulfa, D., Fitriany, F. (2018). Impact of Going-Concern Audit Opinion on Cost of Equity with Institutional Ownership as Moderation, **Advances in Social Science, Education and Humanities Research**, Vol. 348, pp. 145-152.
- Zdolšek, D., Jagrič T. & Kolar, I. (2022). Auditor's going-concern opinion prediction: the case of Slovenia, **Economic Research-Ekonomska Istraživanja**, Vol.35, No.1, pp.106-121.
- Zouaoui, H., Nadjat Naas, M. (2023). Option pricing using deep learning approach based on LSTM-GRU neural networks: Case of London stock exchange, **Data Science in Finance and Economics**, Vol. 3, No. 3, pp. 267–284.
- Zureigat, Q. M. (2015). Determinants of mandatory corporate governance: Evidence from an emerging market. **The International Journal of Business and Finance Research**, 9(3), 105–114. Hammond et al., *Cogent Business & Management* (2023), 10: 2234152 <https://doi.org/10.1080/23311975.2023.2234152> Page 27 of 27.

Appendix 1

Parameter Estimates															
Predictor		Predicted													
		Hidden Layer 1							Hidden Layer 2					Output Layer	
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (2:1)	H (2:2)	H (2:3)	H (2:4)	H (2:5)	[y=0]	[y=1]
Input Layer	Bias	0.023	-0.814	0.906	0.096	-0.171	0.232	0.044							
	x2	-0.287	-0.839	-0.550	0.361	0.297	-0.794	0.244							
	x4	-0.306	0.019	-0.100	0.346	0.316	-0.204	-0.298							
	x6	-0.080	-0.089	0.065	-0.035	0.038	0.350	-0.542							
	x7	0.385	0.094	0.094	-0.209	0.114	0.162	-0.072							
	x11	-0.363	-0.135	0.191	-0.984	-0.969	-0.692	-1.185							
	x16	-0.315	-0.945	-0.538	-0.089	-0.418	-0.780	0.163							
	x25	-0.394	-0.196	0.035	0.207	-0.610	-0.111	0.301							
	x26	0.391	0.285	-0.226	-0.527	-0.306	0.138	-0.055							
	x28	-0.123	0.019	-1.062	-0.239	-0.454	-0.783	-0.339							
Hidden Layer 1	(Bias)								-0.528	-0.055	-0.649	0.877	-0.013		
	H (1:1)								0.272	0.364	-0.008	-0.525	-0.349		
	H (1:2)								-0.487	0.271	-0.182	-1.090	-0.004		
	H (1:3)								0.460	-0.213	-0.497	0.763	-0.290		
	H (1:4)								-0.027	0.300	0.234	0.697	-0.291		
	H (1:5)								0.516	-0.329	0.030	-0.051	-0.450		
	H (1:6)								0.836	-0.378	-0.555	-0.512	-0.384		
	H (1:7)								-0.081	-0.066	-0.378	0.939	0.003		
Hidden Layer 2	(Bias)													-0.239	0.068
	H (2:1)													0.697	-0.833
	H (2:2)													-0.177	0.427
	H (2:3)													-0.144	0.013
	H (2:4)													1.529	-1.386
	H (2:5)													-0.156	0.299

