

Decision Tree Tool for Auditors' Going Concern Assessment in Spain

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Abstract. The COVID-19 pandemic increased uncertainty about the financial future of many organizations, and regulators alerted auditors to be increasingly skeptical in assessing an entity's ability to continue as a going concern. An auditor's assessment of an entity's ability to continue as a going concern is a matter of significant judgment. This paper proposes to use machine learning to construct a Decision Tree Automated Tool, based on both quantitative financial indicators (e.g., Z-scores) and qualitative factors (e.g., partners' judgment and assessment of industry risk given the pandemic). Considering both quantitative and qualitative factors results in a model that provides additional audit evidence for auditors in their going-concern assessment. An auditing firm in Spain used the model as a supplemental guide, and the model's suggested results were compared to auditors' reports to evaluate its effectiveness and accuracy. The model's predictions were significantly similar to the auditors' assessments, indicating a high level of accuracy, and differences between the model's proposed outcomes and auditors' final conclusions were investigated. This paper also provides insights for regulators on both the use of machine-learning predictive models and additional factors to be considered in future going-concern assessment research.

Keywords: Audit, going concern, machine learning, decision tree, COVID19.

1. INTRODUCTION

Relevance and faithful representation of transactions are the fundamental qualitative characteristics for financial reporting in the Conceptual Framework for Financial Reporting (IASB, 2010), and they are essential for proper financial risk assessment. Accounting standards require that financial information be prepared under the assumption that the entity will continue in operation for the foreseeable future and, therefore, that there is no uncertainty about whether the firm will continue to be a “going concern.” However, Paragraph 25 of International Accounting Standards (IAS) 1, “Presentation of Financial Statements,” requires management to disclose any significant doubts about the entity’s ability to continue as a going concern (IASB, 2001):

When management is aware, in making its assessment, of material uncertainties related to events or conditions that may cast significant doubt upon the entity’s ability to continue as a going concern, the entity shall disclose those uncertainties. When an entity does not prepare financial statements on a going concern basis, it shall disclose that fact, together with the basis on which it prepared the financial statements and the reason why the entity is not regarded as a going concern.

Given the importance of the matter, many regulators have advised auditors of situations to be considered in the assessment of potential going-concern uncertainty, as well as some key elements and best practices for financial reporting disclosures (FRC, 2016; IASB, 2021; PCAOB, 2012; AICPA, 2021). Under both the International Standards on Auditing (IAASB, 2009) and the Generally Accepted Auditing Standards (AICPA, 2001), auditors must obtain sufficient appropriate audit evidence to assess the appropriateness of management’s use of the going-concern basis of accounting in the preparation of financial statements. If auditors conclude that a material uncertainty persists, they must include a specific paragraph to that effect in the audit report (FASB, 2014; IAASB, 2016¹).

The COVID-19 pandemic’s impact was felt unevenly by different industries in the world economy, triggering a worldwide wave of financial distress and bankruptcies

¹ International Standards on Auditing (ISA) 570. Paragraph 19 “If the auditor concludes that management’s use of the going concern basis of accounting is appropriate in the circumstances but a material uncertainty exists, the auditor shall ...: (b) Disclose clearly that there is a material uncertainty related to events or conditions that may cast significant doubt on the entity’s ability to continue as a going concern and, therefore, that it may be unable to realize its assets and discharge its liabilities in the normal course of business.”

(Washingtonpost, 2021). Corporate bankruptcies in the U.S. reached a 10-year high in 2020 (Globest, 2021). Among the industries most affected were entertainment companies and oil and gas companies specially because of the restriction of movements during the lockdown period and, also, all restrictions on travelling and indoor spaces. Nearly seven thousand companies sought reorganization under Chapter 11 of the U.S. Bankruptcy Code in 2020, representing an increase of at least 30 percent over filings in any of the four years preceding 2020 (Washingtonpost, 2021). Services sectors other than wholesale and retail, service industries in the U.K. appear to be doing substantially worse than they were at the beginning of 2020.² In general, the transportation, automotive, electronics, and retail industries were hit hardest.³ Confronted with different risks, such as decreasing customer demand and volatile financial markets, different industries required different actions to respond the impact of COVID-19 (Ernst & Young, 2020).

Meanwhile, regulators emphasized the importance of informing stakeholders of uncertainty about a company's continuity (AICPA, 2020; FRC, 2020; PCAOB, 2020; IAASB, 2020a; IAASB, 2020b; CEAOB, 2020; ESMA, 2020). The auditor's role as protector of the capital markets has never been more critical (AICPA & Chartered Institute of Management Accountants, 2020). However, as the importance of that role increased, so did the enormous pressure on auditors to find alternative ways to collect audit evidence and complete their work during the pandemic. Working remotely forced auditors to make full use of remote access to relevant files, workflow, and file sharing solutions. Even so, they were less likely to be present on site at the companies being audited to observe how those companies were handling the crisis, posing an unprecedented challenge to auditors issuing going concern opinions (Wilson, 2020).

Previous research provides no single best method for deciding whether the auditor's opinion must include the going-concern paragraph, making the auditor's opinion a so-called "going concern opinion" (GCO). Some researchers conclude that only quantitative indicators of a company are sufficient to assess a potential going-concern situation, and academic literature suggests that the Z-Score is still a very reliable predictor of possible bankruptcy (Altman, 1968; Altman et al., 2014).

² <https://blogs.lse.ac.uk/businessreview/2020/05/07/how-is-covid-19-affecting-businesses-in-the-uk/>

³ https://www.allianz-trade.com/en_global/news-insights/economic-insights/no-stone-untuned-how-covid19-is-disrupting-every-industry.html

However, auditor judgment also influences the assessment of going-concern status, which suggests that qualitative factors are necessary components of the auditor's going-concern assessment (Hopwood et al., 1994). Auditor judgment could be influenced, in turn, by an auditor's firm culture, experience, training, and size of the auditor's firm (Tagesson and Öhman, 2015; Svanberg and Öhman, 2016).

Machine learning, now used in a variety of fields, improves data analysis and leads to more evidence-based decision-making (Jordan and Mitchell, 2015). This paper provides a two-fold strategy for preparing a machine learning-based, automated, predictive model that considers both quantitative and qualitative indicators to assist auditors in making going-concern assessments. The low explainability of opaque models (i.e., "black-boxes") is the critical challenge that prevents auditors from using complex machine-learning algorithms in decision-making (AICPA, 2020; CPAB, 2021). A rule-based decision tree is a transparent ("white-box") step-by-step procedure that produces audit evidence that is more clear than impenetrable black-box machine learning algorithms.

Data used to build the model (22 variables related to 2,909 companies) was obtained from the 2019 audit opinions of an auditing firm in Spain. The variables were chosen based on research into the use of Z-Scores in the prediction of potential bankruptcies (Altman, 1968) and other variables related to recent accounting scandals (Steer, 2018). The data was used to build a machine-learning-based automated model to predict the inclusion of a going-concern paragraph in the audit opinion. The qualitative variables drawn from the auditor assessment were based on (1) auditors' knowledge about the entity's risk, according to their experience and expertise, and (2) the auditing firm's risk assessment of the industry of the entity being audited. The quantitative variables drawn from the company's financial ratios included widely used indicators, such as calculated Z-Scores, revenue as a percentage of assets, and working capital as a percentage of assets.

Classification differences between the model and the final auditors' report in 2020 were also investigated. In more than half of all cases, three main types of circumstances (subsequent financing, group financial support, or subsequent improvements to cash flow) explained the inconsistencies between the model results and the final outcome in the auditors' report. This study provides evidence that automated predictive models can assist auditors in drawing conclusions in a critical area, such as evaluating the need for a going-concern paragraph in the

auditor's report. Recalibration of the model is critical and an ongoing analysis must be performed each to account for economic changes mainly because economic conditions may change each variable and the weigh/importance that the model may give to each variable may also change over time.

No other academic literature has considered a model of the going-concern assessment that included both qualitative and quantitative factors. This study may contribute to the literature by offering an efficient white-box, predictive, decision tree model of the going-concern assessment. In addition, other audit firms elsewhere could benefit from the methodology. All partners who have used the provided data shared the same cultural values, as they belong to the same firm and have a common perception of going-concern risks in relation to the entities being audited.

The resulting model correctly predicted the issuance of a going-concern opinion in eighty-three percent of cases and demonstrates significant benefits in practice. Because its qualitative factors can be adapted to any environment, it can also be potentially used by auditors in other firms or jurisdictions. Consequently, this paper provides valuable information about the use of machine learning in both auditors' going-concern assessments and the improvement of the overall audit quality of future decision tree models, thus enhancing the protection of the public interest.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the going-concern opinions, the prediction model, and variables. Section 3 introduces the data and methodology. Section 4 shows the empirical results. Section 5 discusses current limitations and opportunities for future research. Section 6 concludes the paper.

2. LITERATURE REVIEW

2.1. Importance of going-concern opinions

In preparing financial statements, auditing standards require management to first evaluate the entity as a going concern (FASB, 2014; IAS 1). A diligent going-concern assessment is critical for the public interest and economic stability: uncertainty over the future survival of the entity could change the decisions of investors and other market participants (Zéman and Lentner, 2018).

In those jurisdictions where an independent audit is required, or for those entities that have engaged an independent auditor to perform an audit of their financial

information under auditing standards (such as ISA and GAAS), the auditor must follow specific standards and procedures to evaluate management's assessment of the ability of the entity to continue as a going concern, covering at least the same period as the one used by management. Auditing standards require the auditor to verify management's assessment, based on the auditor's knowledge and all evidence obtained during the audit. Investors consider the going-concern opinion relevant in valuing a company's common stock and, therefore, relevant to pricing stocks (O'Reilly, 2010; Schaub, 2006). In addition, going-concern opinions are helpful in predicting bankruptcy and can provide some explanatory power in predicting the resolution of the bankruptcy (Chen & Church, 1996; Bessell et al. 2003). Ajona et al. (2012) find that the inclusion of a going-concern paragraph in Spain is critical, as many companies in Spain have gone bankrupt after the inclusion of such paragraph.

2.2. Prediction models

Research into modeling the going-concern prediction has a long history. Early studies in the going-concern opinion literature used discriminant analysis to model the decision (e.g., Altman & McGough, 1974; McKee, 1976). However, because going-concern prediction cannot rely on the contradictory assumptions of a multivariate normal distribution of explanatory variables and equal covariance metrics between two groups (Carson et al., 2013), models for predicting going-concern opinions shifted from discriminant analysis to logit analysis (e.g., Menon & Schwartz, 1987; Harris & Harris, 1990), probit analysis (e.g., Koh & Brown, 1991), neural networks (e.g., Serrano-Cinca, 1996), decision tree (Koh & Low, 2004), support vector machine (Martens et al., 2008), and also a machine-learning random forest model (e.g., Hsu & Lee, 2020). For instance, Bellovary et al. (2007) identified twenty-seven statistical models developed to predict issuance of a going-concern opinion, including multivariate discriminant analysis (MDA). To date, however, the auditor's going-concern opinion has been an inferior predictor of bankruptcy, compared to the predictions of statistical models (Hopwood et al., 1994; Zhang et al., 2022b). Statistical methods have been used to assist auditors in issuing going-concern opinions (Koh, 1991). The more sophisticated the algorithms, the better their performance (Zhang et al., 2022b).

Although the advantage of statistical models in predicting bankruptcy is well-established, according to Gutierrez et al. (2020), auditors presently do not use

statistical models systematically as a diagnostic tool in making going-concern assessments. Instead, auditors typically rely on a checklist that includes various indicators of financial distress suggested by going-concern standards.

Existing auditing standards, such as AS 1105 (PCAOB, 2010) and AS 1215 (PCAOB, 2004) require the auditor to explain and document the result of any machine learning models used, a task that black-box models make difficult (Zhang et al., 2022a; AICPA, 2020; CPAB, 2021). Using an explainable white-box model would alleviate this issue. Therefore, one reason for using a checklist is the tradeoff between the superior performance of machine-learning algorithms and their explainability (Zhang et al., 2022a; Virág & Nyitrai, 2014). As a machine-learning model includes more variables, increases dimensionality, and uses more sophisticated calculations, its predictability improves but its explainability decreases (Zhang et al., 2022a; DARPA, 2016; Baryannis et al., 2019). The low explainability of opaque models (i.e., “black-box” models) is a critical challenge for auditors, which prevents them from using complex machine learning algorithms in decision-making (AICPA, 2020; CPAB, 2021).

To satisfy auditing standards, a white-box model, such as a decision tree, must have two key characteristics: (1) the features must be understandable, and (2) the machine learning process must be transparent (Zhang et al., 2022a; Hall & Gill, 2019; Molnar et al., 2021). However, to our knowledge, little research has been done to investigate how to create such a white-box model for the going-concern assessment or how an explainable white-box model can assist auditors in making going-concern assessments.

2.3. Predictors

The determinants of GCOs have been studied extensively in the literature. The decision to issue a GCO is complicated and requires the issuing auditor’s judgment (PCAOB, 2012; Carson et al., 2013). Specifically, client factors, auditor factors, auditor-client relationships, and other environmental factors are major determinants of GCOs (Carson et al., 2013; Brunelli, 2018). Those factors can be further divided into quantitative (objective) and qualitative (subjective) variables. Audit quality and good audit judgment are therefore based upon various qualitative factors (Francis, 2004).

Going-concern assessments require quantitative analysis. Financial distress, debt default, and leverage have all been shown to significantly influence the auditor's going-concern decision (Achyarsyah, 2016). Most archival studies that focus on quantitative variables measure the distress level of firms in one of two ways: (1) distance to distress (Merton, 1974), calculated as the firm's market value minus the value of its debt, divided by the volatility of its assets; or (2) financial ratios. Altman's Z-Scores dominate the field. A combination of several quantitative financial ratios are used to calculate a Z-Score, which has been used with a high degree of accuracy to determine the risk of a potential bankruptcy (Altman 1968; Altman 1983; Altman et al. 2017). The Z-score could also be used as a combined model of accounting and auditing data (Muñoz-Izquierdo et al., 2020). The Altman model predicts bankruptcy in a significant majority of companies (Salimi, 2015) in the international context (Altman et al., 2014), in the U.S. (Altman et al., 2017), in Europe (Chieng, 2013), and in Spain (Fitó Bertran et al., 2018). However, Carreras Peris (2017) argue that Z-Scores may not be helpful in assessing the risk of bankruptcy among construction companies in Spain, compared models by Ohlson (1980) and Ismail (2014). Additional quantitative Key Performance Indicators ("KPIs") could be useful to enhance any proposed predictive bankruptcy model (Steer, 2018).

Although essential, the qualitative factors of GCOs are often ignored in building automated models. In other words, the auditor's going-concern decision is inherently subjective, which influences audit quality (Harris & Harris, 1990; Haron et al., 2009; Lipe, 2008). The going-concern judgment is based on the auditor's knowledge, such as financial knowledge, event knowledge, and procedural knowledge (Biggs et al., 1993). Also, the auditor's experience level and the client's industry are key to producing high-quality audit work and accurately assessing potential going-concern probabilities (Blandón et al., 2020). Auditor characteristics may also influence the output of the GCO assessment (Carson et al., 2013). Matsumura et al. (1997) propose a game-theoretic model that allows the client to avoid a going-concern opinion, and find that the auditor's forecast of entity viability impacts the auditor's tendency to express fewer going-concern opinions.

Studies examining the effects of audit size have had mixed results. Tagesson and Öhman (2015) find a positive relationship between audit fee amounts and the likelihood of including a going-concern paragraph in the audit report and

demonstrate that Big Four auditors (used to refer collectively to Deloitte, Ernst & Young (EY), KPMG, and Price Waterhouse Coopers (PwC), the four largest professional auditing service networks in the world) are more likely to issue such warnings than other auditors. However, Gallizo Larraz and Saladrigues Solé (2016) find that smaller auditing firms are more likely to issue going-concern audit opinions. In addition, research shows a skeptical audit culture is more likely to maintain auditor objectivity than less supportive cultures, emphasizing the importance of office culture in the assessment of going-concern judgments (Svanberg & Öhman, 2016). Spain's audit quality (measured by auditors' independence and knowledge) also affects the probability that a financially distressed Spanish company will receive a going-concern opinion (Ruiz-Barbadillo et al., 2004).

Both quantitative and qualitative aspects should be included when selecting predictors of auditor's going-concern assessments. However, there is a research gap in combining them to construct a white-box model to assist auditors in issuing going-concern opinions.

3. DATA AND METHODOLOGY

3.1. Data

After the start of the COVID-19 pandemic in early 2020, and with many industries facing unfavorable futures as a result, regulators urged auditors to carefully analyze material uncertainties about management's ability to prepare financial statements assuming the entity was a going concern (AICPA, 2020; FRC, 2020; PCAOB, 2020; IAASB, 2020a; IAASB, 2020b; CEAOB, 2020; ESMA, 2020).

The auditing firm that supplied data for this research used a scorecard or checklist that asked partners to consider certain financial variables about the entity being audited, and some qualitative factors about industry risk to determine whether the inclusion of a GCO would be necessary. An example of this checklist is shown in Appendix A. The checklist produced a going-concern risk score for each engagement. This study analyzed data from the scorecards to create a simple machine learning white-box tool to assist auditors in deciding whether to issue a GCO. The timeline for the study is shown in Figure 1.

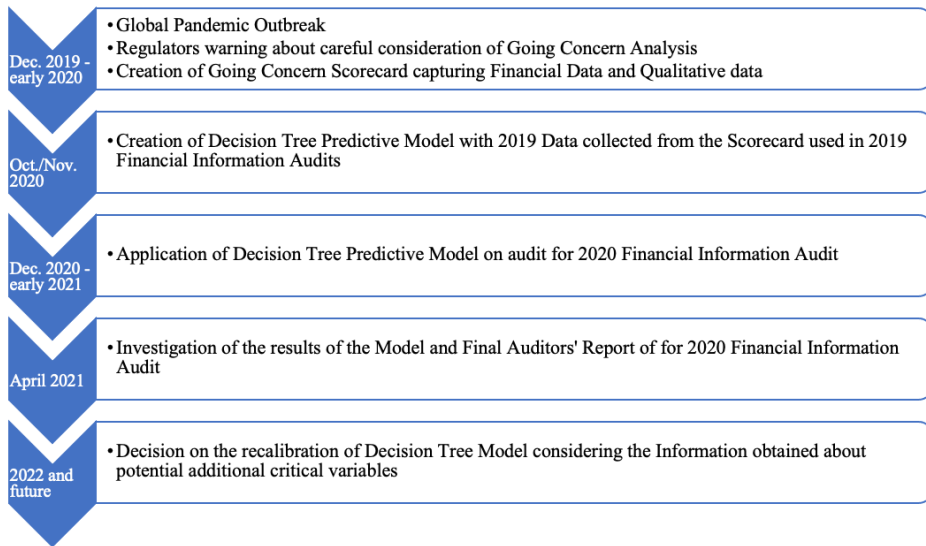


Figure 1. Timeline for obtaining data

Because the purpose of the study was to create a model to predict potential inclusion of a going concern paragraph during the 2020 audit season (the year impacted by the pandemic), the last available audited financial information for training the model was related to 2019 (the year immediately prior to the pandemic). However, the model considers both qualitative and quantitative information. As quantitative elements, the Z-Score elements and other financial KPI elements, as indicated in the literature review, are often-used and reliable determinants of bankruptcy risk. In this study, these indicators have been complemented by qualitative elements based upon the auditor's risk perception of the company being audited and the auditor's risk score for the industry of the company being audited. In order to predict the 2020' audit, quantitative and qualitative information was accessed in December 2020. The qualitative information used allows to consider abnormal financial events such as the 2020 pandemic effects. Finally, an investigation of the model output conclusion and the final auditors' reports draws conclusions about the effectiveness of the model in April 2021.

Table 1 displays the sample composition of 2,909 audit opinions issued by the auditing firm in 2019. Of the total 2,909 opinions issued, 133 (4.6%) were issued with going-concern paragraphs in the audit reports; the remainder (2,776 (95.4%)) were issued without going-concern paragraphs in the audit reports. Twenty-two variables were obtained for each case, and there was no missing data.

Year	2019
The number of audit opinions issued	2,909 (100%)
The number issued without going-concern paragraphs (GCO=NO)	2,776 (95.4%)
The number issued with going-concern paragraphs (GCO=YES)	133 (4.6%)
The number of variables per case	22

Table 1. Sample composition

Data on twenty-two variables, as shown in Appendix B, was obtained for all audited entities for the 2019 audits in the following three key categories: (1) the response variable is a dichotomous dummy variable set to 1 if the auditor's report included a going-concern paragraph and 0 otherwise; (2) the qualitative predictor variables of partner risk assessment; and (3) the quantitative predictor variables representing the financial results of the audited entity. To give a final risk assessment score, partners must have considered financial, operating, and other circumstances (IAASB, 2016, paragraphs A3-A6).

3.2. Using a decision tree to model GCO

The data from 2019 was used to build the decision tree model for predicting the issuance of a GCO. The decision tree based on 2019 data was then applied in the 2020 audit process, as shown in Figure 2.

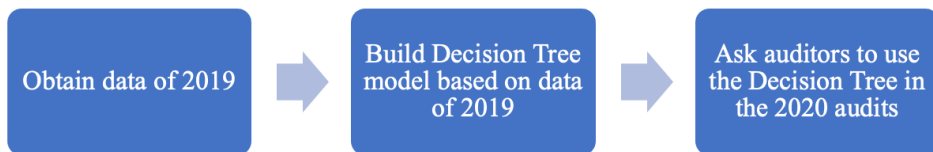


Figure 2. Data flow design

The 2019 dataset was divided into two parts: eighty percent of the 2019 opinions were used for training and the remaining twenty percent were used for testing. To optimize pruning of the decision tree, the Complexity Parameter⁴ (CP) is used as a hyperparameter (Therneau et al., 2013). Ten-fold cross-validation was used on the

⁴ The complexity parameter (cp) in rpart library is the minimum improvement in the model required at each node. A value of cp = 0 obtains a full-grown tree because nodes are divided until no improvement is achieved. Higher values of cp will obtain pruned trees with less nodes.

training dataset to select the optimum hyperparameter value, and the *Area Under the ROC Curve*⁵ value was used as the primary performance metric. The number of positive going-concern cases in the 2,909 companies used for training the model was limited (133 YES and 2,776 NO), which could cause the model to give biased results. In fact, following the aforementioned process, a tree model with high accuracy was obtained (up to 96 percent of cases were correctly classified) but with a low level of sensitivity⁶ (only 0.22 in the test set (i.e., 22 percent of companies in the test set with ‘YES’ GCO were correctly identified)). This result implies that the initial model would not have been useful for predicting GCO because auditors’ decisions would misclassify “YES” cases.

Consequently, some techniques for handling class imbalance problems caused by oversampling techniques were implemented to adequately calibrate the model (Gosain & Sardana, 2017). To obtain an equal number of YES and NO cases, all YES training data cases were “over-sampled,” penalizing the misclassification of YES samples. In addition, the length of the tree had to be adjusted by appropriate selection of its CP to provide an appropriate balance between precision and complexity. In this respect, a proper and balanced CP was deemed necessary. Without any adjustment, the model would achieve its highest sensitivity and accuracy. In contrast, there were more than fifty questions to be evaluated, as the model would contemplate every single circumstance. To obtain a balanced number of questions without sacrificing the accuracy or sensitivity of the model. A diagram illustrating the performance of the model via ROC as a function of the Complexity Parameter is shown in Figure 3 below and used to obtain a less complex but with a high level of accuracy. The maximum ROC (accuracy) considering a less complex decision tree would be with a Complexity Parameter (CP) of 0.015. This parameter demonstrates that a simple and intuitive decision tree without too many decision nodes could be highly accurate in assessing the issuance of going-concern opinions. In this case, we constructed the decision tree with a Complexity Parameter of 0.015, which results in the optimal combination of high accuracy and efficiency. The model’s overall accuracy is high (83 percent), with sensitivity levels up to 82.707 percent (meaning the final model correctly predicted almost 83 percent of YES GOC cases), as demonstrated in Table 2.

⁵ ROC curve shows the trade-off between the accuracy/sensitivity of the model and the specificity of the model itself (number of nodes/questions made).

⁶ Same as True Positive Rate. Refers to the percentage of “YES” GCO companies the model was able to correctly identify.

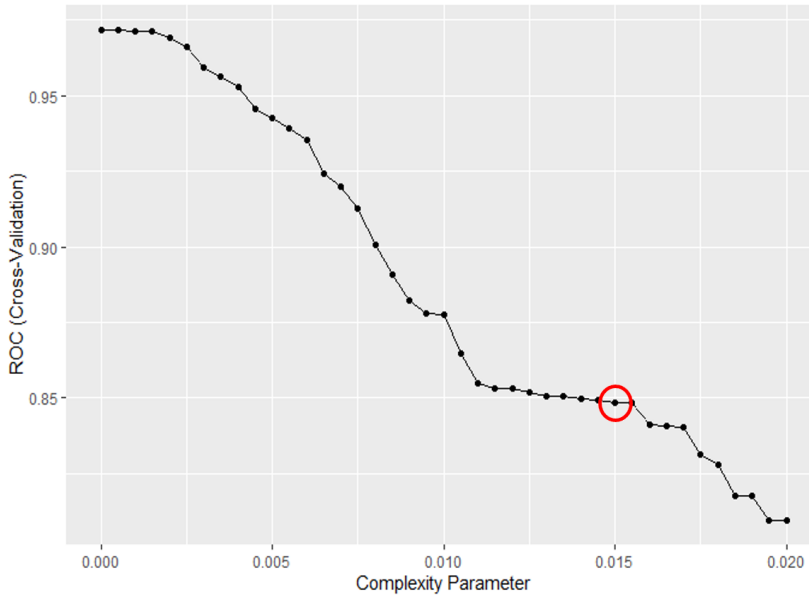


Figure 3. Complexity parameter and ROC

We used the R-based Rpart library to build the model. Once the optimal complexity was selected, we constructed the final decision tree model using all samples in the dataset to maximize the amount of data available for the tree to learn. Cross-validation performance for this final tree showed results similar to its earlier incarnation, indicating that the model was not overfit. The main resulting figures of the model are as follows:⁷

Accuracy	0.83
Sensitivity	0.82707
Specificity	0.82745
Pos Pred Value	0.1867
Neg Pred Value	0.99
Prevalence	0.045
Detection Rate	0.037
Detection Prevalence	0.202
Balanced Accuracy	0.827

Table 2. Final model performance metrics on all samples

⁷ The script is available to public at https://github.com/yugu431/Decision-Tree_Going-Concern

4. EMPIRICAL RESULTS

Figure 4 demonstrates the decision tree model output from R. The deeper the orange of the nodes and leaves, the more likely the result is “YES.” The decision tree goes through at most seven and at least three decision nodes to determine the issuance of a GCO. Figure 5 illustrates the importance of each variable to the final decision.

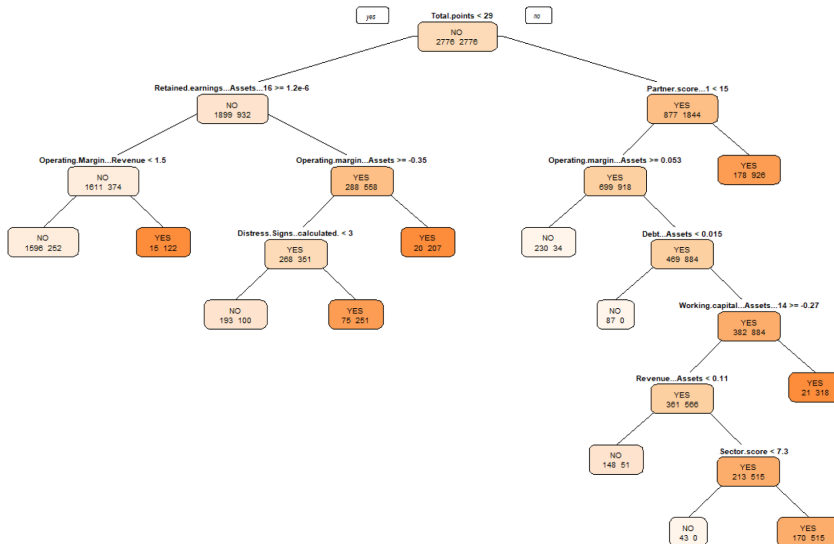


Figure 4. The decision tree

Figure 6 depicts the conceptual decision tree model. The green boxes identify qualitative factors: (1) *Partner’s Score for the Company*; (2) *Firm Score for the Industry*. The blue boxes are quantitative factors:

- (1) *Total Points on the Going Concern Score Card Checklist*
- (2) *Operating Profit/Assets;*
- (3) *Debt/Total Assets;*
- (4) *Working Capital/Assets;*
- (5) *Sales Revenues/Assets;*
- (6) *Other Equity Reserves/Assets;*
- (7) *Operating Profit/Sales Revenues;*
- (8) *Operating Profit/Assets;*

(9) Checklist Distress Sign Score.

Operating Profit/Assets appears twice in the conceptual Decision Tree model in Figure 6.

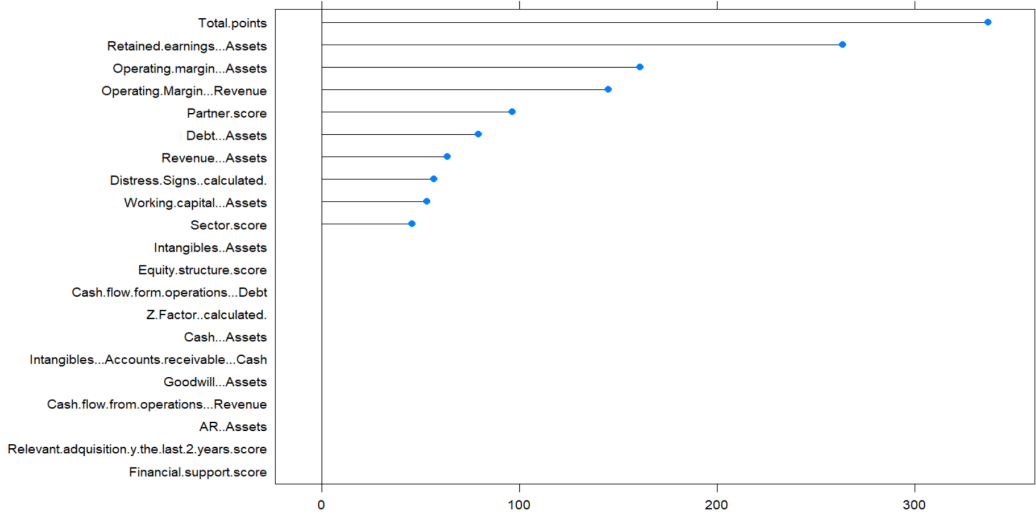


Figure 5. The main variables that the final decision tree considers relevant

The blue arrows, pointing to grey output areas above and below, indicate recommendations for whether to include a going concern paragraph in the auditor’s report based on the values of the relevant boxes. For example, the first decision (and the most consequential factor) is whether an entity’s *Total points in the Going Concern Scorecard Checklist* value is greater than or equal to 29. If it is, then a value for *Partner’s Score for the Company* greater than or equal to 14 would indicate that auditors should consider including a Going Concern paragraph in the auditor’s report. If the *Partner Score* value is less than 14, the next decision considers the *Operating Profit/Asset* ratio. If the ratio is greater than or equal to 0.053, the model indicates that auditors should not issue a GCO. If the *Operating Profit/Asset* ratio is less than 0.053 and the *Debt/Total Assets* ratio is less than 0.015, no GCO is indicated. If the *Working Capital/Assets* ratio is less than -0.27 (meaning the entity does not have working capital to support its business operations), the model suggests including a going concern paragraph in the auditor’s report. Otherwise, the decision tree proceeds to the next decision, which considers the ratio of Sales Revenue to Assets. If the ratio is lower than 0.11, there is no GCO concern. If not, the model will continue to the final decision, a subjective indicator of the

firm score for the industry. If the firm score is greater than or equal to 7, the industry is considered high-risk and the model suggests adding a going-concern paragraph to the auditor’s report. If the firm score is less than 7, the industry is not considered high-risk and the model recommends no going-concern paragraph in the auditor’s report.

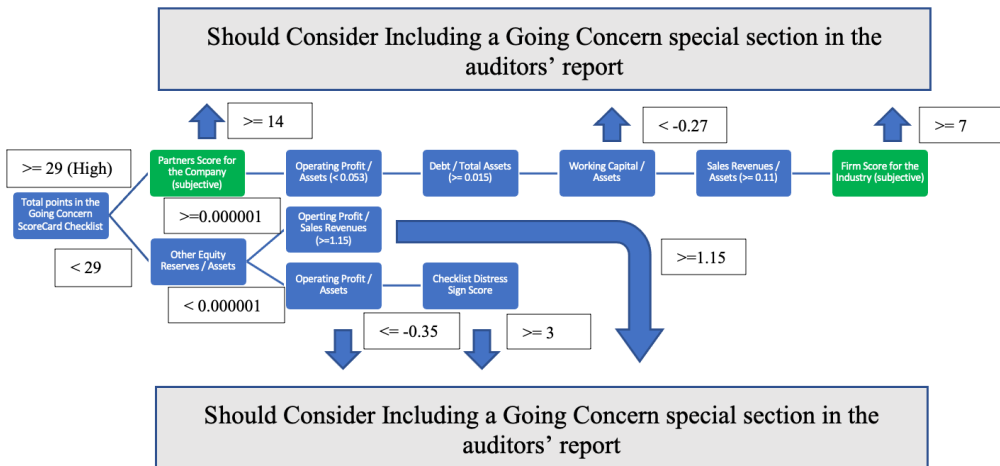


Figure 6. The conceptual decision tree model

This decision tree model was constructed with 2019 data and used by auditors with an auditing firm in Spain to make going-concern assessments during audits of 2020 financial statements. As shown in Table 3, ninety-three percent of the model’s recommendations whether to include a going concern paragraph were consistent with the auditor’s final GCO conclusions.

	Real = No	Real = Yes	
Model = No	2,215	11	
Model = Yes	243	146	93.0% ⁸
	9.3% ⁹		

Table 3. The confusion matrix

⁸ 93.0% ≈ 146/(11 + 146)

⁹ 9.3% ≈ 243/(2215 + 11 + 243 + 146)

However, the model was not perfect. As seen in Table 3, in 243 cases, the decision tree model indicated a GCO but auditors chose not to include the GCO in the audit report. Similarly, in eleven cases, the Decision Tree model did not indicate a GCO but auditors decided to include the GCO in the audit report. It is worth noting that the training results obtained during the fitting process followed a similar distribution of errors.

The 243 cases in which the model recommended a going-concern opinion but no such opinion was issued could indicate that the going-concern decision was not properly evaluated. In such cases, the decision not to issue a going-concern opinion should be corroborated by the auditing firm's risk managers, and the auditing firm should investigate each such case closely. In applying the model in practice, we recommend that the auditing firm's risk managers be consulted before the auditor's opinion is issued, to double-check the rationale for not following the model's recommendation to enable the Firms' System of Quality and Control verify the signing partner decision before the auditors' opinion is signed. The results of such an investigation, the rationale for the auditor's decision, and the characteristics of the firm being audited should be used to enhance the model.

In this case, we performed a root cause analysis on a random selection of 150 cases (more than half of the population of inconsistencies, or 61.7% of 243 cases), which provided some insight. Additional variables might have had a significant impact and require further evaluation to determine whether they should be considered in future investigations.

Figure 7 provides an overview of these 150 cases. There appear to be three chief reasons why the model indicated "YES" but the auditors opted for "NO." First, in 36% of the cases, there is evidence that the company could obtain additional financial support from other companies in the same ownership group. Second, 21% of cases are a result of seeking subsequent external financing. Third, in 43% of the cases, there is positive evidence of subsequent cash flows verified by the auditor after the end of the audit period and before the auditor's opinion is signed (conclusion of the audit).

Companies need to show they have effective mitigation plans that can increase cash flows sufficiently to keep them afloat for at least twelve months and alleviate substantial doubt as to their ability to survive (ESMA, 2020; Dohrer & Mayes, 2020; Wang, 2021). Wang (2021) also finds that information extracted from

financial reports about efforts to increase debt, restructure debt, increase revenues, and sell assets all might help to mitigate the unfavorable market reaction to a going-concern opinion. FRC (2020) emphasizes mitigation actions in its review of the financial reporting effects of COVID-19. It expects management will include plans in financial reports that are sufficiently granular to allow auditors and other users to understand clearly whether the company will survive for at least twelve months past the effective date of the financial statements.

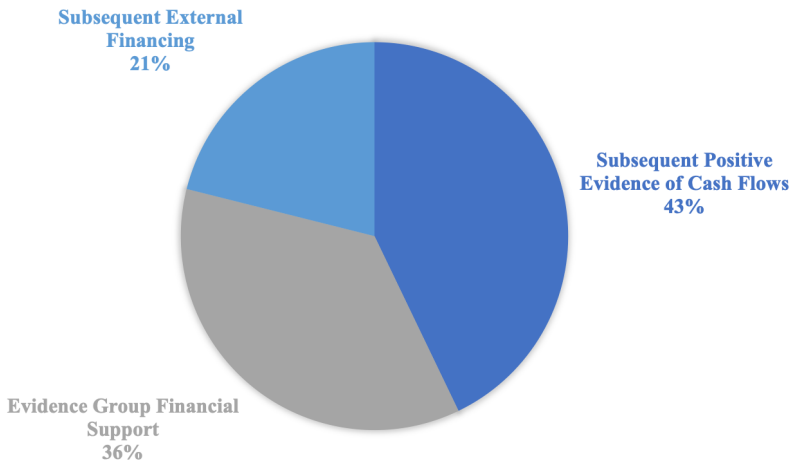


Figure 7. Investigation of 243 cases that model indicated “YES” and auditor opted “NO”

Similarly, we also examined cases in which the decision tree model indicated there should be no GCO, but the auditors chose to include a going-concern opinion in the audit report. The results of ten cases (90.9%) of the eleven total cases are shown in Figure 8. Most of the inconsistencies are attributable to random factors, rather than the model itself. For example, in thirty percent of cases, the inconsistency was due to changes in circumstances between the date as of which the model was applied and the conclusion date of the final report. As an example, new lines of credit were obtained by the date of the auditor’s report that were not available during the audit itself. Another thirty percent of cases were issued in instances in which the parent company of a consolidated group had going-concern opinions that could affect subsidiaries. Two cases were due to human error in completing the checklist. In one case, the scorecard produced a number very close to the threshold of the going-concern decision. In the remaining case, the inconsistency was due to reasons not relevant to this investigation.

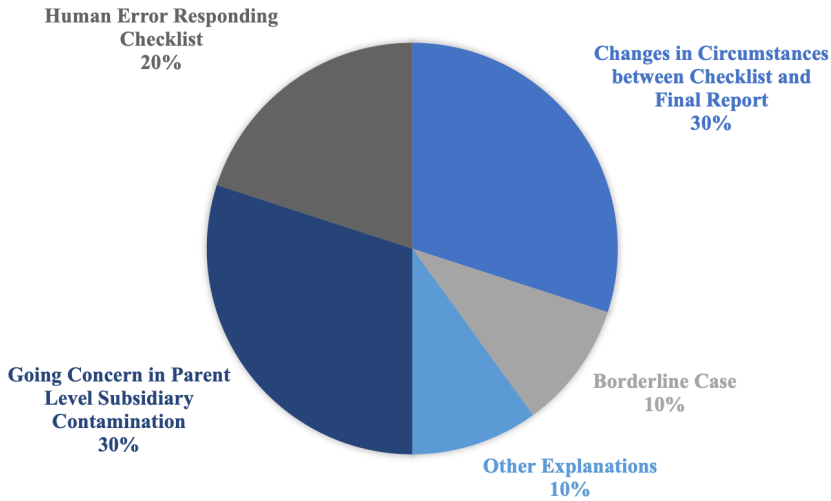


Figure 8. Investigation of ten cases that model indicated “NO” and auditor opted “YES”

5. DISCUSSION

This study proposes an automated decision tree as an aid to improve and enhance the evaluation and documentation of auditors’ going-concern opinion (GCO) assessments, in part as a response to increasing concern about the GCO decision-making process during the COVID-19 pandemic. The model produced highly accurate predictions after being validated and employed by an auditing firm in Spain and assisted auditors in documenting their assessment by embedding their audit judgments. The model could also be beneficial for regulators when considering the capacity of white-box machine learning to capture auditors’ decision-making processes.

Explanations for inconsistencies between the model and auditor behaviors were explored. As indicated above, the reasons are clear for the false negative (model indicating “NO” and auditors opting for “YES”) and false positive (model indicating “YES” and auditors opting for “NO”) cases. Therefore, to increase the efficiency, future work and future decision tree models should consider new variables, such as mitigation plans (whether firms have external financing, or the coverage ratio of the liability). Also, the model should be continuously updated with new data each year, as Figure 9 displays. More research based upon the results obtained and further investigation could be performed, aiming for a model recalibration each year.

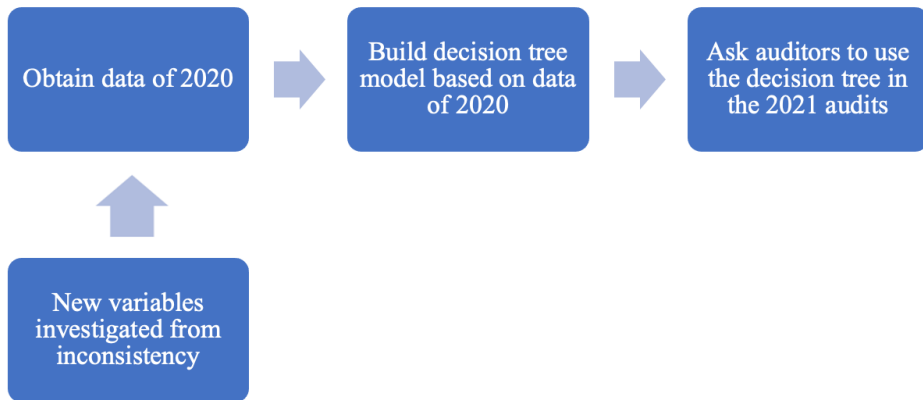


Figure 9. Future Research Directions

This paper has four limitations. First, because it was built from data from only one audit firm, and because firm cultures vary among firms and countries, the particular model tested here may not be readily generalizable. However, the proposed methodology is generalizable to other audit firms. Each firm should consider its own data and variables, especially subjective variables, and create its own decision tree. However, the procedure established in this study could be easily extrapolated and could benefit firms setting up their own predictive models based upon white-box machine-learning technology.

Second, the model has been built considering data available for only a short period (one year, 2019). Therefore, the model could have been different or even more accurate if more periods were used to build the model.

Third, the model was not designed to predict real business failures. Rather it was built to aid auditors' decision-making processes by formalizing auditors' past judgment history with qualitative and quantitative data. Comparing the results of the model with data on actual business failures among the firms used to construct and test the model could be an avenue for future research.

Fourth, the decision tree method is the only algorithm used in this study. Aside from the explainability factor, future research may evaluate and compare other algorithms for algorithm selection.

6. CONCLUSIONS

COVID-19 posed considerable pressures and difficulties for auditors in assessing audited entities as going concerns. Auditing standards (IAASB, 2016; FASB, 2014) require auditors to apply professional judgment in going-concern issues. This study provides a tool to aid auditors in their assessment of the risk of entity failure and, consequently, their analysis of whether or not to include a going-concern paragraph in the auditor report, as required by the applicable auditing standards. The automated tool is a decision tree that would help auditors decide whether their report should include a going-concern paragraph. The resulting predictions are significantly similar to actual auditors' decisions, suggesting the model is effective in providing additional evidence about the conclusion reached by auditors.

This paper's contribution is providing a two-fold strategy for preparation of an intuitive, white-box, easy-to-use predictive model based upon simple decision tree questions that incorporate qualitative and quantitative data to assist auditors in making going-concern assessments. Quantitative indicators consider an entity's financial figures based on Z-Scores, supported by other quantitative indicators. Qualitative financial indicators add important information about: (1) auditors' knowledge about the entity's risk, considering their experience and expertise, and (2) the auditing firm's risk assessment of the industry of the company being audited. Considering that all data used in this study comes from one audit firm in one country, there is a risk that different audit quality and cultures could impact the results, as qualitative scores may be perceived differently.

The data used for this study was obtained from a single auditing firm. It can be assumed that the risk perception of the firm's partners is consistent because they share a common training experience and audit methodology. This research could be easily replicated in other auditing firms and cultures by using their risk assessment (qualitative indicators) methods. Auditors should consider making use of this model by inputting their own data and preparing their own prediction model, as it can be a beneficial tool in evaluating whether a going concern paragraph is needed in the auditor's report. This paper also serves as an example for regulators in applying machine learning for better quality audits.

Acknowledgment: We thank Dr. Miklos Vasarhelyi from Rutgers University, Dr. Chanyuan (Abigail) Zhang from Rutgers University, Dr. Érica Custódio Rolim from IESE Business School, Kelly Deannine Langdon from Deloitte, Dr. Carlos Bellón Núñez-Mera from Universidad Pontificia de Comillas and Steven Katz from Rutgers University for their contributions and comments to this paper.

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APPENDIX A

Scorecard Going Concern Checklist – 2019

1. Z Factor

- 1.1. Working capital/Assets
- 1.2. Retained earnings/Assets
- 1.3. Operating margin/Assets
- 1.4. Cash flow from operations/Debt
- 1.5. Revenue/Assets

Total Z Factor Score = (Working capital/Assets*1.2) + (Retained earnings/Assets* 1.4) + (Operating margin/Assets *3.3) + (Cash flow from operations/Debt*0.6) + Revenue/Assets

- I) Points: If Z Factor Score equals 0, then 10 points
- II) Points: If Z Factor Score is greater than 0 to 1.82, then 5 points
- III) Points: If Z Factor Score is greater than 1.81 to 3, then 0 points

2. Distress signs

- 2.1. Intangibles/Accounts receivable + Cash
- 2.2. Cash flow from operations/Operating margin
- 2.3. Goodwill/Assets
- 2.4. Relevant acquisition in the last 2 years score: (Yes or No)

Distress Signs Score = (Intangibles/Accounts receivable + Cash) + (Cash flow from operations/Operating margin) + (Goodwill/Assets) + (Relevant acquisition by the last 2 years score)

- I) Points: If the Distress Signs Score equals 0, then 0 points
- II) Points: If the Distress Signs Score is greater than 0 to 1, then 6 points
- III) Points: If the Distress Signs Score is greater than 1 to 1.5, then 7 points
- IV) Points: If the Distress Signs Score is greater than 1.5 to 2, then 8 points
- V) Points: If the Distress Signs Score is greater than 2 to 2.5, then 9 points

VI) Points: If the Distress Signs Score is greater than 2.5 to 2.99, then 10 points

3. Sector Score: Score based on entity sector

4. Partner score: Score based on the partner's knowledge of the entity, more points, worse situation (0-20)

5. Financial Support score: Qualitative, based upon Partners' assessment: more points indicate a higher risk of not receiving financial support (0-20)

6. Solvency risk score: Qualitative based upon Partners' assessment: Good = 0 Points, enough = 5 Points, poor = 10 Points

7. Equity structure score: Shareholders with problems or low solvency = 10 points, shareholders without problems = 5 Points, Solvent whole owned company = 0 Points

8. Total Points: Final Score of the checklist.

Total Points = Partner score + Sector score + Financial support score + Solvency risk score + Equity structure score + Z Factor + Distress Signs

I) Points: If Total Points are less than 30, then "Partners' decision."

II) Points: If Total Points are equal to or greater than 30 and less than 60, "Review with the second partner."

III) Points: If Total Points are equal to or greater than 60 and less than 80, "Review with expert network."

IV) Points: If Total Points are equal to or greater than 80, then "Review with the technical team."

APPENDIX B

Variables Definitions

Category	Variables included in Modeling (R Script)	Definitions
Going concern opinion	GCO	Whether the auditor's report had a going concern paragraph or not
Partners risk assessment (Qualitative)	Partner score	Engagement partner evaluation of going concern situation (see Appendix A)
	Financial support score	Engagement partner's evaluation of financial support from group or entity owner (see Appendix A)
	Sector score	Score based on entity sector (see Appendix A)
	Equity structure score	Score based on entity structure
	Z Factor (calculated)	The Z-Score is a linear combination of four or five common business ratios, weighted by coefficients. The coefficients were estimated by identifying a set of firms that had declared bankruptcy and then collecting a matched sample of firms that had survived, with matching by industry and approximate size

Financial results (Quantitative)	Distress Signs (calculated)	(assets) (see Appendix A) Score based on the result of a calculation (see Appendix A)
	Total points (Scorecard GCO Checklist)	Calculation based on other columns (see Appendix A)
	Operating margin/Assets	
	Cash flow from operations/Debt	
	Revenue/Assets	
	Intangibles/Accounts receivable + Cash	
	Goodwill/Assets	
	Relevant acquisition in the last 2 years score	
	Working capital/Assets	
	Retained earnings/Assets	
	Debt/Assets (1)	
	Intangibles/Assets (1)	
	Accounts Receivables (AR)/Assets	
	Cash/Assets (1)	
	Operating Margin/Revenue (1)	
	Cash flow from operations/Revenue (1)	

(1) Calculated from the data included in Scorecard Going Concern Checklist – Appendix A