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THE CONCEPT OF APPLYING A MODEL OF INFORMATION CODED IN STRUCTURES TO ASSESS THE RELIABILITY OF MANAGEMENT REPORTS OF LISTED COMPANIES

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Purpose: This article aimed to present an algorithm for recording information using graphs and a concept for applying it to assessing the consistency and continuity of annual management reports (which are part of the annual financial statements of listed companies) to detect manipulation of these reports.

Design/methodology/approach: This article uses a model of information encoded in graph structures, which allows for structuring the information contained in management reports and identifying inconsistencies and discontinuities in the description. The model is based on building logical connections between information elements and identifying discontinuities and inconsistencies.

Findings: Implementation of the model to analyze the management report of Circor International revealed numerous inconsistencies and discontinuities in the report, which may indicate attempts to conceal or distort information. The model also revealed repetitive fragments of information that could have been reduced, which impacts the assessment of the report's information capacity.

Research limitations/implications: Due to the size and complexity of the generated graphs, complete analysis requires significant computational resources, which may limit the scale of applications. Future research should focus on reducing the computational resources needed.

Practical implications: The presented model can be a valuable tool for auditors, financial analysts, and supervisory authorities to assess the credibility of management reports and to detect potential financial manipulation early.

Social implications: Enhancing the effectiveness of detecting fraudulent practices based on financial statements promotes fair competition in financial markets, which is crucial for the economy.

Originality/value: The article introduces a novel approach to financial statement analysis by applying a model of information encoded in graphs, which is a new proposal in the field of methods for detecting financial manipulation.

Keywords: earnings manipulation, fraud detection, management report.

Category of the paper: Conceptual paper.

1. Introduction

Business practice shows that some financial statements are manipulated, meaning they don't provide a true and fair view of a company's operations. This poses a significant problem for all users of these statements, as they are unable to accurately assess the entity's financial situation and its ability to continue operations. Therefore, numerous tools have been developed and continue to be developed to detect such manipulation.

2. Review of Previous Research

The most well-known model is the Beneish model from 1999 (Beneish, 1999), while others, somewhat less popular but also well-known, include the Dechowa model (Dechow et al., 2011), Christensen (Christensen et al., 2010), Kamiński (Kamiński et al., 2004), etc. These models are based solely on the financial part of financial statements and, based on logistic regression trained on honest and dishonest companies, allow for the relatively effective identification of manipulated financial statements.

There are many models for detecting manipulation of financial statements, and they use many tools. In addition to various econometric, ML and AI models (e.g., logistic regression, ANN, LDA, QDA, FNN, Bayesian Belief Network, genetic algorithms, DT, SVM, Naive Bayes), models are based on analyst calls (Larcker, Zakolyukina, 2012), non-financial variables (e.g., Gaganis, 2009), words included in management reports (Purda, Skillicom, 2015), traits extracted from oral speech (Hobson et al., 2012), opinions on social media (Dong et al., 2018), M&A activity (Erickson et al., 2006), religion (Koerber, Neck, 2006), renumeration of directors (Armstrong et al., 2010), time of CEO employment (Eickson et al., 2006), court cases (Hribar et al., 2011; Perols, 2011), words used in analyst calls (Larcker et al., 2012), corporate governance implementation (Mahesarani, Chariri, 2016), insider trading factors (Summers, Sweeney, 1998), context-based features (Abbasi et al., 2012), CEO personality (Grazioli et al., 2011), CEO duality (Feng et al., 2011), outside directors (Armstrong et al., 2010), being above or below investor expectations (Perols, Lougee, 2011). Despite numerous ideas and the development of quantitative methods, research is ongoing on new ways to detect fraud and enhance the predictive ability of new models and algorithms.

This publication aimed to present the concept of a model of information encoded in (graph) structures and to propose methods of implementing this model to detect manipulated financial statements based on the graph structuring of information contained in management reports.

3. Presentation of the model of information encoded in structures

One element of the model for recognizing manipulated financial statements described in Chapter 3 is the structure-encoded information model (Bielecki, Schmittel 2022; Bielecki, Stocki, 2023). This model is based on research suggesting that lies lack coherence and consistency (Blair et al., 2018; Witkowski, 2024; Zaucha, 2023). For the financial manipulation detection model, Bielecki's model was used to develop a tool for detecting inconsistencies and potential repetitions in management reports. Building such a graph will enable the detection of inconsistencies in the description, calculate the number of such discrepancies, and describe the report using two key metrics: information capacity (defined below) and the number of repetitions, as well as the number of inconsistencies found in the report. This is an innovative application of Professor Bielecki's structure-encoded information theory.

Definition of a Graph Generated by a Relation

Let a set X consist of elements $x_1,\dots,x_n$, and let R be a relation on set X. On set X, we construct a graph connecting the elements $x_1\dots.x_n$ with directed edges $e_1,\dots e_m$. We obtain a directed graph (orgraph) G:={V,E}, where V is the set of nodes and E is the set of its directed edges.

A graph G is generated by a relation R if V=X and (xi, xj) ∈ E if and only if xiRxj, for i, j ∈ {1, …, n}. The graph generated by the relation R on the set X will be denoted as G(X,R) (Bielecki, Schmittel, 2022, p. 1329), hereinafter.

This definition proposes organizing a set of information as elements or facts that are related to each other. The original 2022 publication referred to atoms in chemical molecules, while the 2023 publication referred to memory maps (e.g., the components of motivation as perceived by managers). Therefore, the definition (and model) applies to a set of information, at least some of which can be linked by some relationship (for example, causality, the passage of time, or chemical bonds).

In the case of management reports, the events described therein are expected to be coherent, consistent, and continuous. One event either leads to another or occurs chronologically before the next, and usually generates some consequences for the company. This corresponds to the creation of a directed graph, in which subsequent events are arranged using directed edges to create a coherent and logical whole. If management does not embellish or seek excuses, the report should be rational and consistent. The connections between events do not have to be unambiguous; it is possible to construct several different relations organizing facts and events. This is stated in the conclusion from the definition of a graph generated by a relation.

A corollary to the definition of a graph generated by a relation: The final set X and the relation R defined on X generate a unique directed graph (orgraph). Furthermore, every orgraph G:={V,E} generates a unique relation R on the set X=VX=V in the following way: if $(x_i,x_j)\in E$, then x_iRx_j (Bielecki, Schmittel, 2022, p. 1329). It follows from Corollary 2.2 that the same information items can be ordered in many ways, depending on the relation R used.

In addition, the model assumes that "R is an antireflective relation on X, i.e., $\forall x \in X$:(xRx). This means that the graph G has no loops, i.e., edges of the form (x,x), because no element is in a relation with itself. The set X with relation R will be denoted (X,R)" (Bielecki, Schmittel, 2022, p. 1329).

Another essential element of the model is the so-called node-balls, as they determine the number of steps to be considered around a given vertex in the graph. Defining the neighborhood of edges and nodes allows us to determine how far they are from the central element and how many steps it takes to reach such an element from the central element. This definition also allows us to determine the similarity between two selected elements, according to A. Bielecki, we can only speak of similarity between edges or vertices when the entire ball (node or edge, respectively) is comparable (the definition of comparability will be given below).

Definition 2.3 of the Vertex Ball

Let G = (V, E) be a directed graph (orgraph). A vertex ball $B_{node}G(x,1)$ with radius 1 and center at vertex $x \in V$ is called a subgraph (V_1,E_1) such that:

$$V1:=\{y \in V: y=x \vee (x,y) \in E \vee (y,x) \in E\} \text{ and } E_1:=\{(u,v) \in E: u \in V_1 \wedge v \in V_1\}. \quad (1)$$

The vertex ball $B_{node}G(x,n)$ with radius $n \in \{2,3,\ldots\}$ is the union of sets, where $y \in B_{node}G(x,n-1)$. One can also define $B_{node}G(x,0):=(\{x\},\_\_)$.

Furthermore, $r_{node}(G,x)$ (radius of the vertex ball) is the minimal natural number for which $B_{node}G(x,r_{node}(G,x)) = B_{node}G(x,r_{node}(G,x)+1)$" (Bielecki, Schmittel, 2022).

As already mentioned, a vertex ball consists of edges and vertices with a distance from the initial vertex no greater than a chosen number of steps, for example, n = 3. What is essential is that the center of the vertex ball is a vertex, and the construction of this ball is based primarily on vertices. A vertex ball with radius 1 contains a central vertex, all vertices (nodes) at a distance of 1 from the central vertex, and all edges connecting the central vertex to vertices at a distance of 1 from it.

Definition 2.13 of the Edge Ball

Let G = (V, E) be a directed graph. The edge ball $B_{edge}G(e,1)$ of radius 1 and center at edge $e=(u,v) \in E$ is a subgraph of (V_1,E_1) such that $V_1:=\{u,v\}$ and $E_1:=\{(u,v),(v,u)\} \cap E$. The ball $B_{edge}G(e,n)$ of radius $n \in \{2,3,\ldots\}$ is the union of the sets:

$$B_{edge}G(e,n):=\cup c \in E\ B_{edge}G(c,1), \text{ where } c=(x,y) \vee c=(y,x) \text{ and } y \in V_{n-1}, \text{ provided that: } B_{edge}G(e,n-1)=(V_{n-1},E_{n-1}). \quad (2)$$

The radius of the edge ball $r_{edge}(G,e)$ is the smallest natural number such that:

$$B_{edge}G(e,r_{edge}(G,e))=B_{edge}G(e,r_{edge}(G,e)+1)\text{" (Bielecki, Schmittel, 2022, p. 1331).} \quad (3)$$

An edge ball includes both edges and vertices (nodes), but the center of the ball is an edge. For radius 1, such a ball contains only one central edge and two nodes.

The definitions of a vertex ball and an edge ball are necessary to study the similarity (indistinguishability) of information contained in two graphs. The definitions of indistinguishability are presented below.

Definition 2.5 of Vertex (Node) Indistinguishability

Let G=(V,E) be a directed graph (orgraph), and let x,y∈V. Nodes x and y are indistinguishable if they belong to the same connected component of the graph GG, and for every n ∈ N+, the node balls $BG_{node}(x, n)$ and $BG_{node}(y, n)$ are isomorphic. Otherwise, the nodes are distinguishable" (Bielecki, Schmittel, 2022, p. 1330). This definition means that two vertices (nodes) are indistinguishable (i.e., identical) if they are somehow connected, and for every radius of the existing nodal ball around these nodes, these subgraphs are isomorphic, i.e., they have the same structure (i.e., they have the same connections to the same elements).

Definition 2.15. Edge Indiscernibility

Let G=(V,E) be a directed graph (orgraph), and let e1,e2∈E be edges. The edges e1e1 and e2e2 are indiscernible if they belong to the same connected component of the graph GG, and for every n∈ N+, the edge balls $BG_{edge}(e1,n)$ and $BG_{edge}(e2,n)$ are isomorphic. Otherwise, the edges are distinguishable" (Bielecki, Schmittel, 2022, p. 1332).

The simplest way to represent both node and edge indiscernibility is for the chemical molecule H_2O. Both oxygen atoms belong to the same structure and have the same vertex and edge balls. If such a situation were to occur when analyzing management reports, it would mean that the graph could be reduced without losing any information (but only in such applications does graph reduction make sense). Generally, the amount of information at a graph node is calculated using the following formula (Bielecki, Schmittel, 2022, p. 1331):

$$H_{node} = - n * \sum(k=1..K)\ n_k/n * \log(n_k/n) \quad (4)$$

where:

- H_{node} – the amount of nodal information generated by relations $R_1,\ldots,R_n$ on the structure S(X,n),
- n – number of elements in set X,
- K – the number of elements in the family Π (denoting the set of non-empty intersections of equivalence classes of relations $R_1,\ldots,R_n$),
- n_k – to liczba elementów w k-tym zbiorze należącym do rodziny Π.

This formula measures the amount of nodal information, taking into account the overlap of information from different relations in the structure S.

To understand the formula for the amount of nodal information, additional explanation is necessary. As already mentioned, the same set of information can often be organized into a graph in different ways, so the model predicts many different relations that allow information elements to be organized into a directed graph. For each of these relations, indistinguishable edges or vertices may hypothetically occur, and such indistinguishable elements can be grouped into classes (a class is a mathematical construct; for this article, it can be assumed to be a set of indistinguishable elements).

If we now superimpose such classes created by different relations, their intersections will create new classes, of which there are K by definition. For example, {1,2} u {2, 3} = {2} (the number 2 is the intersection of these two classes). The Π family consists of classes resulting from superimposing classes created by different relations (or rather, all relations used to order the graph elements). In the case of management reports, only one relation will be necessary, namely the logical connections between components and the construction of an information structure graph that will allow for the identification of unique elements in the graph. In addition to the continuity of the graph, the report will also contain a significant amount of unique information.

If we now replace vertices with edges in the formula for the amount of nodal information, we obtain the formula for the amount of edge information:

$$H_{edge} = - n * \sum (k=1..K)\ n_k/N * \log(n_k/N), \tag{5}$$

where K denotes the number of elements in the quotient set E/Dedge, and nk is the number of elements in the k-th equivalence class. The quotient set is the number of classes that arise when all edges of the graph are divided into groups of elements indistinguishable according to the Dedge relation (only one, unlike vertices where there can be many such relations).

If we sum up the amount of node and edge information, we get the total amount of information contained in the created structure: H = Hnode + Hedge.

The structure is a graph (the graph's vertices are the set $X = \{x_1, \ldots x_n\}$) and all the relations that organize this graph ($R_1, \ldots R_m$), that is: $S(X, n) := (X, R_1, \ldots R_m)$. In other words, „Let $X=\{x_1,\ldots,x_n\}$ be a finite set $R_1,\ldots,R_n$ relations defined on X. A tuple $(X, R_1,\ldots, R_n)$ is called a structure on the set X".

The final definition required is that of labeling, although it is pretty intuitive.

Definition of labeling. "The canonical projection fL(x)=[x]L is a function that labels the set X". What's important is that labeling is not done randomly; the labels must arise from natural properties of the elements we want to describe. The purpose of labeling is to gain a better understanding and describe the structure of the set X.

4. An example of using an algorithm to implement a model of information encoded in structures to detect manipulation of an economic entity's annual report

Due to the size of the generated graphs, only a small portion of the graph based on the 2019 report of Circor International, a company that was found to have manipulated its reports for 2019-2021, will be displayed.

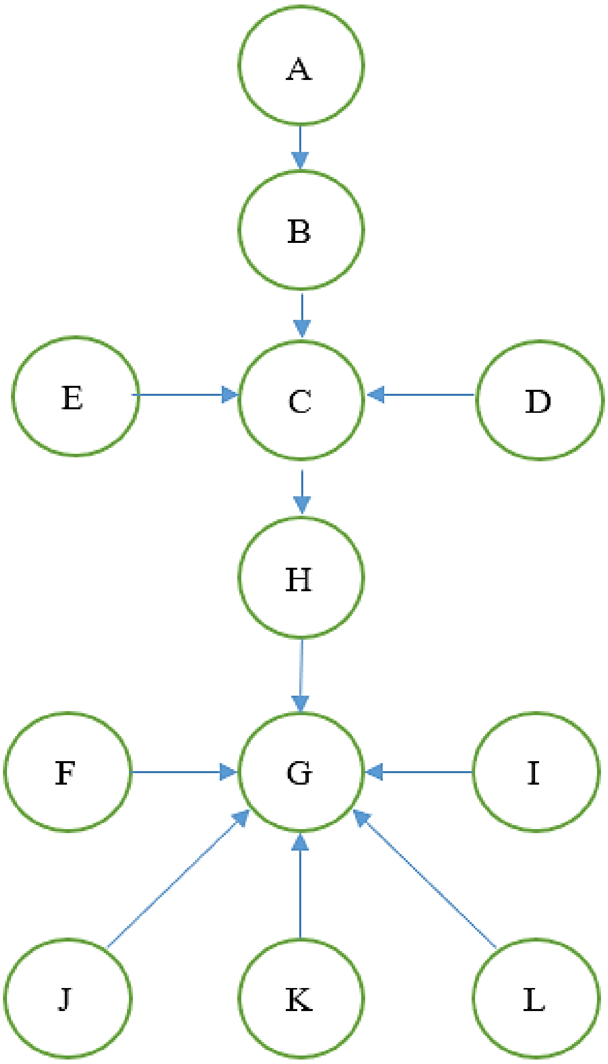

Figure 1. Relationship graph of statements in Circor International's 2019 Management Report.

Source: Circor International's 10-K Report, U.S. Securities and Exchange Commission Edgar System.

Due to the size of the generated graphs, only a small portion of the graph generated from the 2019 report of Circor International, a company proven to have manipulated its 2019-2021 reports, will be shown. Figure 1 shows a consistency analysis of the statements in the introduction to this report. Table 1 explains what the individual nodes in the graph represent.

Table 1.
Description of the meaning of nodes in the graph

Index	Description of nodes
A	Expected investment cuts in oil companies worldwide
B	Reduces production of oil subsystems (which Circor trades)
C	Circor's results may deteriorate
D	No improvement in the maritime sector
E	Signs of a slowdown in the European aerospace and defense markets (including markets where Circor operates)
F	Moderate growth in aerospace and defense markets outside Europe
G	Possible improvement in Circor's results
H	Supplier consolidation
I	Circor invests in technologies most needed by its customers
J	Circor reduces the number of plants
K	Circor standardizes technology
L	Circor improves organizational excellence

Source: own study based on Circor International's 10-K report for 2019.

Further on in the report, the management team analyzes and discusses the financial results achieved and selected elements of the financial statements. Table 2 shows the identified discontinuities in the graph constructed based on their report.

Table 2.
Selected further nodes in the structured graph

Index	Description of nodes
A	Investments in oil companies worldwide are expected to be reduced.
AB	Moderate growth is forecast in petrochemical markets.
AG	Debt remains at a similarly high level to previous years.
AK	Interest expenses have increased significantly (no explanation given for this).
BJ	Cash flow from operating activities has decreased.
BP	Sales revenue has increased.
BQ	The company has improved its net working capital management (inventory, receivables, and payables turnover ratios have improved).
CA-CI	Inconsistencies between the amounts reported in the narrative and the amounts in the debt tables.
M	Numerous actions aimed at improving the company's profitability.
P	Acquisition of companies with lower profitability (as indicated by the value tables).

Source: own study based on Circor International's 10-K report for 2019.

In addition to the inconsistencies and discontinuities shown in Table 2, another element that didn't fit the continuous graph describing the report was the alternating statements about unrelated optimistic and pessimistic forecasts. The management board wrote extensively about negative forecasts, but interspersed them with optimistic forecasts pointing to various segments, countries, and continents. In other words, it didn't provide a general global estimate, but somewhat fragmented information that didn't allow for a complete picture of the situation. Analysis of the report using the graph identified at least 14 inconsistencies that interrupted the continuity of the graph. However, it must be admitted that the report was incredibly informative, especially considering all the numbers included in the tables in the management report. Sometimes, information was repeated, and nodes were indistinguishable—especially when discussing factors positively and negatively impacting the company's performance. Such nodes were standardized (repeats of the same information were removed).

5. Summary and final conclusions

The literature on lying shows that lying is a significant effort for humans. Our amygdala responds to deception with activation, which reflects the stress and negative emotions experienced when lying. Of course, in experienced liars, amygdala activation decreases, and the brain becomes accustomed to lying. Another way to deal with stress and potential remorse is through rationalization, one of the three elements of Cressey's deception triangle. However, it's one thing to eliminate the stress and physical reactions associated with dishonesty, and another to create a coherent, dishonest image of a process, such as a business situation.

Liars easily create stories and rationalizations, but when you examine the details, they are either missing or contradictory. Liars often get lost in their stories and constantly change their versions. Liars usually position themselves as experts or victims, disregarding the feelings and harm of others. These characteristics are the basis for the concept of examining management reports through the structured information contained within them. Theoretically, management has ample time to polish their reports to perfection and eliminate all contradictions and discrepancies. Still, very often it's simply impossible to rationalize something that never happened or unfolded completely differently. The number of inconsistencies and discrepancies detected can be a significant signal that something was being concealed or distorted.

In the analyzed report, the management attempted to embellish the narrative by adding positive statements, especially in places where they described many unfavorable elements. This affected the continuity of the description and the logic of the argument, causing interruptions in the graph.

In summary, the model of information encoded in the graph appears to be an interesting development of algorithms for detecting manipulation of business entity reports.

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ChatGPT 4.0 and Google Translate were utilized to enhance the quality of specific sentences in the article (find synonyms or analogous sentences).

References

1. Abbasi, A.C., Albrecht, A.V., Hansen, J. (2012). Metafraud: a Meta-Learning framework for detecting financial fraud. *MIS Quarterly*, *36(4)*, pp. 1293-1327.
2. Armstrong, C.S., Jagolinzer A.D., Larcker D.F. (2010). Chief Executive Officer Equity Incentives and Accounting Irregularities. *Journal of Accounting Research*, *48(2)*, pp. 225-271. https://doi.org/10.1111/j.1475-679X.2009.00361.x, 15.04.2025.
3. Beneish, D. (1999). The Detection of Earnings Manipulation. *Financial Analysts Journal*, *Vol. 55(5)*, pp. 24-36.
4. Bielecki, A., Schmittel, M. (2022). The information encoded in structures: Theory and application to molecular cybernetics. *Foundations of Science*, *27(4)*, pp. 1327-1345.
5. Bielecki, A., Stocki, R. (2023). The concept of structural information and possible applications. *Zagadnienia Filozoficzne w Nauce*, *75*, pp. 157-183.
6. Blair, J.P., Reimer, T.O., Levine, T.R. (2018). The role of consistency in detecting deception: The superiority of correspondence over coherence. *Communication Studies*, *69(5)*, pp. 483-498.
7. Christensen, T.E., Paik, D.G.H., Williams, C.D. (2010). Market efficiency and investor reactions to SEC fraud investigations. *Journal of Forensic & Investigative Accounting*, *2(3)*, p. 25.
8. Dechow, P.M., Ge, W., Larson, C.R., Sloan, R.G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research*, *28(1)*, pp. 17-82.
9. Dong, W., Liao, S., Zhang, Z. (2018). Leveraging Financial Social Media Data for Corporate Fraud Detection. *Journal of Management Information Systems*, *35(2)*, pp. 461-487. https://doi.org/10.1080/07421222.2018.1451954, 24.04.2025.
10. Erickson, M., Hanlon, M., Maydew E.L. (2006). Is There a Link between Executive Equity Incentives and Accounting Fraud? *Journal of Accounting Research*, *44(1)*, pp. 113-143. https://doi.org/10.1111/j.1475-679X.2006.00194.x, 25.04.2020.
11. Feng, M., Ge, W., Luo, S. Shevlin, T.J. (2011). Why Do CFOs Become Involved in Material Accounting Manipulations? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1260368, 25.04.2025.
12. Gaganis, C. (2009). Classification Techniques For The Identification Of Falsified Financial Statements: A Comparative Analysis. *Intelligent Systems in Accounting, Finance and Management*, *16*, pp. 207-229. https://doi.org/10.1002/isaf, 27.01.2020.
13. Grazioli, S., Johnson, P.E., Jamal, K. (2011). A Cognitive Approach to Fraud Detection. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.920222, 25.04.2025.
14. Hobson, J.L., Mayew, W.J., Venkatachalam, M. (2012). Analyzing Speech to Detect Financial Misreporting. *Journal of Accounting Research*, *50(2)*, pp. 349-392. https://doi.org/10.1111/j.1475-679X. 2011.00433.x, 25.04.2025.

15. Hribar, P., Kravet, T.D., Wilson, R.J. (2011). A New Measure of Accounting Quality. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1283946, 18.04.2025.
16. Kaminski, K.A., Wetzel T.S., Guan, L. (2004). Can Financial Ratios Detect Fraudulent Financial Reporting? *Managerial Auditing Journal*, *19(1)*, pp. 15-28. https://doi.org/10.1108/02686900410509802, 25.04.2025.
17. Koerber, C., Neck, C.P. (2006). Religion in the Workplace: Implications for Financial Fraud and Organizational Decision Making. *Journal of Management, Spirituality and Religion*, *3(4)*, pp. 305-318. https://doi.org/10.1080/14766080609518636, 25.04.2025.
18. Larcker, D.F., Zakolyukina, A.A. (2012). Detecting Deceptive Discussions in Conference Calls. *Journal of Accounting Research*, *50(2)*, pp. 495-540. https://doi.org/10.1111/j.1475-679X.2012.00450.x, 21.04.2025.
19. Mahesarani, D., Chariri, A. (2016). Corporate Governance and Financial Statement Frauds: Evidence from Indonesia. *The 1st International Conference on Economics, Education, Business and Accounting*, *No. December*, pp. 489-495. https://doi.org/10.15294/iceeba.v1i1.41, 25.04.2025.
20. Perols, J., Barbara, L. (2011). The Relation between Earnings Management and Financial Statement Fraud. *Advances in Accounting*, *27(1)*, pp. 39-53.
21. Perols, L., Skillicorn, D. (2011). Financial Statement Fraud Detection: An Analysis of Statistical and Machine Learning Algorithms. *Auditing*, *30(2)*, pp. 19-50. https://doi.org/10.2308/ajpt-50009, 22.04.2025.
22. Purda, L., Skillicorn, D. (2015). Accounting Variables, Deception, and a Bag of Words: Assessing the Tools of Fraud Detection. *Contemporary Accounting Research*, *32(3)*, pp. 1193-1223. https://doi.org/10.1111/1911-3846.12089, 22.04.2025.
23. Summers, S.L., Sweeney, J.T. (1998). Fraudulently Misstated Financial Statements and Insider Trading: An Empirical Analysis. *Accounting Review*, *73(1)*, pp. 131-146.
24. Witkowski, T. (2022). *Psychologia kłamstwa*. Warszawa: Jacek Santorski & Co.
25. Zaucha, J. (2023). Dwa „tryby” mówienia a kłamstwo. *Linguistica Copernicana*, *20*, pp. 139-156.