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The Auditor's Assessment of Fraud Risk: A Fuzzy Logic Approach

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I. Introduction

The financial scandals of the past decade have dramatically heightened the financial community's sensitivity to the potential for fraud. These scandals have financially devastated employees and investors, and severely harmed the reputations of auditors, analysts, and corporate managers. The sheer magnitude of these frauds, along with the subsequent public outcry, has led to increased regulation of firms and auditors. The response included the issuance of Statement on Auditing Standards No. 99 (SAS No. 99), the imposition of the Sarbanes-Oxley Act of 2002, the establishment of the Public Company Accounting Oversight Board (PCAOB), and the release of eight new risk assessment standards.

However, a January 2007 PCAOB report identified deficiencies in auditor's fraud risk assessment practices and showed that auditors were not fully complying with SAS 99 requirements. In addition, the 2008 Ernst and Young 10th Global Fraud Survey revealed that fraud persists worldwide. Furthermore, the recent downturn in the economy has arguably provided additional incentives to engage in fraud. Thus, continued research relative to improving the auditor's fraud risk assessment process is both necessary and timely.

A careful examination of SAS No. 99 reveals additional limitations that may lead to ineffective implementation. SAS No. 99 identifies two *types* of fraud: (1) fraudulent financial reporting and (2) misappropriation of assets. Within each type of fraud, SAS No. 99 further

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identifies three *conditions* known to be associated with fraud: (1) incentives and pressures; (2) opportunities; and (3) attitudes and rationalizations. Each combination of type and condition is associated with specific fraud risk *factors*, most of which have related fraud risk *indicators*. For example, ineffective monitoring of management is a fraud risk factor relating to the condition of opportunities within the fraudulent financial reporting type of fraud. Domination of management by a single person or a small group without compensating controls is a fraud risk indicator of ineffective monitoring of management. The key distinction between a fraud risk factor and a fraud risk indicator is that the indicator is directly observable while the factor is observable only indirectly through the presence of its associated indicators.

The auditor uses the fraud risk indicators and judgment to decide whether a fraud risk factor does or does not exist. This implies a binary assessment of each fraud risk factor without consideration of the extent to which it exists. For example, the *degree* to which monitoring of management is ineffective is important, not simply its existence.

Moreover, not all fraud risk factors are equally valid, that is, some are more suggestive of fraud than are others. For example, the existence of excessive pressure on management to meet the requirements and expectations of third parties may be more suggestive of fraud than the existence of a complex or unstable organizational structure, both of which SAS No. 99 lists as fraud risk factors.

We acknowledge the possibility of using objective financial data to support the use of the SAS No. 99 factors. However, one limitation of using financial statement variables is that, when fraud is present, the data may be fraudulent and thus ratios and trends computed from them may be distorted.

The purpose of this paper is to demonstrate the application of fuzzy logic to fraud risk assessment. We describe an expert system based on fuzzy logic that assesses the risk of fraud within the SAS No. 99 framework. The system works by allowing the auditor to input data regarding the presence or absence[1] of each fraud risk indicator, i.e., the basic observable characteristics of the audit engagement. The system then uses the principles of fuzzy logic to evaluate the degree to which each fraud risk factor is present. Using the relative importance of each fraud risk factor, the system computes the fraud risk associated with each type of fraud and the fraud risk associated with each of the six combinations of fraud type and condition.

This approach has several advantages. First, treating fraud as a fuzzy concept provides the auditor with greater discriminatory power relative to that available using the classical binary notion. By computing a numerical measure, the fuzzy expert system advises the auditor regarding the significance of the fraud risk. This allows the auditor to increase audit procedures on those audits that present the greatest fraud risk, thus enhancing the overall effectiveness of the audit.

Second, by computing fraud risks for each type of fraud, for each condition, and for each combination of type and condition, the system allows the auditor to identify the specific underlying areas that contribute most to the overall fraud risk evaluation. This allows the auditor to increase audit procedures in those areas that present the greatest fraud risk, thus further enhancing the overall effectiveness of the audit process.

Third, the fuzzy expert system provides a model structure that requires the auditor to make explicit judgments, thereby formalizing and documenting the process of fraud risk assessment. This allows for better communication within the audit team and with the client, and enhances process consistency across auditors, engagements, and years.

[1] The system can also accept fractional values to indicate the degree of existence of each fraud risk indicator.

Fourth, the fuzzy expert system establishes a framework for organizational learning. When incorporated with a formal feedback system, such as those found in neural networks, a fuzzy expert system could learn from its mistakes and improve future performance by adjusting its parameters appropriately. Thus, if fraud risk assessments turn out to be inaccurate, the fuzzy expert system can modify itself to improve future assessments of similar situations.

In the next sections, we provide background on the standards related to fraud risk assessment and present an overview of prior research on this topic. Next, we discuss some existing applications of fuzzy logic in accounting and business and describe how the concepts of fuzzy logic apply to fraud risk assessment. We then present an example of a fuzzy expert system for assessing fraud risk, and we conclude with a brief discussion. The appendix briefly covers the fundamentals of fuzzy sets, fuzzy logic, and the fuzzy inference process.

II. Background

In 1997, the Auditing Standards Board (ASB) released SAS No. 82 to improve upon SAS No. 53 and the previously issued SAS Nos. 6, 16, and 17. The ASB designed SAS No. 82 to address the auditor's responsibility to detect fraud. In November 2002, following the wave of corporate scandals, the ASB issued SAS No. 99, *Consideration of Fraud in a Financial Statement Audit*. Below is a brief overview of SAS No. 99.

Like SAS No. 82, SAS No. 99 continues to differentiate between fraudulent financial reporting and misappropriation of assets. However, SAS No. 99 redefines the conditions and provides 64 fraud risk indicators within 14 audit risk factors. Thus, each fraud risk factor resides in one of six categories defined by this two-way classification. See Table 1.

- 4 related to incentives and pressures on management and operating personnel factor related to fraudulent financial reporting (with 15 indicators) and 2 related to misappropriation of assets (with 4 indicators),
- 4 related to opportunities enabling fraud risk factors related to fraudulent financial reporting (with 14 indicators) and 2 related to misappropriation of assets (with 15 indicators),
- 1 related to attitudes and rationalizations by board members, management, or employees to justify fraud risk factors related to fraudulent financial reporting (with 12 indicators) and 1 related to misappropriation of assets (with 4 indicators) (see Table 1).

In many ways, SAS No. 99 is similar to SAS No. 82. However, SAS No. 99

- places greater emphasis on the necessity for the auditor to maintain an attitude of professional skepticism,
- requires discussion by audit team members regarding the possibility of fraudulent financial reporting, including a brainstorming session designed to consider ways in which fraud could occur in the client firm,
- calls for greater inquiry of and interaction with all levels of client employees, and
- renews auditor attention to fraud risk factors throughout the audit engagement (Ramos 2003).

III. Literature Review

The failure to detect fraud can lead to litigation or regulatory action (Palmrose 1987; Feroz et al. 1991; Carcello and Palmrose 1994) and even the demise of the firm, as in the case of Arthur Andersen. Thus, there has long been great interest in fraud detection, which has resulted in considerable research on fraud. One set of studies focuses on identifying the risk factors found in actual fraud cases. Several of these studies compare firms in which fraud occurred with others in which fraud did not occur to assess the predictive value of various fraud risk factors. See, for example, Green and Calderon (1995); Green and Choi (1997); Beneish (1997); Weisenborn and Norris (1997); Summers and Sweeney (1998); Fanning and Cogger (1998); Bell and Carcello (2000); Beasley et al. (2000); and Farber (2005).

The Institute of Internal Auditors (Institute of Internal Auditors, 2006) points out that a substantial number of the fraud risk factors published in a National Association of Corporate Directors' (NACD) report issued prior to the Enron debacle were present in the Enron audit. Examples include unusually rapid growth or profitability compared with other companies in the same industry, significant bank accounts or subsidiary operations in tax-haven jurisdictions for which there appears to be no clear business justification, unusually high dependence on debt, accounting methods that appear to favor form over substance, and overly optimistic news releases or shareholder communications.

Bell and Carcello (2000) develop a logistic regression model for fraud risk based on SAS No. 82 fraud risk factors. Using a sample of 77 firms in which fraud occurred and 305 firms in which fraud did not occur, they find that the most significant risk factors are weak internal control, rapid company growth, inadequate or inconsistent relative profitability, undue management emphasis on meeting earnings projections, evasive or dishonest management, ownership status (public or private) of the entity, and the interaction between weak internal control and aggressive management. They also show that their model outperforms practicing auditors, providing evidence that a formalized decision aid can be useful in identifying fraud.

Heiman-Hoffman et al. (1996) find that auditors rely heavily on their perception of management's character attributes in assessing fraud. Wilks and Zimbelman (2004) address the concern that when auditors perceive management's attitude or character as indicative of low fraud risk, they are insufficiently sensitive to high levels of incentive or opportunity risks in their overall risk assessment. The authors find that auditors who separately assess attitude, opportunity risk, and incentive risk prior to assessing overall audit risk are more sensitive to opportunity and incentive cues when they perceive management's attitude to be suggestive of low fraud risk. They find that decomposing the risks into the separate categories is mostly helpful when opportunities and incentives signal low risk. This lends support to assessing fraud risk by breaking it down into the categories of risk factors suggested by SAS No. 99, which we do in our fuzzy logic system.

Another important area of research focuses on the best way to incorporate fraud risk factors into the audit. Shelton et al. (2001) review the audit manuals and practice aids of the Big 5 firms and two second-tier firms, and interview partners and directors in the national office responsible for developing firm practice materials. They find differences across audit firms in the level of integration, timing, and methods of fraud risk assessment. Most of the firms they studied rely on auditor judgment and incorporate simple checklists or a more complex 8- or 5-point scale scoring system to assess fraud risk. One of the firms requires the auditor to provide narrative responses to questions about risk factors. Two of the firms use expert systems in fraud risk assessment.

Eining et al. (1997), Pincus (1989), and Asare and Wright (2004) study the use of questionnaires and checklists in identifying fraud risk factors. They find that auditors who use a standard risk checklist do not make better risk assessments than those without a checklist. Asare and Wright (2004) conduct an experiment in which they provide 69 auditors with a realistic case involving fraud. They use four versions of the case determined by the presence or absence of a risk checklist and the presence or absence of a standard audit program. They find that auditors who used the standard audit program were less likely to design effective fraud tests, and those using a checklist made lower risk assessments than those not using the checklist. However, those using the checklist were more likely to consult fraud specialists, a positive outcome. They conclude that additional research is needed to consider the complete set of tools available to auditors in fraud risk assessment. Moyes (2008) surveyed CPAs to measure their perceptions of the effectiveness of each fraud risk indicator presented in SAS No. 99 in detecting fraud. Our study contributes to the literature in this area.

Other studies present models for fraud assessment or present innovative technologies for the identification of fraud risk factors (Loebbecke et al. (1989); Green and Choi (1997); Fanning and Cogger (1998); Bell and Carcello (2000); Lin et al. (2003); Patterson and Noel (2003)). Allen et al. (2006) present several conclusions based on their study of the audit risk literature. Their recommendations include using risk assessment methods that have been applied in other fields, such as corporate governance, financial analysis, and debt rating, and developing better fraud risk assessment tools. Our study responds to this call for research relative to new methods of risk assessment.

IV. Applications of Fuzzy Logic to Accounting and Business

Researchers have used fuzzy logic in many accounting and business applications, including sales forecasting, stock selection, financial ratio analysis, decision support systems, commercial loan analysis, and materiality assessments (Kelly 1984). Cooley and Hicks (1983) present a method for evaluation of internal control systems that combines linguistic information with rigorous mathematical aggregation. Chan and Yuan (1990) show how fuzzy set theory can handle imprecision in an expert's estimate of a demand distribution in the context of a stochastic cost-volume-profit analysis. Brewer et al. (1993) provide an overview of fuzzy logic applications in strategic management and finance. Lawrence and Butler (1995) examine the application of fuzzy logic in legacy costing and environmentally conscious manufacturing. De Korvin et al. (1995) showed how accounting expert systems could use fuzzy logic to incorporate ambiguity in cost variance analysis. Rangone (1997) proposed a fuzzy linguistic framework linking organizational effectiveness, key success factors, and performance measures. Von Altrock (1997) discusses several fuzzy logic applications in business and finance.

There have been a limited number of applications of fuzzy logic to auditing. Friedlob and Schleifer (1999) describe how to apply fuzzy logic in several audit situations involving risk and uncertainty. Lenard et al. (2001) used fuzzy logic to model the auditor's going concern decision. More recently, Comunale and Sexton (2005) and Rosner et al. (2006) apply fuzzy logic to create an expert system for assessing the materiality of omissions and misstatements in financial statements.

Several studies utilize fuzzy logic in fraud risk assessment. Feroz and Kwon (1996) compared the performances of a neural network, a fuzzy logic controller, and a logit model in identifying which of two matched firms had been investigated by the SEC, where one of them had been investigated and the other had not. They found that the neural network model appeared to outperform the fuzzy logic controller and that both models performed better than the logit model. However, their sample size is very small and they do not report the results of any statistical hypothesis tests.

Lin et al. (2003) use an integrated system of neural networks and fuzzy logic for fraud detection. Using a sample of firms sanctioned by the SEC for fraudulent financial reporting and a sample of matched firms, they develop a fuzzy logic neural network to classify firms as fraudulent or otherwise. They compare their results to those from a logit model for fraud prediction similar to that of Summers and Sweeney (1998). They find that the logit model is slightly more accurate in identifying non-fraudulent cases, which would help the auditor perform a more efficient audit when fraud is absent, while the fuzzy logic neural network was significantly more accurate in predicting the fraudulent cases, which would help the auditor perform a more effective audit when fraud is present. Their approach, unlike ours, focuses on the values reported in the financial statements, such as financial ratios and trends, rather than qualitative fraud risk factors provided by SAS No. 99. Their model is able to predict the fraud cases fairly accurately but is unable to predict the non-fraud cases as accurately.

Deshmukh and Romine (1996) and Deshmukh et al. (1997) propose the application of fuzzy logic to assess the risk of management fraud using the guidance given in SAS No. 53 and a model developed by Loebbecke et al. (1989). They argue for the aggregation of fraud risk factors rather than valuing each separately. However, they do not provide sufficient detail to permit the auditor to use the approach.

Deshmukh and Talluru (1998) build a model based on their earlier work. They test it on a proprietary dataset from KPMG Peat Marwick consisting of 382 cases previously analyzed by Bell et al. (1993). They use a scale of low, medium, and high for each fraud risk indicator. They find that the model tends to systematically underestimate fraud risk and that the model is weaker than statistical methods. They argue that their study demonstrates how to create a fuzzy system rather than how use it as a decision aid.

Our study extends the three Deshmukh, et al., papers and the Lin et al. paper in several ways. First, we update the fraud risk indicators and fraud risk factors to match those provided in SAS No. 99. Second, we add rule validities to our model to recognize that not all risk factors are equally indicative of fraud. Third, we apply the model to a highly detailed example to demonstrate the operations of the model and its potential advantages. Fourth, we consider the fraud risk indicators and fraud risk factors for both types of fraud (fraudulent financial reporting and misappropriations of assets). Fifth, based on the opinions of experienced auditors, we assign weights to each of the fraud risk indicators that reflect the strength of the fraud risk indicator in identifying the presence of the associated fraud risk factor. Sixth, we demonstrate the use of both fractional and binary fraud risk indicators. Finally, we aggregate the fraud risk indicator values within all three conditions and both types of fraud to identify areas that require closer scrutiny.

V. Applying Fuzzy Logic to Fraud Risk Assessment

We present below an example[2] of a fuzzy expert system that captures the fraud risk factors and fraud risk indicators specified in SAS No. 99. There are two phases in the implementation of the fraud risk assessment system: (1) the design phase, and (2) the operational phase. The design phase, which occurs only once, consists of the steps required to define the system components and to test the system to ensure that it performs as expected. The operational phase, which occurs at each audit engagement, consists of those steps required to apply the system during the audit engagement.

[2] We stress that the following is strictly an example and we make no claim that this system is either complete or necessarily optimal.

The Design Phase

The following steps occur during the design phase, the details of which we explain below:

1. Create checklists consisting of fraud risk indicators.
2. Assign weights to the fraud risk indicators.
3. Define the fuzzy sets *Not at All*, *Slightly*, *Moderately*, *Considerably*, and *Completely*.
4. Establish the fuzzy rules.
5. Establish the validity of each rule.

Create Checklists

We create 14 checklists, one for each of the fraud risk factors. The items on a checklist are the fraud risk indicators associated with the given fraud risk factor. Consider, for example, the fraud risk factor "ineffective monitoring of management." The two items on the checklist for this fraud risk factor are (1) domination of management by a single person or small group without compensating controls, and (2) ineffective board of directors or audit committee oversight over the financial reporting process and internal control.

While our approach follows the guideline of SAS No. 99, it is possible to incorporate additional risk factors. For example, Shelton et al. (2001) identify risk factors from selected studies (Loebbecke et al. (1989); Persons (1995); McMullen et al. (1996); Dechow et al. (1996); Beasley (1996); Summers and Sweeney (1998); COSO (1999); Bell and Carcello (1999)) not found in SAS No. 99. Examples include management domination of the board of directors, the CEO is the firm's founder, the original CEO or president is still in place, less rigorous controls or processes related to interim reporting, a desire to attract additional financing at low cost, and no satisfactory explanation for a change in principal legal counsel, bankers, or other key advisors.

Assign Weights to the Fraud Risk Indicators

Within each checklist, we assign weights to each of the fraud risk indicators that reflect the strength of the fraud risk indicator in identifying the presence of the associated fraud risk factor. The weights need to reflect the collective judgment of the system designers, who may adjust the weights during system testing to ensure that the system performs as desired. We then normalize the weights to sum to 100 within each checklist.

For example, Table 2 shows the checklist for the fraud risk factor "Financial stability or profitability is threatened by economic, industry, or entity operating conditions," which is the first fraud risk factor in the incentive/pressures condition within the fraudulent financial reporting type. The weights indicate that, for example, the existence of "Operating losses making the threat of bankruptcy, foreclosure, or hostile takeover imminent" is a much stronger indicator of this fraud risk factor than is the existence of "New accounting, statutory, or regulatory requirements." These indicators have weights of 70 and 20, respectively, but other system designers may choose other weights. Note that the sum of the weights equals 390. Therefore, we normalize each weight by dividing it by 390 (see Table 2).

To establish the weights, we asked 17 auditors (7 managers and 10 partners) from four accounting firms with an average of almost 18 years of experience to assign a weight between 0 and 100 to each fraud risk indicator. Fifteen of the auditors hold an undergraduate degree and two hold a masters degree. Two of the accounting firms are in the Big Four and two are regional firms operating in the northeastern region. One regional firm employs over 100 people while the other employs 48. The weights presented in Tables 2 are the medians of the reported weights. The normalized weights appear in Tables 2 and 5. The intraclass correlation coefficient of the weights equals 0.8769, indicating that over 87% of the variation in weights is associated with variation across fraud risk indicators. Thus, we conclude that the auditors in our study are reliable raters of the weights.

Define the Fuzzy Sets Not At All, Slightly, Moderately, Considerably, and Completely

In the design phase, the audit firm defines preliminary membership functions for the five fuzzy sets, *Not at All*, *Slightly*, *Moderately*, *Considerably*, and *Completely* as functions of x, the sum of the normalized weights within each fraud risk factor. For example, the preliminary membership function for *Slightly* might be defined as

$$\hat{\mu}_{Slightly}(x) = \begin{cases} \frac{x}{15} & 0 \le x \le 15 \\ 2 - \frac{x}{15} & 15 \le x \le 30 \\ 0 & x \ge 30 \end{cases}$$

which is shown in Figure 1. Similar preliminary membership functions are required for *Not at All*, *Moderately*, *Considerably*, and *Completely*[3] (see Figure 1).

Consider, for example, the fraud risk factor "Financial stability or profitability is threatened by economic, industry, or entity operating conditions" shown in Table 2. Suppose that the last three fraud risk indicators are present. Then the sum of the normalized weights equals 43.6 (20.5 + 17.9 + 5.1) and this fraud risk factor has preliminary membership of 0.547 in *Moderately*. We derive this preliminary membership by substituting x=43.6 into the preliminary membership function for *Moderately*. Using the other four membership functions, we find that this fraud risk factor has preliminary membership of 0.679 in *Considerably* and zero in the other three fuzzy sets. We compute the final membership values from the results of the preliminary membership functions by scaling the results to sum to one. The sum of the preliminary

[3] Other preliminary membership function definitions and other terms are possible.

memberships is 1.226 (0.547 + 0.679). Thus, in this example, the final membership values are 0.446 for *Moderately* (0.547/1.226) and 0.554 for *Considerably* (0.679/1.226).

Establish the Fuzzy Rules

Assume that the audit firm establishes fuzzy rules of the following type:

IF (Fraud Risk Factor exists Z) THEN (High Fraud Risk)

where Z represents the names of the fuzzy sets, *Not at All*, *Slightly*, *Moderately*, *Considerably*, and *Completely*. SAS No. 99 identifies 14 fraud risk factors and we have five levels of Z; therefore there are 70 (14 times 5) fuzzy rules. The truth-value for a fuzzy rule is equal to the membership associated with the antecedent.

Establish the Validity of Each Rule

Next, the audit firm establishes validities[4] for each of the 70 rules. For example, Table 3 shows validities for the five fuzzy rules for the risk factor dealing with complex or unstable organizational structure. For each of the 70 rules, the membership in the fuzzy set High Fraud Risk equals the product of the validity of the rule times the truth-value of the antecedent of the rule. For example, suppose that the rule that states:

IF (Financial stability or profitability is SLIGHTLY threatened by economic, industry, or entity operating conditions) THEN (High Fraud Risk)

has 0.20 membership in the set V of valid rules. Suppose further, by contrast, that the rule that states:

IF (Financial stability or profitability is CONSIDERABLY threatened by economic, industry, or entity operating conditions) THEN (High Fraud Risk)

[4] The validities presented here are for illustration only and may not reflect appropriate values in all situations.

has 0.80 membership in the set V of valid rules. Thus, the audit firm is expressing the opinion that a considerable threat to financial stability or profitability provides greater evidence of high fraud risk than does a slight threat (see Table 3).

Operational Phase

The following steps occur during the operational phase, the details of which we explain below:

1. Auditor detects the presence of each fraud risk indicator, either in a binary manner, (presence or absence) or as a proportion (degree to which the fraud risk indicator is present)
2. System computes total normalized weight within each fraud risk indicator
3. System computes the final membership value of each fuzzy rule
4. System computes the maximum final membership value within each fraud risk factor
5. System computes a weighted average of these maxima within each category
6. System computes the fraud risk for each type of fraud
7. Auditor interprets the fraud risks

Detection of Fraud Risk Indicators

During the course of an audit engagement, the auditor may make a binary decision regarding the presence, indicated by a 1, or absence, indicated by a 0, of each fraud risk indicator. However, the system works equally well with any value between 0 and 1 so that the auditor may express an intermediate judgment regarding the presence of each fraud risk indicator. Thus, an auditor who believes that a certain fraud risk factor exists to a limited extent can reflect that belief using a number greater than 0 but less than 1.

Compute Total Normalized Weight within Each Fraud Risk Indicator

The system then sums the normalized weights within each of the 14 fraud risk factors. It then uses the sum to compute the preliminary and final membership values for the antecedent of each fuzzy rule. The final membership value for a fuzzy rule also serves as its truth-value.

Compute Final Memberships Values for Each Fuzzy Rule

The truth-value of each fuzzy rule multiplied by the validity of that rule equals the membership of the engagement in the fuzzy set *High Fraud Risk* implied by that fuzzy rule.

Compute Final Memberships Values for Each Fraud Risk Factor

The system computes the maximum final membership value within each of the 14 fraud risk factors. This represents the membership of the engagement in the fuzzy set *High Fraud Risk* implied by the fraud risk factor.

Compute Final Memberships Values for Each Fraud Risk Category

The system computes a weighted average of these maxima within each of the 6 combinations of type of fraud and fraud condition. The weight applied to maximum value is the maximum validity associated with any of the five fuzzy rules within that fraud risk factor. The rationale for using the maximum validity is that it provides a measure of the overall strength of the fraud risk factor in determining fraud risk.

Compute Fraud Risk for Each Type of Fraud

The system computes the fraud risk for each type of fraud by computing the average fraud risk across all 3 combinations within the given type of fraud. By equally weighting the categories, we are assuming that each category is equally effective in assessing fraud risk.

Interpret the Fraud Risks

The auditor interprets the fraud risks using Table 4 or another similar set of interpretations. Loosely speaking, a fraud risk in a given category is the weighted percentage of the fraud risk indicators present in that category (see Table 4).

VI. Example of a Fuzzy Logic Fraud Risk Assessment System

The following is an illustration of how an auditor can use fuzzy logic to assist in assessing fraud risk within the framework of SAS No. 99. Assume that the audit client, Spencer Electronics, sells wholesale electronic appliances, such as toasters, shavers, hair dryers, cameras, and computers, to retailers. The company, which has been in business since 1990, went public in 1999 with the help of a new CEO, who invested millions of his own money to purchase 10% of the company stock to "align his own interests with those of the stockholders." The CEO publicly predicted that, because of an aggressive marketing campaign and cost reduction plan, the company would achieve substantial increases in gross margin and introduce several new products in the next few years. In fact, in the audit year, which was the first year of fraud, the gross margin percentage actually decreased by 11.9% from the prior year. The CEO also provided attractive and lucrative employment contracts to upper management that included bonuses with strong financial incentives to raise the share price of the company.

At the same time, however, he managed to disenfranchise lower echelon personnel in several ways. First, his cost-cutting strategy involved the layoff of several lower-level employees in the shipping and receiving, inventory, and accounting departments at the end of 2001. He retained the supervisory employees in those departments and, in fact, increased their responsibilities since there were now fewer employees to complete the required tasks. However, to keep costs down, he instituted a no-salary-increase policy for a minimum of eighteen months. Although, the supervisory employees were unhappy about this, many had a long history with the company and, for various reasons, did not feel that changing jobs was an option. In addition, they felt fortunate that they had survived the layoffs, and thus they did not openly protest.

Nevertheless, they were disenchanted. These negative feelings were the catalyst for the supervisor of the inventory, shipping, and receiving areas (considered to be a competent and reliable employee) to begin pocketing a substantial number of smaller expensive inventory items, such as hand-held computers, MP3 players, and digital cameras. The theft reduced the physical inventory but not the accounting records, which ultimately resulted in an overstatement of inventory on the financial statements in 2002 and 2003.

Weakened internal controls facilitated the theft. In accordance with his original job description, the supervisor was able to authorize transactions and even override the system in given situations. However, the layoff of employees in several departments resulted in less segregation of duties and less oversight. In addition, controls such as mandatory vacations were no longer enforced. The supervisor of the inventory, shipping, and receiving areas opted to take vacation pay without time off because of his financial situation, and management readily accepted this. Given the supervisor's increased responsibilities, management felt the company was better off maintaining continuity in operations unhampered by the absence of a key employee for a two-week or longer vacation period. Upper management was also preoccupied with its own tribulations and thus this fraud and the resulting inventory overstatement went undetected.

At this time, the company was experiencing greater competition and the company's relative performance began to decline. It experienced several quarters of lower-than-expected sales and earnings in 2001 and 2002 – the percentage change in sales from 2001 to 2002 was negative 3% – and cash flow was not as good as it had been. Indeed, the percentage change in cash flow from operations from 2001 to 2002 was negative 83% and the net percentage change in cash flow was negative 60%. Although the auditors had issued unqualified opinions on the financial statements, it was later discovered that the company's annual financial statements were overstated in years 2002 and 2003 and concealed net losses in both years.

Senior executives had been directly involved in operations on a daily basis and had perpetrated the fraud by bypassing existing controls and the accounting information system. They had devised an intricate scheme where they recorded fictitious sales, receivables transactions, and purchases of inventory. They had avoided making standard entries in the sales, purchases, and cash disbursements journals as required by existing internal controls and recorded the fictitious transactions manually. They also were able to bypass normal accounts payable controls by maintaining a supply of blank checks on two different bank accounts and using them to make disbursements. The CEO, however, was very charismatic and possessed excellent leadership and social skills. He was very solicitous of the auditors and gave the impression of being dedicated to ethical standards and controls, and willing to enlist the advice of managers, employees, and auditors in implementing improvements.

The company went bankrupt in 2005. Had the auditors used the proposed fuzzy logic system, they would have identified the presence (using either a binary or a proportional approach) of the fraud risk indicators shown in Table 5 (see Table 5).

Table 6 shows the fraud risks for each type of fraud and for each of the 6 combinations of type and condition using the binary approach for fraud risk indicators. We see that the fraud risks for fraudulent financial reporting and for misappropriation of assets are 28% and 26%, respectively. Table 7 shows the fraud risks for each type of fraud and for each of the 6 combinations of type and condition using the proportional approach for fraud risk indicators. We see that the fraud risks for fraudulent financial reporting and for misappropriation of assets are 25% and 28%, respectively. Using Table 4, we conclude that there is considerable risk of each type of fraud. The fraud risks within each of the 6 categories ranges from small to great. Note, in particular, that there is a great risk of fraudulent financial reporting due to incentives and pressures using both binary and proportional fraud risk indictors suggesting that the auditor needs to investigate this area very carefully (see Tables 6 and 7).

VII. Discussion and Conclusion

Fraud risk assessment is a highly complex process that is a part of every audit engagement. Over time, regulatory requirements have steadily increased the amount of time and effort required of the auditor to assess fraud. It follows, therefore, that fraud risk assessment presents an ideal opportunity for technological assistance, specifically in the form of an expert system.

We have shown that a fuzzy logic system can assist the auditor in assessing the risk of fraud in an audit engagement. This approach provides the auditor with greater discriminatory power relative to that available using the classical binary notion, allows the auditor to identify the specific underlying areas that contribute most to the overall fraud risk evaluation, provides a model structure that requires the auditor to make explicit judgments, and establishes a framework for organizational learning. In general, we expect that these advantages will increase overall audit effectiveness in fraud assessment.

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APPENDIX – FUNDAMENTALS OF FUZZY LOGIC

Zadeh (1965) was the first to introduce the concepts of fuzzy sets and fuzzy logic. He and his followers developed an axiomatic paradigm that generalizes the classical concept of a set by allowing an item to have partial membership in a set, as opposed to being either entirely in the set or entirely out of the set.

In the classical definition of a set *S*, an item, *x*, either is an element of *S*, denoted $x \in S$, or is not an element of *S*, denoted $x \notin S$. Such definitions are "crisp" in the sense that the boundaries of *S* are sharp and membership in *S* is unambiguous. We define a *fuzzy set S* by its *membership function* $\mu(x)$, a real-valued function that specifies the *degree of membership* of *x* in *S*. We restrict $\mu(x)$ to the range $0 \leq \mu(x) \leq 1$, with $\mu(x) = 1$ indicating full membership of *x* in *S*, and $\mu(x) = 0$ indicating that *x* has no membership in *S*.

As illustrated above by the fuzzy set $T=\{x \mid x \text{ is a tall man}\}$, fuzzy sets allow us to define a set in the presence of linguistic ambiguity without the need to specify an often arbitrary and distorting crisp set definition. In this example, we could define a membership function for *T* by defining the variable h_x to be the height of man *x*, in feet, and setting

$$\mu_T(x) = \begin{cases} 0, \text{if } h_x < 5 \\ \frac{1}{2}(h_x - 5), \text{if } 5 \leq h_x \leq 7 \\ 1, \text{if } h_x > 7 \end{cases}$$

Figure A1 shows this function (see Figure A1).

Note that we could define *T* as a classical set by specifying $T = \{x \mid h_x \geq 6\}$. In fuzzy set notation, this is equivalent to specifying the membership function

$$\mu(x) = \begin{cases} 1, \text{if x is a man who is at least six feet tall} \\ 0, \text{otherwise} \end{cases}$$

In this sense, classical sets are special cases of fuzzy sets.

Fuzzy logic operates on fuzzy sets by defining membership functions for the complement of a fuzzy set and for the union and intersection of two fuzzy sets. If *S* and *T* are fuzzy sets with membership functions $\mu_S(x)$ and $\mu_T(x)$, then the membership function of S', the complement of *S*, is

$$\mu_{S'}(x) = 1 - \mu_S(x)$$

the membership function of the union $S \cup T$ is

$$\mu_{S \cup T}(x) = \max\{\mu_S(x), \mu_T(x)\}$$

and the membership function of the intersection $S \cap T$ is

$$\mu_{S \cap T}(x) = \min\{\mu_S(x), \mu_T(x)\}$$

These definitions allow us to perform the fuzzy logic versions of the classical logical functions NOT, OR, and AND, respectively. We define the *truth-value* of the statement "*x* is in *S*" as $\mu_S(x)$, which leads to $1 - \mu_S(x)$ as the truth-value for "*x* is not in *S*." The truth-value of "(*x* is in *S*) OR (*y* is in *T*)" is $\max\{\mu_S(x), \mu_T(y)\}$, and the truth-value of "(*x* is in *S*) AND (*y* is in *T*)" is $\min\{\mu_S(x), \mu_T(y)\}$. As in classical logic, we may build fuzzy logic expressions of arbitrary complexity.

The classical implication statement $S \subset T$ is equivalent to $S' \cup T$. If S and T are fuzzy sets, then the membership function of $S \subset T$ is, from above,

$$\mu_{S \subset T}(x, y) = \max\{1 - \mu_S(x), \mu_T(y)\}$$

Fuzzy Rules

A *fuzzy rule*, *r*, is a logical implication statement of the form

r: IF A, THEN *y* is in *T*

where A is a logical expression involving fuzzy sets, *y* is an item of unknown value about which the fuzzy rule makes inference, and *T* is a fuzzy set. For example, a company executive interested in forecasting the firm's sales for the next quarter might believe

r_1: IF {*i* is low AND *c* is high} THEN *s* is high

where *i* is a relevant interest rate, *c* is a measure of consumer confidence, and *s* is sales for the next quarter. We must define three fuzzy sets: I_{Low} for low interest rate, C_{High} for high consumer confidence, and S_{High} for high sales for next quarter.

We use *r* to make an inference about *y* with respect to *T*. To do so, let α_r be the truth-value of the antecedent statement A. Then the fuzzy rule infers a degree of membership of *y* in *T* to be

$$\mu_T(y) = \alpha_r$$

In other words, *y* is a member of *T* to the extent that A is true. In the sales forecasting example, suppose that *i*=7% and *c*=53% (the percentage of consumers who believe that the economy is strong). Suppose further that these values have memberships equal to $\mu^I_{Low}(7\%) = 0.4$ and $\mu^C_{High}(53\%) = 0.7$ in the fuzzy sets I_{Low} and C_{High}, respectively. Then

$$\alpha_r = \min\{0.4, 0.7\} = 0.4$$

is the truth-value of the antecedent to rule r_1, leading to the inference that $\mu^S_{High}(i, c) = \mu^S_{High}(7\%, 53\%) = 0.4$.

We also consider rules themselves to be (partial) members of the fuzzy set *V* of all valid rules. Thus, a fuzzy rule *r* has membership $\mu_V(r)$ in *V*. In this case, the fuzzy rule infers a degree of membership of *y* in *T* to be

$$\mu_T(y) = \alpha_r \mu_V(r)$$

In this case, *y* is a member of *T* to the extent that A is true and *r* is a member of *V*. In the sales forecasting example, suppose that the executive assigned fuzzy rule r_1 the membership $\mu_V(r_1) = 0.8$ in the set *V* of valid rules. The rule r_1 would lead to the inference $\mu^S_{High}(i,c) = \mu^S_{High}(7\%, 53\%) = (0.4)(0.8) = 0.32$.

Rule-Based Fuzzy Expert Systems

A *rule-based fuzzy expert system* consists of a collection, *R*, of fuzzy rules together with a fuzzy set, *V*, of valid rules and a membership function $\mu_V(r)$ defined for all $r \in R$. In a given situation, the fuzzy expert system makes inferences about one or more items of interest by evaluating the antecedent expressions of each rule and assigning fuzzy set memberships to the items. Because different rules may produce inferences for the same item, the fuzzy expert system may infer several different degrees of memberships of an item in a given fuzzy set and with degrees of membership in several different fuzzy sets. In the sales forecasting example, the fuzzy expert system might consist of four fuzzy rules and three fuzzy sets for sales, S_{Low}, S_{Med}, and S_{High}, for low, moderate, and high quarterly sales. The four rules might produce

$$\begin{aligned} r_1 &: \mu^S_{High}(\cdot) = 0.32 \\ r_2 &: \mu^S_{Mod}(\cdot) = 0.65 \\ r_3 &: \mu^S_{Low}(\cdot) = 0.12 \\ r_4 &: \mu^S_{Low}(\cdot) = 0.20 \end{aligned}$$

Note that the four fuzzy rules provide degrees of membership of *S* in all three fuzzy sets, and that rules 3 and 4 provide two different degrees of membership in S_{Low}.

In some applications, we may not need to proceed further. The executive in our example might be satisfied to interpret these degrees of membership to predict that sales in the next quarter will be moderate to high. However, in other applications, we must convert the fuzzy inference results to crisp outcomes. We refer to this last step as *defuzzification*.

To illustrate the defuzzification process in the sales forecasting example, suppose that the executive has specified the membership functions for S_{Low}, S_{Med}, and S_{High} shown in Figure A2. These membership functions suggest typical values for each of the three fuzzy sets. We might select \$6 million as the typical value for S_{Low}, \$8 million for S_{Med}, and \$10 million for S_{High}. We compute a crisp value for S as the weighted average of these typical values, using the degrees of membership as weights:

$$S_{Crisp} = \frac{(0.32)(10) + (0.65)(8) + (0.12)(6) + (0.20)(6)}{0.32 + 0.65 + 0.12 + 0.20} = \frac{10.32}{1.29} = 8$$

Thus, the executive would forecast quarterly sales of \$8 million for the next quarter (see Figure A2).

Figure A1: Membership function for the set of tall men.

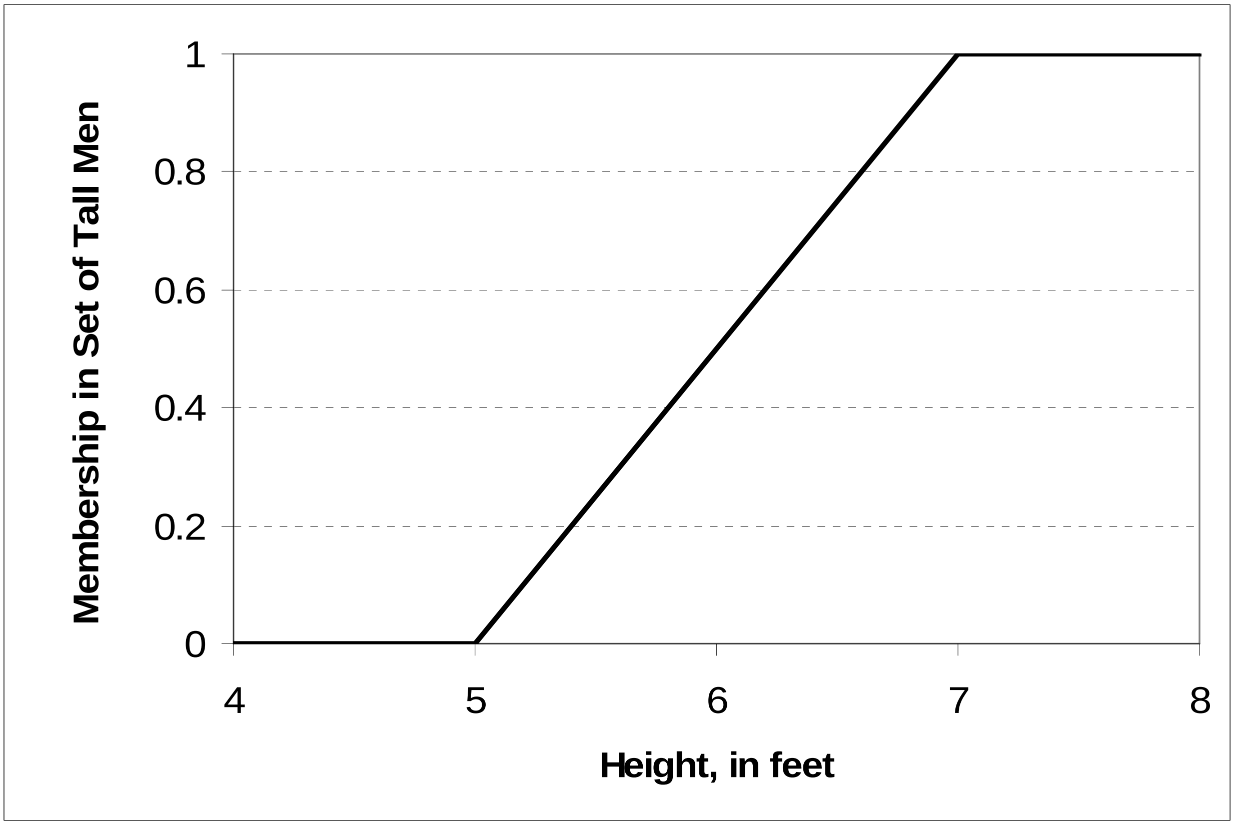

Figure A2: Membership functions for low, moderate, and high quarterly sales forecasts.

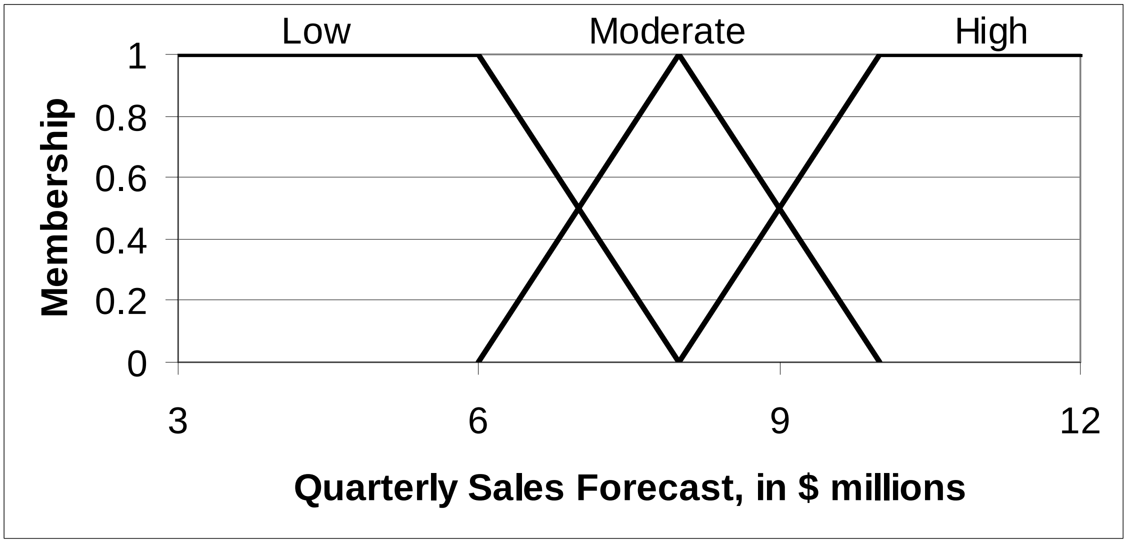

Figure 1: Example of a membership function for the fuzzy set *Slightly*.

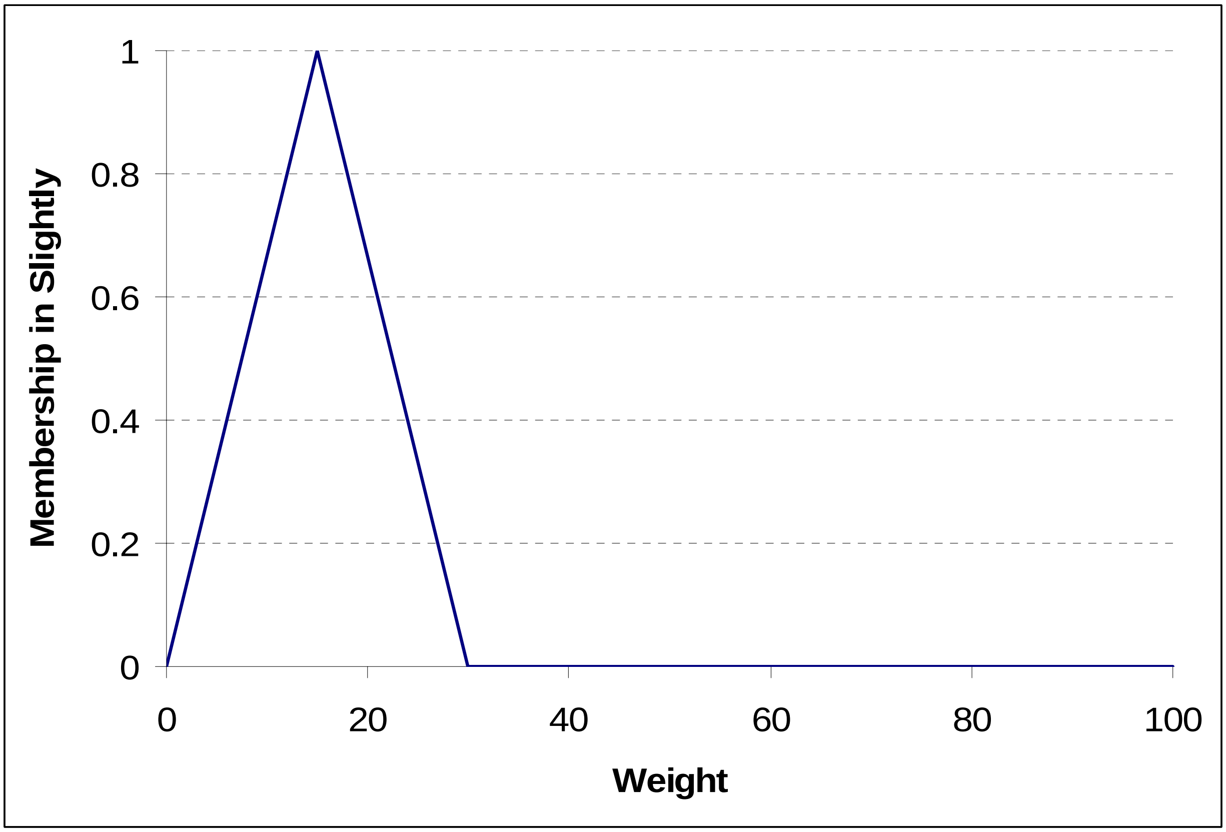

Table 1: The six fraud risk categories defined by SAS No. 99, with associated fraud risk factors.

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="2">Types of Fraud</th></tr>
<tr><th>Fraudulent Financial Reporting</th><th>Misappropriation of Assets</th></tr>
<tr><td rowspan="3">Conditions</td><td>Incentives/Pressures</td><td>IF [Financial stability/profitability threatened by economic/industry/entity operating conditions] THEN High Risk
IF [Excessive pressure exists for management to meet requirements/expectations of third parties] THEN High Risk
IF [Information indicates management/board of directors' personal financial situation is threatened by entity's financial performance] THEN High Risk
IF [Excessive pressure on management/operating personnel to meet financial targets set up by board of directors or management, including sales/profitability incentive goals] THEN High Risk</td><td>IF [Personal financial obligations in personnel with access to cash/other assets susceptible to theft] THEN High Risk
IF [Adverse relationships between entity and employees with access to cash/other assets susceptible to theft] THEN High Risk</td></tr>
<tr><td>Opportunities</td><td>IF [Nature of industry/entity's operations provides opportunities to engage in fraudulent financial reporting] THEN High Risk
IF [Ineffective monitoring of management] THEN High Risk
IF [Complex/unstable organizational structure] THEN High Risk
IF [Internal control components deficient] THEN High Risk</td><td>IF [Certain characteristics/circumstances exist] THEN High Risk
IF [Inadequate internal control exists over assets susceptible to misappropriation] THEN High Risk</td></tr>
<tr><td>Attitudes/ Rationalization</td><td>Existence of attitudes and rationalizations by board members, management, or employees that allow them to engage in or justify fraudulent financial reporting.</td><td>Existence of attitudes and rationalizations by employees that allow them to justify misappropriation of assets.</td></tr>
</table>

Table 2: Fraud risk indicators, weights, and normalized weights for the fraud risk factor "Financial stability or profitability is threatened by economic, industry, or entity operating conditions."

Fraud Risk Indicator	**Weight**	**Normalized Weight**
High degree of competition or market saturation, accompanied by declining margins.	50	12.8
High vulnerability to rapid changes, such as changes in technology, product obsolescence, or interest rates.	50	12.8
Significant declines in customer demand and increasing business failures in either the industry or overall economy.	50	12.8
Operating losses making the threat of bankruptcy, foreclosure, or hostile takeover imminent.	70	17.9
Recurring negative cash flows from operations or an inability to generate cash flows from operations while reporting earnings and earnings growth.	80	20.5
Rapid growth or unusual profitability, especially compared to that of other companies in the same industry.	70	17.9
New accounting, statutory, or regulatory requirements.	20	5.1
Sum	**390**	**100**

Table 3: Validities associated with the five fuzzy rules "IF organizational structure is _____ complex or unstable, THEN High fraud risk," where the adjectives below are inserted into the space.

	Not at All	Slightly	Moderately	Considerably	Completely
Validity	**0**	**0.1**	**0.3**	**0.5**	**0.6**

Table 4: Interpretations of the fraud risks.

Fraud Risk	**Interpretation**
Less than 5%	Very small
5% − 10%	Small
10% − 20%	Moderate
20% − 30%	Considerable
30% − 40%	Significant
Greater than 40%	Great

Table 5: Normalized weights and presence of fraud risk factors (binary and proportional basis) defined by SAS No. 99 for the sample case.

	Incentives/Pressures to Engage in Fraudulent Financial Reporting	**Normalized Weight**	**Presence (Binary)**	**Presence (Prop)**
A1	High degree of competition or market saturation, accompanied by declining margins	12.8	1	0.9
2	High vulnerability to rapid changes, such as changes in technology, product obsolescence, or interest rates	12.8		0.3
3	Significant declines in customer demand and increasing business failures in either the industry or overall economy	12.8		0.1
4	Operation losses making the threat of bankruptcy, foreclosure, or hostile takeover imminent	17.9		
5	Recurring negative cash flows from operations or an inability to generate cash flows from operations while reporting earnings and earnings growth	20.5		
6	Rapid growth or unusual profitability, especially compared to that of other companies in the same industry	17.9		0.3
7	New accounting, statutory, or regulatory requirements	5.1		
B1	Profitability or trend level expectations of investment analysts, institutional investors, significant creditors, or other external parties, including expectations created by management in, for example, overly optimistic press releases or annual report messages	26.7	1	0.8
2	Need to obtain additional debt or equity financing to stay competitive – including financing of major research and development or capital expenditures	23.3		0.2
3	Marginal ability to meet exchange listing requirements or debt repayment or other debt covenant requirements	25.0		
4	Perceived or real adverse effects of reporting poor financial results on significant pending transactions, such as business combinations or contract awards	25.0		0.2
C1	Significant financial interests in the entity	31.3	1	0.9
2	Significant portions of their compensation (for example, bonuses, stock options, and earn-out arrangements) being contingent upon achieving aggressive targets for stock price, operating results, financial position, or cash flow	37.5	1	0.9
3	Personal guarantees of debts of the entity	31.3		
D1	There is excessive pressure on management or operating personnel to meet financial targets set up by the board of directors or management, including sales or profitability incentive goals	100.0	1	0.8

	Opportunities – Fraudulent Financial Reporting	Normalized Weight	Presence (Binary)	Presence (Prop)
A1	Significant related-party transactions not in the ordinary course of business or with related entities not audited or audited by another firm	18.8		
2	A strong financial presence or ability to dominate a certain industry sector that allows the entity to dictate terms or conditions to suppliers or customers that may result in inappropriate or non-arm's-length transactions	14.1		
3	Assets, liabilities, revenues, or expenses based on significant estimates that involve subjective judgments or uncertainties that are difficult to corroborate	16.5		
4	Significant, unusual, or highly complex transactions, especially those close to period end that pose difficult "substance over form" questions	18.8		
5	Significant operations located or conducted across international borders in jurisdictions where differing business environments and cultures exist	14.1		
6	Significant bank accounts or subsidiary or branch operations in tax-haven jurisdictions for which there appears to be no clear business justification	17.6		
B1	Domination of management by a single person or small group (in a non-owner-managed business) without compensating controls	54.8	1	0.6
2	Ineffective board of directors or audit committee oversight over the financial reporting process and internal control	45.2		
C1	Difficulty in determining the organization or individuals that have controlling interest in the entity	30.4		
2	Overly complex organizational structure involving unusual legal entities or managerial lines of authority	34.8		
3	High turnover of senior management, counsel, or board members	34.8		
D1	Inadequate monitoring of controls, including automated controls and controls over interim financial reporting (where external reporting is required)	33.3	1	0.8
2	High turnover rates or employment of ineffective accounting, internal audit, or information technology staff	33.3		
3	Ineffective accounting and information systems, including situations involving reportable conditions	33.3		

	Attitudes/Rationalizations – Fraudulent Financial Reporting	Normalized Weight	Presence (Binary)	Presence (Prop)
A1	Ineffective communication, implementation, support, or enforcement of the entity's values or ethical standards by management or the communication of inappropriate values or ethical standards	5.9	1	0.8
2	Non financial management's excessive participation in or preoccupation with the selection of accounting principles or the determination of significant estimates	7.9		
3	Known history of violations of securities laws or other laws and regulations, or claims against the entity, its senior management, or board members alleging fraud or violations of laws and regulations	9.4		
4	Excessive interest by management in maintaining or increasing the entity's stock price or earnings trend	8.9	1	0.8
5	A practice by management of committing to analysts, creditors, and other third parties to achieve aggressive or unrealistic forecasts	8.9	1	0.8
6	Management failing to correct known reportable conditions on a timely basis	7.9		
7	An interest by management in employing inappropriate means to minimize reported earnings for tax-motivated reasons	8.9		
8	Recurring attempts by management to justify marginal or inappropriate accounting on the basis of materiality	7.9		
B1	Frequent disputes with the current or predecessor auditor on accounting, auditing, or reporting matters	7.4		
2	Unreasonable demands on the auditor such as unreasonable time constraints regarding the completion of the audit or the issuance of the auditor's report	8.8		
3	Formal or informal restrictions on the auditor that inappropriately limit access to people or information or the ability to communicate effectively with the board of directors or audit committee	9.2		
4	Domineering management behavior in dealing with the auditor, especially involving attempts to influence the scope of the auditor's work or the selection or continuation of personnel assigned to or consulted on the audit engagement	9.3		0.1

	Incentives/Pressures to Engage in Misappropriation of Assets	**Normalized Weight**	**Presence (Binary)**	**Presence (Prop)**
A	Personal financial obligations may create pressure on management or employees with access to cash or other assets susceptible to theft to misappropriate those assets	100.0		
B1	Known or anticipated future employee layoffs	33.3	1	0.7
2	Recent or anticipated changes to employee compensation or benefit plans	33.3	1	0.7
3	Promotions, compensation, or other rewards inconsistent with expectations	33.3	1	0.9

	Opportunities – Misappropriation of Assets	**Normalized Weight**	**Presence (Binary)**	**Presence (Prop)**
A1	Large amounts of cash on hand or processed	26.2		
2	Inventory items that are small in size, of high value, or in high demand	26.2	1	0.95
3	Easily convertible assets, such as bearer bonds, diamonds, or computer chips	24.6		
4	Fixed assets that are small in size, marketable, or lacking observable identification of ownership	23.0		
B1	Inadequate segregation of duties or independent checks	9.3	1	0.95
2	Inadequate management oversight of employees responsible for assets, for example, inadequate supervision or monitoring of remote locations	9.9	1	0.95
3	Inadequate job applicant screening of employees with access to assets	7.4		
4	Inadequate recordkeeping with respect to assets	9.9	1	0.9
5	Inadequate system of authorization and approval of transactions (for example, in purchasing)	9.9		
6	Inadequate physical safeguards over cash, investments, inventory, or fixed assets	11.1	1	0.9
7	Lack of complete and timely reconciliations of assets	9.3	1	0.7
8	Lack of timely and appropriate documentation of transactions, for example, credits for merchandise returns	9.3		
9	Lack of mandatory vacations for employees performing key control functions	7.4	1	0.8
10	Inadequate management understanding of information technology, which enables information technology employees to perpetrate a misappropriation	8.0		
11	Inadequate access controls over automated records, including controls over and review of computer systems event logs	8.6		0.3

	Attitudes/Rationalizations – Misappropriation of Assets	**Normalized Weight**	**Presence (Binary)**	**Presence (Prop)**
A1	Disregard for the need for monitoring or reducing risks related to misappropriations of assets	23.4	1	0.7
2	Disregard for internal control over misappropriation of assets by overriding existing controls or by failing to correct known internal control deficiencies	26.6	1	0.9
3	Behavior indicating displeasure or dissatisfaction with the company or its treatment of the employee	23.4	1	0.9
4	Changes in behavior or lifestyle that may indicate assets have been misappropriated	26.6		

Table 6: The output of the fuzzy logic fraud assessment system for the sample case using binary assessment of fraud risk indicators.

	Fraudulent Financial Reporting	Misappropriation of Assets
Incentives and Pressures	**47%**	**31%**
Opportunities	**21%**	**32%**
Attitudes and Rationalizations	**15%**	**16%**
Fraud Risk	**28%**	**26%**

Table 7: The output of the fuzzy logic fraud assessment system for the sample case using proportional assessment of fraud risk indicators.

	Fraudulent Financial Reporting	Misappropriation of Assets
Incentives and Pressures	**50%**	**15%**
Opportunities	**16%**	**35%**
Attitudes and Rationalizations	**8%**	**35%**
Fraud Risk	**25%**	**28%**