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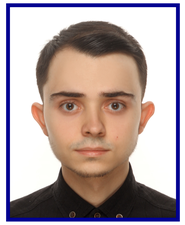
BICA VPS 2023

A Bayesian Network-Based Model for Fraud Risk Assessment.

Pavel Y. Leonov*[1], Viktor M. Sushkov[1], Stanislav V. Vishnevsky[1], Valentin A. Romanovsky[1] [1]National Research Nuclear University MEPhI (Moscow Engineering Physics Institute), Kashira Hwy, 31, Moscow 115409, Russia. pyleonov@mephi.ru

Pavel Y. Leonov



Viktor M. Sushkov

SUMMARY

We proposed a model for assessing the risk of fraud committed by business entities based on a Bayesian network. The model adopts a modern methodology for classifying fraud risk factors, referred to as the Fraud pentagon. The evaluation within the model incorporates financial statements, accounting data, and expert assessments regarding the internal controls. The effectiveness of classifying companies as fraudulent and bona fide using the model has been experimentally tested. It has been found that the risk-oriented approach underlying the model makes it possible to substantially reduce labor inputs for audit while maintaining high credibility of the results.

INTRODUCTION

Today, the detection of fraud committed by business entities is an acute problem facing both external and internal financial control authorities. Fraud not only inflicts significant financial harm upon companies, but also poses a threat to the country's economic security. This is due to the high qualifications of perpetrators, the increasing sophistication of fraudulent schemes, and deficiencies in current methods of fraud detection.

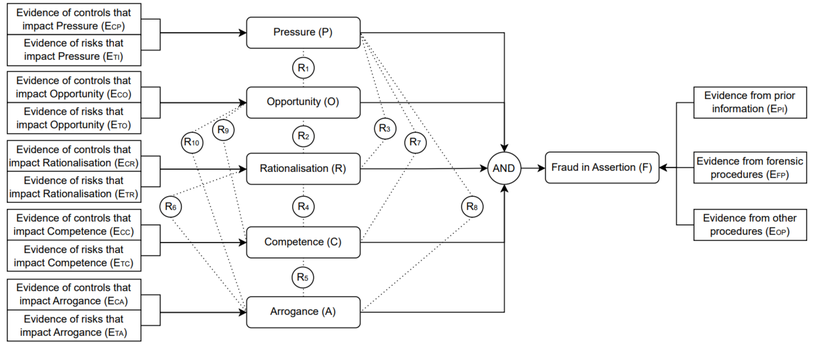
APPROACH

In 2011, J. Marks proposed the Fraud pentagon model. The following five factors are considered to be necessary and sufficient for fraud to occur – rationalization, pressure, arrogance, opportunity, and competence. This approach is an optimal choice for building a fraud risk assessment model.

METHODS

Bayesian networks (BN) provide a flexible and interpretable model that incorporates prior knowledge, accounts for complex relationships, and handles both quantitative and qualitative data effectively. This makes BN most effective for fraud risk assessment.

To account for the unavailability of direct observations of the fraud variable, an evidence diagram was utilized in the modeling process (Figure 1).



$$FR = P(F|E_{CP}E_{TP}E_{CO}E_{TO}E_{CR}E_{TR}E_{CC}E_{TC}E_{CA}E_{TA}E_{OP}E_{FP}) = \frac{\rho_1\rho_2\rho_3\rho_4\rho_5\rho_6\rho_7\rho_8\rho_9\rho_{10}\lambda_{CP}\lambda_{TP}\lambda_{CO}\lambda_{TO}\lambda_{CR}\lambda_{TR}\lambda_{CC}\lambda_{TC}\lambda_{CA}\lambda_{TA}\lambda_{OP}\lambda_{FP}\pi_P\pi_O\pi_R\pi_C\pi_A\pi_F}{D} \quad (1)$$

In (1) E is evidence relating to the reduction or increase in the level of risk associated with a particular factor, ρ is the strength of the relationship between the risk factors, λ is the likelihood ratio reflecting the strength of evidence E, π is the ratio of the a priori probabilities of the risk factors, $D = \sum_{i=1}^{32} \mathrm{D}_i$ is the coefficient representing the sum of all 32 possible states, given that the presence of fraud is determined by the presence of risk factors.

RESULTS

As an example of utilizing the proposed model to calculate fraud risk, we selected the fraudulent company Alpha. All the characteristics are directly associated with the components of the Fraud pentagon. These characteristics were derived through the analysis of financial statements, accounting data, and information about the company's internal controls.

ANALYSIS

The fraud risk according to the formula (1) is 94%, which confirms the ability of the model to accurately identify fraudulent companies. We have also assessed 15 additional fraudulent companies and 156 bona fide ones. The results of these assessments consistently displayed fraud risk levels between 80% and 95% for the fraudulent companies, affirming the model's effectiveness in detecting high fraud risks. Conversely, the bona fide companies exhibited fraud risk levels ranging from 5% to 15%, further attesting to the model's ability to differentiate between unscrupulous and fair business entities.

DISCUSSION

This result shows that the use of this model will save a lot of labor costs of financial control entities for analysis of bona fides of companies using risk-based approach.

CONCLUSIONS

1. The proposed model is built upon the most comprehensive and logical framework for categorizing factors that contribute to fraud risk, namely the Fraud pentagon.
2. A Bayesian network has been selected as the method for classifying fraud risk.
3. The model's proven efficacy has the potential to significantly reduce the cost of assessing the integrity of companies during financial control activities. Moreover, the model's adaptability allows for customization to meet the requirements of internal control services, financial monitoring entities, auditing firms, and government oversight bodies.