# Chapter 2.44 The Use of Fuzzy Logic and Expert Reasoning for Knowledge Management and Discovery of Financial Reporting Fraud

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## ABSTRACT

This chapter examines the use of fuzzy clustering and expert reasoning for the identification of firms whose financial statements are affected by fraudulent financial reporting. For this purpose, we developed a database consisting of financial and nonfinancial variables that evaluated the risk offraud. The variables were developed using fuzzy logic, which clusters the information into various risk areas. Expert reasoning, implemented in an Excel spreadsheet model, is then used as a form of knowledge management to access the information and develop the variables continuously over the life of the company. At the conclusion of the chapter, the authors discuss emerging trends and future research opportunities. The combination of fuzzy logic, expert reasoning and a statistical tool is an innovative method to evaluate the risk of fraudulent financial reporting.

## INTRODUCTION

In the light of recent reporting of the alleged financial reporting abuses in some of the major publicly-held companies in the U.S. (e.g., Enron and WorldCom), it has become increasingly important that management, auditors, analysts and regulators be able to assess and identify fraudulent financial reporting. This chapter is an attempt to use some of the latest statistical methods, expert reasoning and data mining techniques to achieve this objective.

Knowledge management can be used to a company's advantage in day-to-day decisionmaking. From a financial standpoint, a company must accumulate and disclose information to its employees, customers and investors. This information database can enable a company to support and maintain a competitive position. For instance, one way that a company can justify its financial health is by developing a knowledge management database of financial and nonfinancial variables to evaluate the risk of employee and financial reporting fraud. Collecting data using information processing and organizing the data through knowledge management can create a database for fraud detection and facilitate organizational data mining. Such a database can assist in knowledge discovery and help a company acquire and develop variables useful for the detection of fraud. The database can consist of historical data about the company as well as data for other companies in the industry. This database may be used by banks for lending decisions, by audit firms in an audit or by the company's management to gather and assess new information. These variables could also be evaluated to determine if the company has reached a stress level susceptible to fraud or for identifying fraud indicators.

The auditor's responsibility for detecting financial statement fraud is described in SAS No. 82, Consideration of Fraud in a Financial Statement Audit (American Institute of Certified Public Accountants (AICPA), 1997). Because fraud detection often involves an auditor's judgment in an unstructured environment, there is a possibility that the auditor may enhance the decision-making process with the assistance of a decision model. Using publicly available information, models can be designed to aid an auditor in detecting and evaluating financial statement fraud. Previous studies have focused on the examination of "red flags," or fraud risk factors, as likely indicators of fraud (Bell & Carcello, 2000; Pincus, 1989). Today, the auditor has the responsibility for detecting financial-statement fraud along with the audit of the company's financial statements.

This chapter presents a description, testing and summary of methods of analysis used in fraud determination. First, it is shown how financial and nonfinancial statement data (data based on analysis of company annual reports) can be used to develop membership coefficients that are evaluated in a fuzzy logic approach to data analysis. The fuzzy logic analysis applied to fraud detection is used to cluster the information into various risk areas. The cluster approach also identifies variables that can be used in a logistic regression (logit) model for fraud determination. Expert reasoning can then be applied to "mine" new information and develop the variables continuously over the life of the company. In this chapter, we also discuss the use of an additional fuzzy model for comparison purposes and to assess model accuracy. The chapter contributes to the fraud literature by incorporating a nonfinancial fuzzy logic variable in a statistical model.

The following sections of the chapter provide the background of fraud modeling and of fuzzy logic, and the methodology used to develop the study, including a description of the sample firms. The sample description is followed by a discussion of the financial variables that are developed and used in the models presented in the chapter. The discussion of variables includes a description of the research procedure that identifies nonfinancial variables used in the fuzzy logic clustering method. The next section presents results and analysis of the models. The last part of the chapter discusses emerging trends and future opportunities in this line of research, along with a conclusion. 14 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-

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