sciendo

Predicting Auditor's Opinion on Financial Statements of Public Enterprises Based on Indicators of the Beneish M-score Model

Amra Gadžo, Associate professor

Faculty of Economics, University of Tuzla;

amra.gadzo@untz.ba

Sanel Halilbegović, Associate professor

Faculty of Economics, International Burch University;

sanel.halilbegovic@ibu.edu.ba

Alma Osmanović Đaković, MA, Professor of physics

High school Tuzla;

alma.osmanovic@untz.ba

Adisa Hodžić, BA in Economics

Faculty of Economics, University of Tuzla;

adisa.hodzic@untz.ba

Abstract

Considering the burning problem of corruption and non-transparency of public enterprises in the Federation of Bosnia and Herzegovina (FBiH), the paper aims to investigate whether the Beneish M-score model can be used to predict inaccurate financial statements. Where, the cause of inaccurate financial statements are intentional or unintentional errors.

Paper type: Research article

Received: December 02, 2022
Accepted: December 22, 2022

Citation: Gadžo, A., Halilbegović, S., Osmanović Đaković, A., Hodžić, A. (2022), "Predicting Auditor's Opinion on Financial Statements of Public Enterprises Based on Indicators of the Beneish M-score Model", Journal of Forensic Accounting Profession, Vol. 2, No. 2, pp. 1 – 13.

DOI: https://doi.org/10.2478/jfap-2022-0006

On a sample of 200 financial statements of public enterprises and related audit reports issued by the Audit Office of the Institutions in FBiH, we made a link between the Beneish M score model with its partial indicators (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) and four types of opinions: positive, opinion with distraction, negative and refraining from giving opinions. The research was conducted using descriptive statistics and an artificial neural network with the "scaled conjugate gradient backpropagation (trainscg)" algorithm for pattern recognition and classification. The research results show that it is possible on the basis of 8 partial indicators (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) i.e. 24 balance sheet position for their calculation, predict the auditor's opinion on the quality of financial statements of public companies with an accuracy ranging between 98 and 100% in repeated procedures. The results of the research have their practical usefulness and can serve to researchers, creditors, customers, suppliers and state auditors in planning resources and priorities for performing financial audits at public companies in the FBiH.

Keywords: *Beneish M-score, Artificial neural networks, Predicting auditors' opinions, Public enterprises*

1. Introduction

Government-owned enterprises (GOEs) are those mainly owned by the state or one of its organizational segments. They are founded in different organizational forms for the purpose of performing the operations of public general interest. The founding of GOEs prevents the creation of the monopolistic position in the private sector in the fields important for general advancement and undisturbed functioning of the society. In doing so, GOEs need to be financially sound and make positive business results. The same as the companies in the private sector, GOEs are subjected to market tests. GOEs' prices of products, goods and services need to provide income that would cover all business cost and to generate business results that would warrant long-term growth and development of enterprise and improvement in performing the main business activity.

The most important GOEs in Bosnia and Herzegovina (BiH) are in the sectors of energy, telecommunications, traffic, and utilities. The characteristics of GOEs in BiH are involvement of politics and state in their work, inefficient usage of public resources, high level of corruption, and lack of transparency in their work. According to the Corruption Perceptions Index (CPI) for 2021, BiH is ranked 110th out of 180 countries, which is also the worst rank since 2012. This put BiH into a group of countries that globally have constant regress (Transparency

International, 2020). Some two fifths of the GOEs do not disclose evidence on implemented anticorruption programs and do not publicly announce their business results (Transparency International, 2018). More than 50% of the BiH GOEs do not have internal acts that would provide transparency, objectivity and impartiality of the employment process. Almost 70% of these enterprises do not disclose information on employment or employee structure (Transparency International BiH, 2018).

Various corruptive forms, lack of transparency into business operations of GOEs, lack of accountability of public management, and insufficient institutional supervision of their business activities directly affect the quality of their financial statements and their susceptibility to various types of financial fraud. Therefore, this paper aims at making the first step in developing a mathematical model of probability assessment of (in)correctness of financial statements made by GOEs in Bosnia and Herzegovina Federation (FBiH).

2. Overview of previous studies

A large number of scientists addressed the issue of how to distinguish financial statements being manipulated from those that were not. Messod D. Beneish, the professor at Indiana University, set in 1997 a screening model for assessing the probability of financial report fraud based on eight partial indicators. He later revised his model and reduced it to five partial indicators (1999). Beneish claimed that this model can accurately identify 76% of manipulators and incorrectly identify only 17.5% of non-manipulators. Beneish's model gained huge popularity and numerous researchers tested and confirmed the efficiency of his model in various countries, based on a sample of enterprises that were proved to have faked their financial statements (Sendyona, 2020, Halilbegovic et al., 2020, Alfian and Triani, 2019, Dmitrijević and Danilović, 2017, Kamal et al., 2016, Herawati, 2015).

The efficiency of the model in detecting fraudulent financial reporting in different countries on a sample of the enterprise that proved to have been manipulators shows inconsistency. It was 82% in Malaysia (Kamal, Salleh, Ahmad, 2016), 79.41% on sample in small and medium-sized enterprises in BiH (Halilbegovic et al., 2020), and 60% in Indonesia (Alfian and Triani, 2019).

Some researchers applied the Beneish model in attempting to group enterprises into two sets – manipulators and non-manipulators. Then, they established the key differences in the data between these two groups of financial statements (Nor Aqilah et al., 2021, Kamal et al., 2016, Kokić et al., 2018, Hariri et al., 2017, Chinmoy and Debnath, 2015).

Some authors tested whether the first Beneish model with eight partial indicators is more efficient that the new version with five partial indicators. Hołda (2020) stated that the Beneish M score (BMS) model with eight partial indicators is more appropriate than the version with five indicators for detecting the manipulating enterprises in the Polish economic reality (environment). The analysis showed that the BMS model with eight indicators identified manipulators with 100% accuracy and was able to identify non-manipulators. The efficiency of the model with five indicators was much lower.

According to the GMT-Research, the application of the BMS model on 3,600 Asian enterprises with market capital over one billion dollars was unsuccessful. The formula could not be calculated for 19% of the sample. The results showed that in five years, between 2010 and 2015, 33% of the enterprises manipulated their financial statements, which was characterized as very unlikely.

Sawangarreerak and Thanathamathee (2021) in their study identified six financial items related to fraud: (1) gross profit, (2) primary business income, (3) ratio of primary business income to total assets, (4) ratio of capitals and reserves to total debt, (5) ratio of long-term debt to total capital and reserves, and (6) ratio of accounts receivable to primary business income. They tested a total of 35 indicators by applying neural network and data analytics. According to the research by Irwandi et al. (2019), financial stability and the nature of the industry have a significant effect of managing the real profit. We document the most common types of misstatements and find that the overstatement of revenues, misstatement of expenses, and capitalizing costs are the most frequent types of misstatements (Dechow et al., 2011).

According to the Zarei, H., Yazdifar, H., Dahmarde Ghaleno, M. and Azhmaneh, R. (2020) results demonstrated high explanatory power of financial ratios and type of audit firm (the national audit organization vs other local audit firms) in explaining qualifications through audit reports. The model they created with the selected racio numbers is reliable, with 72.9% accuracy in classifying the total sample correctly to explain changes in the auditor's opinion.

According to the research of Stalebrink & Sacco (2007) in the Austrian economy, fraud in the financial statements of public companies originates from political rather than economic reasons and is carried out by newly elected politicians rather than permanent staff of public companies. Also due to the smaller share of creditors and investors who are interested in financial reports in the government sector, the percentage of detection of fraud in financial reports is lower than in the private sector. As a result, financial reporting fraud techniques tend to last a relatively long time before they are discovered.

Based on the review of previous research, conclusions and recommendations, we designed our research in such a way that the results are representative for public companies in the Federation of Bosnia and Herzegovina.

3. Methodology

The research population consists of public companies whose majority share in the capital belongs to the federal, cantonal or local level of government. The data for the model were collected from the financial statements of GOEs in FBiH and their audit reports prepared by the Audit Office of the Institutions in FBiH. The research included the data for the time period of 16 years (2004-2019). After the data processing, the sample included 200 financial statements and their accompanying audit reports, available at the time when the research was conducted.

Through the research, we connected the partial indicators of the BMS model (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) with four types of opinion: Unqualified opinion, Qualified opinion, Adverse opinion and Disclaimer of opinion. The research was conducted using descriptive statistics and using an artificial neural network with the "scale conjugate gradient backpropagation" algorithm for pattern recognition. Correlation search between 1600 input data (200x8) and 200 output data.

In pattern recognition problems, we want the neural network to classify the input data into a set of output categories. We created a two-layer feed forward network, with sigmoid hidden and softmax outer neuron layer (patternnet). Network training algorithm: scaled conjugate gradient backpropagation (trainscg). The role of pattern recognition is to check whether the neural network can distinguish and classify the data based on the eight input parameters of the partial indicators of the Beneish M-Score model into one of the four auditor opinions (unqualified opinion, qualified opinion, adverse opinion and disclaimer of opinion). However, it should be emphasized that neural networks are computer adaptive models that have many mathematical functions at their disposal when searching for correlations.

Pursuant to International Standard on Auditing (ISA) 240 (sections 2 and 3) and The International Standards of Supreme Audit Institutions (ISSAI) 1240 (section 5), misstatements in the financial statements can arise from either fraud or error. The distinguishing factor between fraud and error is whether the underlying action that results in the misstatement of the financial statements is intentional or unintentional. Although fraud is a broad legal concept, for the purposes of the ISAs/ISSAIs, the auditor is concerned with fraud that causes a material misstatement in the financial statements. Two types of intentional misstatements are relevant to the auditor – misstatements resulting from fraudulent financial reporting and misstatements resulting from misappropriation of assets. Although the auditor may suspect or, in rare cases, identify the occurrence of fraud, the auditor does not make legal determinations of whether fraud has actually occurred. Therefore, the term misstatement shall be used onwards without specifying if error is intentional or not.

As the input set of data for the model, we used 24 balance sheet positions (Table 1), eight partial indicators of the BMS model (Table 2) and all the variables presented in Tables 1 and 2.

Table 1: Balance sheet positions

Ord. no.	Financial statement items	ADP	Attribute code
1.	Accounts receivable t	047	A1
2.	Sales income t	201	A2
3.	Accounts receivable t-1	047	A3
4.	Sales income t-1	201	A4
5.	Operating expenses t-1	212	A5
6.	Operating expenses t	212	A6
7.	Operating assets t	035	A7
8.	Property, plant and equipment t	008	A8
9.	Short-term financial investments t	053	A9
10.	Business assets t	067	A10
11.	Operating assets t-1	035	A11
12.	Property, plant and equipment t-1	008	A12
13.	Short-term financial investments t-1	053	A13
14.	Business assets t-1	067	A14
15.	Depreciation t-1	220	A15
16.	Depreciation t	220	A16
17.	Administrative expenses t	156	A17
18.	Administrative expenses t-1	156	A18
19.	Short-term liabilities t	140	A19
20.	Long-term liabilities t	131	A20
21.	Short-term liabilities t-1	140	A21
22.	Long-term liabilities t-1	131	A22
23.	Business profit/loss t	229	A23
24.	Net cash flow from operating activities t	404	A24

**ADP – a unique number of every balance sheet position from various financial statements, it is used for automatic data processing and unambiguous identification*

For calculating eight partial indicators (Table 2), we used 24 balance sheet positions (Table 1).

Table 2: Partial indicators of the BMS model

Ord. no.	Indicator	Abbreviation	Formula
1	Days Sales in Receivables Index	DSRI	DSRI = (Accounts receivables (t) / Sales income (t)) / (Accounts receivables (t-1) / Sales income (t-1))
2	Gross Margin Index	GMI	GMI = ((Sales income (t-1) – Operating expenses (t-1)) / Sales income (t-1)) / ((Sales income (t) – Operating expenses (t)) / Sales income (t))
3	Asset Quality Index	AQI	AQI = (1 – (Operating assets (t) + Property, plant and equipment (t) + Short-term financial investments (t)) / Business assets (t)) / (1 – (Operating assets (t-1) + Property, plant and equipment (t-1) + Short-term financial investments (t-1)) / Business assets (t-1))
4	Sales Growth Index	SGI	SGI = Sales income (t) / Sales income (t-1)
5	Depreciation Index	DEPI	DEPI = (Depreciation (t-1) / (Property, plant and equipment (t-1) + Depreciation (t-1))) / (Depreciation (t) / (Property, plant and equipment (t) + Depreciation (t)))
6	Sales, General and Administrative Expenses Index	SGAI	SGAI = (Other operating expenses (t) / Sales income (t)) / (Other operating expenses (t-1) / Sales income (t-1))
7	Leverage Index	LVGI	LVGI = ((Short-term liabilities (t) + Long-term liabilities (t)) / Business assets (t)) / ((Short-term liabilities (t-1) + Long-term liabilities (t-1)) / Business assets (t-1))
8	Total Accruals Total Assets	TATA	TATA = (Profit/loss (t) – Cash flow from operating activities (t)) / Business assets (t)

Source: Author's analysis

3. Research results and discussions

The research results show that the classic BMS model (with multipliers) cannot be used to detect inaccurate financial statements for public companies in FBiH. The reason is that the partial indicator multipliers are not adapted to our market conditions. The results of applying the classic mathematical BMS model are given in table 3.

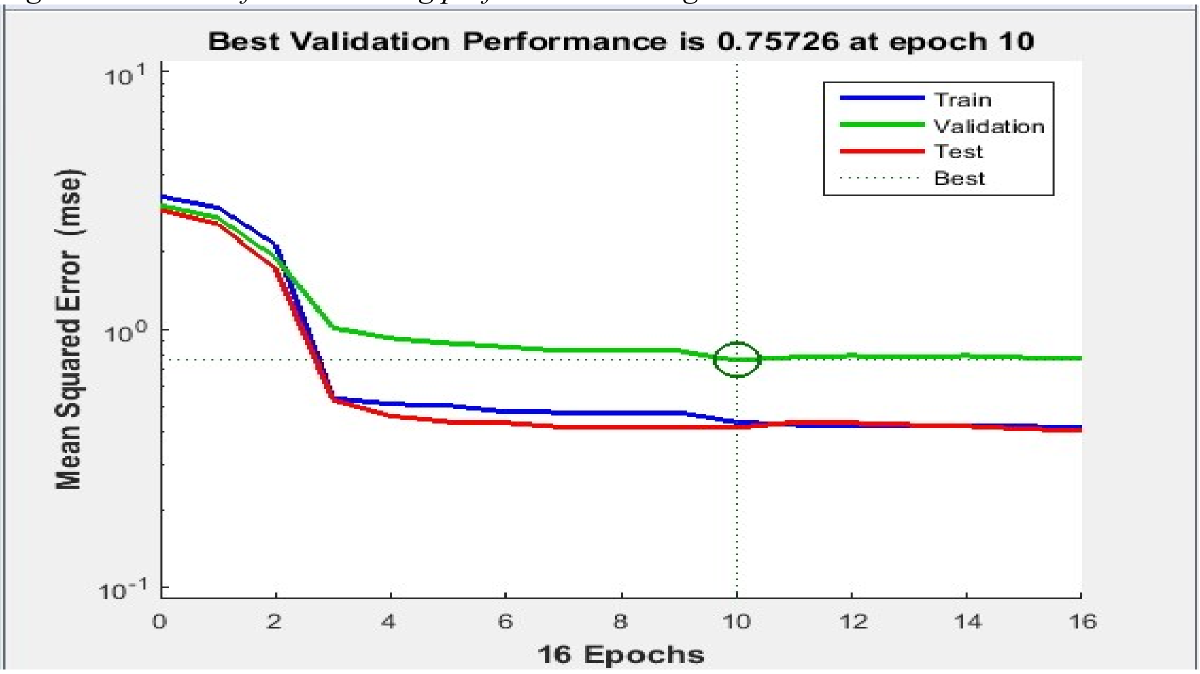
Table 3: Results of the application of the classic BMS model

Description	Frequency	%	Average	STDEV
BMS larger than -2,22	53	26,50	65,262	357,678
BMS less than -2,22	147	73,50	-3,473	2,668

Source: Author's analysis

Given the assumption that the classic BMS model will not have a useful value, this research is focused on the possibility of applying its partial indicators. During the training of the artificial neural network, eight input parameters (partial indicators of the Beneish M-Score model) are connected to the output values (auditor's opinion). The network recognized the way of classifying 8 partial indicators of the Beneish M-Score model into auditor opinions with a very small mean square error of 0.757 (Figure 1).

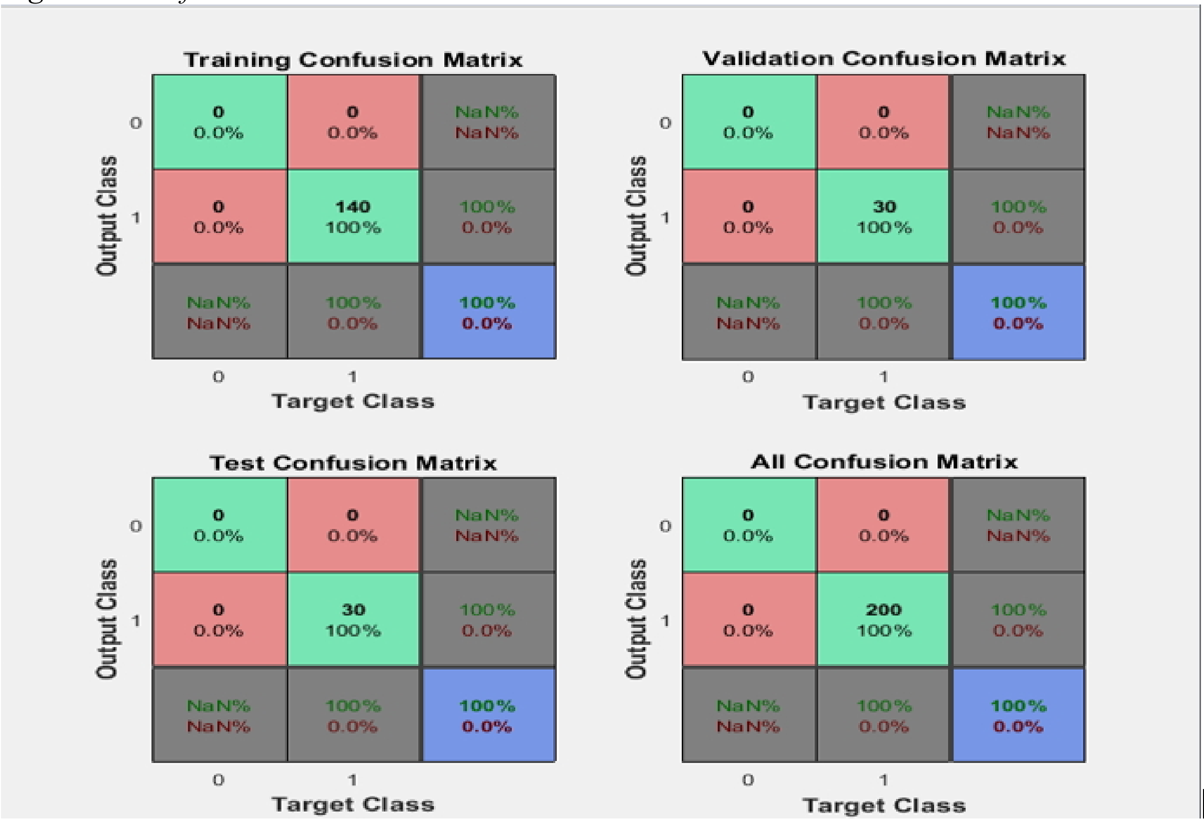
Figure 1: Results of ANN training performance testing



Source: Author's analysis

The neural network normally divides all input-output data into three groups randomly, 60% of the data is used for training the network, 20% for validation and 20% for testing the network. The result of the neural network is the Confusion matrix (Figure 2).

Figure 2: Confusion matrix



Source: Author's analysis

We observe the last matrix as the result of all data: along the diagonal (green color) are all correctly classified data, the opposite diagonal (red color) is incorrectly classified data. In the blue square we see the result 100% the network managed to correctly classify into one of the four opinions of the auditor eight values of the partial indicators of the Beneish M-Score model that were used as input parameters. In repeated tests, the neural network gave an accuracy between 98% and 100% due to the random selection of data.

With the existence of this algorithm, the auditor can get the result of the auditor's opinion for the financial statements of a public company in the FBiH without going to the field. This network is a tool for forensic auditing of the public sector. It can help identify those public companies where financial statements are likely to be inaccurate. This approach is also recommended by the Moscow Declaration (INTOSAI, 2019) for state auditors: "SAIs should promote the principle of availability and openness of data, source codes and algorithms.... SAIs should strive to make better use of data analytics in audits, including adapting strategies such as planning such audits, building experienced data analysis teams, and introducing new techniques into public sector audit practices”….” SAIs are encouraged to 'educate' auditors for a future that can use data analytics, tools offered by artificial intelligence and advanced qualitative methods, which are able to improve innovation; and act as strategic players, those who exchange knowledge and produce projections."

Based on the conducted research, we can conclude that there is a direct connection between the eight partial indicators of the Beneish M-Score model and the auditor's opinion. There was also no manipulation/influence on the auditor's opinion during the inspection, because we have not observed any deviation from the established correlation. With this, we undoubtedly conclude that 24 balance positions for calculating partial indicators of the BMS model can be used in the assessment of the probability of obtaining a certain auditor's opinion.

4. Conclusions and recommendations

On the basis of the conducted research on 200 financial reports of public companies in the Federation of BiH, which were audited by the Office for Auditing Institutions in the Federation of BiH, we have made important conclusions and recommendations. First, the classic form of the BMS model (complete mathematical formula) cannot be used to detect incorrect financial reports of public companies in FBiH. The reason for this is the unadjusted multipliers for the 8 partial indicators (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) in the original mathematical formula. Second, partial indicators of the BMS model, calculated on the basis of 24 balance positions, are adequate for predicting the accuracy of financial statements, i.e. auditor's opinions. The ANN network has shown in repeated tests that the accuracy of predicting the auditor's opinion on financial statements is between 98 and 100% in repeated procedures. Therefore, this algorithm is a good forensic audit tool that has practical utility.

A recommendation for further research is to develop a customized mathematical formula for the BMS model (with customized multipliers) for easier application in practice. Due to the simplicity of application, such a mathematical model would become a standardized tool for testing the quality of financial reports of public companies in FBiH.

Literature

Alfian, F. & Triani, N. N. A. (2019). Fraudulent Financial Reporting Detection Using Beneish M-Score Model in Public Companies in 2012-2016. *Asia Pacific Fraud Journal 4*(1)**,** pp. 27-42.

Beneish, M. D. (1999). The Detection of Earnings Manipulation. *Financial Analysts Journal 55*(5), pp. 24–36. Available at: https://doi.org/10.2469/faj.v55.n5.2296

Dechow, P. M., Ge, W., Larson, C. R. & Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary accounting research* (28)**,** pp. 17-82.

Dmitrijević, D. & Danilović, M. (2017). Otkrivanje prevara u kompanijama u Republici Srbiji primenom Beneish-ovog modela. *Anali Ekonomskog fakulteta u Subotici 53*(37)**,** pp. 311-325.

GMT Research. *Beneish's M-score.* [Online]. *Available at:* https://www.gmtresearch.com/en/accounting-ratio/beneishs-m-score.

Halilbegovic, S., Celebic, N., Cero, E., Buljubasic, E. & Mekic, A. (2020). Application of Beneish M-score model on small and medium enterprises in Federation of Bosnia and Herzegovina. *Eastern Journal of European Studies 11*(1), pp. 146-163.

Hariri, H., Pradana, A. W. S. & Widjajanti, S. L. (2017). Predicting Financial Statements Corporate Fraud: Beneish M-score Model. *JEMA: Jurnal Ilmiah Bidang Akuntansi dan Manajeme, 14*(2)**,** pp. 93-100.

INTOSAI (2019). *Moskovska deklaracija*. Available at: https://www.vrifbih.ba/wp-content/uploads/2020/12/Moskovska-deklaracija.pdf

Irwandi, S. A., Ghozali, I., Faisal, I. & Pamungkas, I. D. (2019). Detection of fraudulent financial statement: Beneish M-score model. *WSEAS Transactions on Business and Economics 16*(1)**,** pp. 271–281.

Kamal, M. E. M., Salleh, M. F. M. & Ahmad, A. (2016). Detecting financial statement fraud by Malaysian public listed companies: The reliability of the Beneish M-Score model. *Jurnal Pengurusan (UKM Journal of Management) 46*, pp. 23-32.

Kokić, T., Gligorić, M. & Knežević, G. (2018). Use of Beneish Model on Serbian Super League Football Clubs. *FINIZ 2018-The Role of Financial and Non-Financial Reporting in Responsible Business Operation***,** pp. 118-122.

Roy, C. & Debnath, P. (2015). Earnings Management Practices in Financial Reporting of Public Enterprises in India: An Empirical Test with M-Score. *Available at:* https://ssrn.com/abstract=2551713.

Sawangarreerak, S. & Thanathamathee, P. (2021). Detecting and Analyzing Fraudulent Patterns of Financial Statement for Open Innovation Using Discretization and Association Rule Mining. *Journal of Open Innovation: Technology, Market, and Complexity 7*(2)**,** pp. 128.

Sendyona, C. C. (2020). Enron Scandal: Evidence of a Missed Opportunity to Detect and Hald Fraud and Bankruptcy. *Europea Journal of Accounting, Auditing and Finance Research 8*(5)**,** pp. 54-65.

Stalebrink, O.J. & Sacco, J.F. (2007). Rationalization of financial statement fraud in government: An Austrian perspective. *Critical Perspectives on Accounting 18*(4), pp. 489–507. Available at: https://doi.org/10.1016/j.cpa.2006.01.009

Sutainim, N. A., Mohammed, N. F. & Kamaluddin, A. (2021). Application Of Beneish M-Score Model In Detecting Probable Earnings Manipulation In Malaysian Public Listed Companies. *Integrated Journal of Business and Economics 5*(1)**,** pp. 86-100.

Tarjo, T. & Herawati, N. (2015). Application of Beneish M-Score Models and Data Mining to Detect Financial Fraud. *Procedia - Social and Behavioral Sciences 211*, pp. 924-930.

Transparency International BiH. (2018). *Dobro upravljanje u javnim preduzećima u Bosni i Hercegovini: analiza transparentnosti, odgovornosti i integriteta javnih preduzeća*. Available at: https://ti-bih.org/wp-content/uploads/2018/04/Izvrsni-sazetak-mart_2018.pdf

Transparency International. (2021). Corruption Perceptions Index 2021. Available at: https://www.transparency.org/en/cpi/2021?gclid=Cj0KCQiA4uCcBhDdARIsAH5jyUkpN38G8Vm68hOYXU6SMUTGSvVQIzuP3vyPPPjvzUmMD43hXMqT0usaApNtEALw_wcB

Zarei, H., Yazdifar, H., Dahmarde Ghaleno, M. and Azhmaneh, R. (2020). Predicting auditors' opinions using financial ratios and non-financial metrics: evidence from Iran. *Journal of Accounting in Emerging Economies 10*(3), pp. 425-446. Available at: https://doi.org/10.1108/JAEE-03-2018-0027

Sažetak

Obzirom na gorući problem korupcije i netransparentnosti poslovanja javnih preduzeća u Federaciji Bosne i Hercegovine (FBiH), rad ima za cilj istražiti da li se Beneish M-score model može koristiti u predviđanju netačnih finansijskih izvještaja. Pri tome, uzrok netačnih finansijskih izvještaja su pogreške koje mogu biti namjerne ili nenamjerne. Na uzorku od 200 finansijskih izvještaja javnih preduzeća i pripadajućih revizorskih izvještaja izdatih od strane Ureda za reviziju institucija u FBiH, doveli smo u vezu Beneish M score model te njegove parcijalne indikatore (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) sa četiri vrsta mišljenja: pozitivno, mišljenje sa skretanjem pažnje, negativno i uzdržavanje od davanja mišljenja.

Istraživanje je sprovedeno primjenom deskriptivne statistike te upotrebom vještačke neuralne mreže sa korištenim "scaled conjugate gradient backpropagation (trainscg)" algoritmom za prepoznavanje uzoraka i njihovu klasifikaciju. Rezultati istraživanja pokazuju da je moguće na bazi 8 parcijalnih pokazatelja (DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA) tj. 24 bilanse pozicije za njihov proračun, predvidjeti mišljenje revizora o kvalitetu finansijskih izvještaja javnih preduzeća sa tačnošću koja se kreće između 98 i 100% u *ponovljenim postupcima. Rezultati istraživanja imaju svoju prakstičnu korisnost i mogu poslužiti kako istraživačima, kreditorima, kupcima, dobavljačima tako i državnim revizorima u planiranju resursa i prioriteta obavljanja finansijske revizije kod javnih preduzeća FBiH.*

Ključne riječi: *Beneish M-score, vještačke neuralne mreže, predviđanje mišljenja revizora, javna preduzeća*