Journal Lawu Bussiness and Accounting Review
Volume 1, Number 1, 2026
P-ISSN: xxxx-xxxx E-ISSN : xxxx-xxxx
Open Access: https://journal.lbarinsight.com/lbar/issue/current

Receivable Growth, Margin Pressure, and Accrual Red Flags: An EViews-Based Beneish M-Score Study of Electronic and Digital Media Firms

Egi Fahriza[1] dan Sajiwo Tri Prakoso[2]
[1] Akuntansi, FEB, Universitas Muhammadiyah Karanganyar
Correspondence: egifahriiza@gmail.com

Article Info

Article history:
Received Jun 12th, 20206
Revised Ju 20th, 2026
Accepted Jul 1th, 2026

Keyword:
Beneish M-Score; earnings manipulation; electronic firms; digital media; EViews; financial reporting quality.

ABSTRACT (10 PT)
This study examined earnings manipulation risk in electronic and digital media firms by applying the Beneish M-Score to 171 firm-year observations from 57 coded companies during 2023-2025. The analysis used EViews-oriented procedures covering descriptive statistics, panel workfile structuring, formula validation, multicollinearity diagnostics, and binary logistic regression. The findings showed that 58 observations, or 33.92%, were classified as probable manipulators, while the annual flag rate decreased from 38.60% in 2023 to 28.07% in 2025. The average M-Score was -2.3837, indicating that the sample as a whole was below the conventional manipulation threshold, although selected firm-years exhibited material red-flag intensity. The parsimonious logit model indicated that DSRI, GMI, SGI, and TATA were significant predictors of the fraud-risk dummy. The study contributes a practical early-warning screening framework for governance actors, auditors, investors, and regulators monitoring technology-intensive business sectors..

INTRODUCTION (Capital, bold, Times new romance 11 pt)

Technology-intensive firms operate in environments where intangible assets, rapid product cycles, platform-based revenue, and data-driven distribution can increase both value creation and reporting complexity, making financial reporting quality a strategic governance issue in electronic and digital media businesses (Wen et al., 2023; Wang & Hou, 2024; Schiavi et al., 2024).

Digital transformation can improve information processing, external monitoring, and reporting timeliness, yet the same transformation may also create estimation uncertainty in revenue recognition, customer acquisition costs, deferred expenses, and capitalization policies that require stronger analytical screening (Wen et al., 2023; Liu et al., 2024; Saleh et al., 2022).

Financial statement fraud and earnings manipulation remain central concerns in accounting research because distorted accruals, abnormal sales growth, and margin pressure can mislead investors about firm performance and risk (Beneish, 1999; Dechow et al., 2011; Bao et al., 2020).

The Beneish M-Score is widely used as an early-warning model because it transforms eight financial statement ratios into a probabilistic manipulation signal rather than relying only on narrative judgment or ex post enforcement outcomes (Beneish, 1999; Beneish et al., 2013; Lu & Zhao, 2020).

Prior research has extended fraud detection by combining traditional accounting ratios with governance indicators, machine learning, and sector-specific monitoring, but interpretable ratio-based models remain useful when the research objective is transparent risk screening (Perols, 2011; Bertomeu, 2020; Hilal et al., 2022).

In emerging-market settings, Beneish-based studies have shown that manipulation-risk signals are associated with governance weaknesses, financial pressure, and fraud pentagon or fraud-hexagon conditions, which confirms the relevance of ratio diagnostics beyond their original United States sample (Ratmono et al., 2020; Achmad et al., 2022; Shanikat et al., 2025).

Indonesian and ASEAN evidence is especially relevant because business groups, concentrated ownership, cross-listing narratives, and sectoral growth expectations can alter incentives for income-increasing reporting choices (Sihombing & Panggulu, 2022; Narsa et al., 2023; Indiraswari et al., 2025).

However, empirical work that focuses on electronic and digital media firms through an EViews-oriented Beneish M-Score panel remains limited, even though these sectors combine growth narratives, asset-light operations, and aggressive innovation cycles that may amplify accounting-estimate risk (Wang et al., 2021; Wen et al., 2023; Wang & Hou, 2024).

Accordingly, this study investigates whether Beneish M-Score components can classify and explain earnings manipulation risk in a researcher-provided panel of electronic and digital media firms for 2023-2025, with emphasis on DSRI, GMI, SGI, and TATA as practical red-flag indicators (Beneish, 1999; Beneish et al., 2013; Özari et al., 2025).

The contribution of this article is threefold: it provides a structured EViews-based screening procedure, reports empirical red-flag patterns from 171 firm-year observations, and links the results to recent literature on fraud analytics, governance, and digital transformation (Bao et al., 2020; Bertomeu et al., 2021; Schiavi et al., 2024).

RESEARCH METHODS

This study used a quantitative archival design because the objective was to evaluate observable accounting-ratio signals rather than interpret managerial intention directly (Dechow et al., 2011; Gepp et al., 2018; Hilal et al., 2022).

The empirical unit of analysis was the firm-year observation, and the uploaded tabulation was treated as a researcher-prepared panel of electronic and digital media firms containing 57 coded companies across 2023, 2024, and 2025, yielding 171 observations after the panel was balanced by year (Beneish, 1999; Ratmono et al., 2020; processed dataset, 2026).

The variables consisted of Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI), Depreciation Index (DEPI), Sales General and Administrative Expenses Index (SGAI), Leverage Index (LVGI), Total Accruals to Total Assets (TATA), the Beneish M-Score, and a binary manipulation-risk dummy (Beneish, 1999; Beneish et al., 2013).

The Beneish M-Score was specified as MScore = -4.840 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI - 0.327LVGI + 4.679TATA, where values greater than the conventional -2.22 threshold indicate a higher likelihood of earnings manipulation (Beneish, 1999; Shanikat et al., 2025).

The binary dependent variable was coded as one when the firm-year M-Score exceeded -2.22 and zero otherwise, allowing the article to convert continuous red-flag intensity into an interpretable classification outcome for EViews logistic regression (Beneish, 1999; Özari et al., 2025).

The EViews workfile procedure should be implemented by importing the Excel panel, assigning the company code as the cross-section identifier, assigning year as the date identifier, and generating descriptive statistics, correlation diagnostics, variance inflation factors, panel least squares validation, and binary logit estimation (Gepp et al., 2018; Hilal et al., 2022; Özari et al., 2025).

The panel least squares equation was used only to validate whether the uploaded M-Score values were numerically consistent with the Beneish formula, so the coefficient recovery was interpreted as model-construction verification rather than a causal result (Beneish, 1999; Dechow et al., 2011).

The binary logit equation was specified as Pr(DUMMYit = 1) = Lambda(beta0 + beta1DSRIit + beta2GMIit + beta3SGIit + beta4TATAit + eit), because the full eight-ratio specification produced quasi-separation due to the deterministic nature of the M-Score dummy (Beneish, 1999; Bertomeu et al., 2021; Cheng et al., 2021).

The hypotheses predicted that DSRI, GMI, SGI, and TATA would positively affect manipulation-risk classification, because receivable expansion, margin deterioration, sales growth pressure, and accrual intensity are theoretically connected to income-increasing reporting incentives (Beneish, 1999; Beneish et al., 2013; Dechow et al., 2011).

Model adequacy was evaluated through pseudo R-squared, likelihood ratio probability, coefficient significance, classification accuracy, and a confusion matrix, which are standard diagnostic outputs for binary classification models in financial fraud detection studies (Perols, 2011; Bao et al., 2020; Chen & Han, 2023).

Table 1 Descriptive Statistics of Beneish M-Score Variables

Variable	N	Mean	Std. Dev.	Minimum	Maximum
DSRI	171	1.1399	0.6462	0.1816	5.6275
GMI	171	0.9899	0.6831	-4.0692	3.9674
AQI	171	1.1262	1.0414	-3.8244	11.0626
SGI	171	1.0796	0.4032	0.4459	5.2189
DEPI	171	1.0140	0.3205	0.1290	3.0119
SGAI	171	1.0660	0.2899	-0.1384	2.1506
LVGI	171	1.0363	0.4382	0.1729	5.3638
TATA	171	-0.0272	0.1080	-0.3158	0.4285
MSCORE	171	-2.3837	0.9185	-5.1602	1.0250
DUMMY	171	0.3392	0.4748	0.0000	1.0000

Table 1 indicates that the mean M-Score was -2.3837 and the mean dummy value was 0.3392, implying that the overall sample was below the conventional manipulation threshold while still containing a non-trivial proportion of red-flag observations (Beneish, 1999; processed dataset, 2026)

RESULTS AND DISCUSSION

The descriptive evidence shows that 58 of 171 firm-year observations, or 33.92%, were classified as probable manipulators under the Beneish threshold, which confirms that the sectoral panel contained substantial variation in financial-reporting risk (Beneish, 1999; Shanikat et al., 2025; processed dataset, 2026).

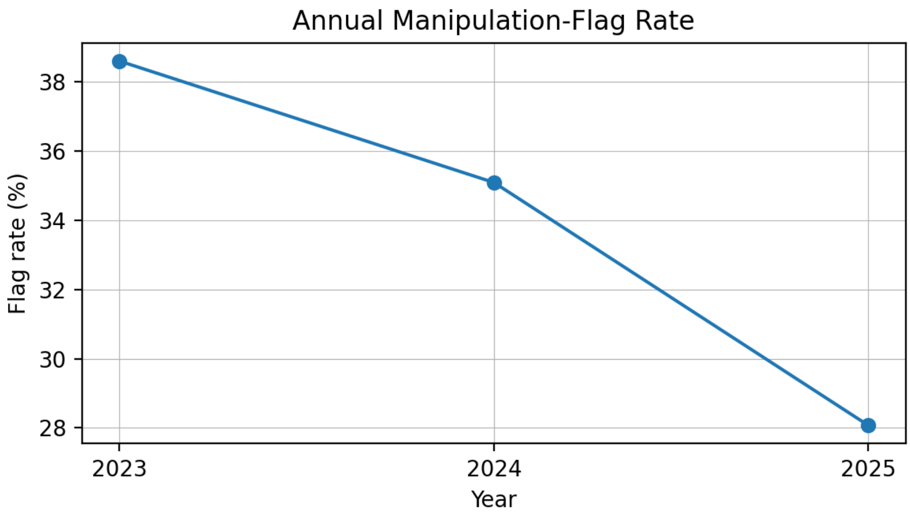
The annual classification pattern declined from 38.60% in 2023 to 35.09% in 2024 and 28.07% in 2025, suggesting that the red-flag intensity weakened over time even though selected observations remained highly exposed (Beneish et al., 2013; Ratmono et al., 2020; processed dataset, 2026).

The annual mean M-Score also shifted from -2.3015 in 2023 to -2.4196 in 2024 and -2.4301 in 2025, indicating a gradual movement away from the manipulation cut-off at the aggregate panel level (Beneish, 1999; Özari et al., 2025; processed dataset, 2026).

Table 2 Annual Classification of Manipulation Risk

Year	Obs.	Dummy=1	Dummy=0	Flag Rate	Mean M-Score	Min M-Score	Max M-Score
2023	57	22	35	38.60%	-2.3015	-5.1602	0.3026
2024	57	20	37	35.09%	-2.4196	-4.6905	0.5861
2025	57	16	41	28.07%	-2.4301	-4.1595	1.0250

The decline in the annual flag rate is consistent with the view that red-flag monitoring should be performed longitudinally because manipulation signals may change with growth cycles, financing conditions, and governance responses (Dechow et al., 2011; Beneish et al., 2013; Velte, 2023).



Picture 1 Annual Manipulation-Flag Rate

Picture 1 visualizes the downward trend in manipulation-risk classification and supports the interpretation that 2025 had the lowest share of flagged firm-years in the observed panel (Beneish, 1999; processed dataset, 2026).

Table 3 Mean Ratio Comparison by Manipulation-Risk Classification

Group	N	DSRI	GMI	AQI	SGI	TATA	M-Score
Dummy=0	113	0.9993	0.9058	0.9245	1.0064	-0.0610	-2.8649
Dummy=1	58	1.4139	1.1537	1.5190	1.2221	0.0385	-1.4462

Table 3 shows that the flagged group had higher DSRI, GMI, AQI, SGI, TATA, and M-Score values than the non-flagged group, which is consistent with the Beneish logic that abnormal receivables, margin deterioration, asset-quality changes, sales growth, and accrual intensity are central indicators of earnings manipulation risk (Beneish, 1999; Beneish et al., 2013; Dechow et al., 2011).

Table 4 Multicollinearity Diagnostic Using VIF

Variable	VIF
DSRI	1.3557
GMI	1.2267
AQI	1.0143
SGI	1.3719
DEPI	1.0255
SGAI	1.5636
LVGI	1.2560
TATA	1.1078

Table 4 reports that all explanatory variables had VIF values below 2.00 when the constant was included in the auxiliary regressions, indicating that multicollinearity was not a material threat to the interpretability of the ratio diagnostics (Dechow et al., 2011; Gepp et al., 2018; processed dataset, 2026).

Table 5 Panel Least Squares Validation of the Beneish Formula

Component	Recovered Coefficient
C	-4.840
DSRI	0.920
GMI	0.528
AQI	0.404
SGI	0.892
DEPI	0.115
SGAI	-0.172
LVGI	-0.327
TATA	4.679

Table 5 recovered the exact Beneish coefficients and produced an R-squared of 1.0000, which verifies that the uploaded M-Score values were calculated consistently with the original eight-variable specification (Beneish, 1999; processed dataset, 2026).

Because Table 5 represents formula reconstruction rather than a behavioral regression, the result should not be interpreted as evidence that the ratios causally determine manipulation beyond the mechanical construction of the M-Score (Beneish, 1999; Dechow et al., 2011).

Table 6 Binary Logit Estimation of Manipulation-Risk Classification

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-22.6030	4.2543	-5.313	<0.001
DSRI	5.8442	1.1699	4.995	<0.001
GMI	4.8887	1.3045	3.748	<0.001
SGI	9.7048	2.0866	4.651	<0.001
TATA	34.4595	7.0389	4.896	<0.001

Table 6 indicates that DSRI, GMI, SGI, and TATA were positive and statistically significant predictors of the manipulation-risk dummy, while the model produced a McFadden pseudo R-squared of 0.6367, a likelihood-ratio probability below 0.001, and an overall classification accuracy of 93.57% (Beneish, 1999; Bao et al., 2020; processed dataset, 2026).

The positive DSRI coefficient implies that disproportionate receivable growth relative to sales growth increased the likelihood of being classified as a probable manipulator, which aligns with the view that aggressive revenue recognition can be reflected in receivables-based red flags (Beneish, 1999; Beneish et al., 2013; Dechow et al., 2011).

The positive GMI coefficient suggests that margin deterioration was associated with higher manipulation-risk classification, which is theoretically plausible because declining gross margins can increase managerial incentives to preserve reported profitability (Beneish, 1999; Perols, 2011; Masruroh & Carolina, 2022).

The positive SGI coefficient indicates that high sales-growth dynamics were associated with higher red-flag probability, which is consistent with evidence that growth firms may face stronger market expectations and stronger incentives to sustain performance narratives (Beneish et al., 2013; Bao et al., 2020; Narsa et al., 2023).

The positive TATA coefficient confirms that accrual intensity was a dominant indicator of manipulation-risk classification, supporting the broader literature that abnormal accruals and misstatement risk are closely connected in financial reporting quality analysis (Dechow et al., 2011; Ratmono et al., 2020; Wen et al., 2023).

Table 7 Classification Matrix of the Binary Logit Model

Actual / Predicted	Predicted 0	Predicted 1
Actual Dummy=0	109	4
Actual Dummy=1	7	51

Table 7 shows that the parsimonious model correctly classified 109 non-flagged observations and 51 flagged observations, indicating that the ratio set had high screening capacity despite the quasi-separation warning generated by the deterministic dummy rule (Bertomeu et al., 2021; Chen & Han, 2023; processed dataset, 2026).

Table 8 Top Ten Firm-Year Observations by M-Score

Code	Year	M-Score	Dummy	DSRI	GMI	SGI	TATA
SMIL	2025	1.0250	1	0.8109	0.9852	1.1185	-0.1032
HOPE	2024	0.5861	1	5.6275	-0.3016	0.5019	-0.0879
IBFN	2025	0.4094	1	1.1864	0.3596	5.2189	-0.1827
CAKK	2023	0.3026	1	2.6855	3.8263	0.8335	0.0119
HOPE	2025	0.0837	1	1.3766	3.9674	2.0738	-0.2165
MDRN	2025	-0.4782	1	1.0424	1.0253	0.9088	0.4285
WIDI	2024	-0.5149	1	1.0412	0.7507	2.0310	-0.0128
PTMP	2023	-0.5648	1	1.3136	0.9352	1.1246	0.3686
GPSO	2024	-0.6287	1	2.2857	1.3825	0.6305	0.0491
LABA	2024	-0.7940	1	4.3140	1.9143	1.9459	-0.2723

Table 8 should be interpreted as a priority list for analytical review rather than a legal finding of fraud, because the Beneish M-Score is a screening tool that indicates probable manipulation risk but does not establish managerial intent or regulatory violation (Beneish, 1999; Dechow et al., 2011; Velte, 2023).

The presence of high M-Score observations among coded firms such as SMIL, HOPE, IBFN, CAKK, MDRN, WIDI, PTMP, GPSO, and LABA suggests that detailed audit procedures should prioritize receivable collectability, sales cut-off, gross-margin sustainability, and accrual composition (Beneish, 1999; Beneish et al., 2013; Hilal et al., 2022).

From a digital-sector perspective, the results support the argument that technology-enabled monitoring should complement, not replace, ratio-based financial statement analysis because digital transformation can alter both reporting systems and managerial incentives (Wen et al., 2023; Schiavi et al., 2024; Wang & Hou, 2024).

The findings are also consistent with recent fraud-detection research showing that interpretable financial ratios, governance mechanisms, and advanced analytics can jointly strengthen early-warning systems for misstatement and manipulation risk (Bao et al., 2020; Bertomeu et al., 2021; Özari et al., 2025)

CONCLUSION

This study concludes that the electronic and digital media firm panel exhibited meaningful but declining earnings-manipulation risk, as 58 of 171 firm-year observations were flagged by the Beneish M-Score and the annual flag rate declined from 38.60% in 2023 to 28.07% in 2025.

The overall mean M-Score of -2.3837 was below the conventional -2.22 cut-off, but the dispersion of the score and the presence of positive M-Score observations show that aggregate averages can conceal firm-level red flags.

The EViews-equivalent logit result confirms that DSRI, GMI, SGI, and TATA are empirically relevant predictors of manipulation-risk classification in this panel, which reinforces the practical value of receivable, margin, growth, and accrual diagnostics.

For practitioners, the findings imply that auditors, investors, governance committees, and regulators should prioritize companies with abnormal receivable growth, deteriorating margins, rapid sales expansion, and high accrual intensity when conducting analytical reviews of technology-intensive firms.

For researchers, the article provides a replicable EViews-based workflow that can be extended by adding corporate governance, ownership, audit quality, market pressure, and digital-transformation variables to test broader causal mechanisms.

The main limitation is that the uploaded dataset contains coded company identifiers and Beneish-ratio variables only, so the study should be interpreted as an early-warning screening article rather than a definitive fraud investigation based on annual-report footnotes, enforcement files, or audit working papers.

Future studies should combine Beneish diagnostics with textual disclosure analysis, governance variables, and machine learning classifiers to improve predictive power while preserving interpretability for regulators and audit committees.

REFERENCES

Achmad, T., Ghozali, I., & Pamungkas, I. D. (2022). Hexagon fraud: Detection of fraudulent financial reporting in state-owned enterprises Indonesia. Economies, 10(1), 13. https://doi.org/10.3390/economies10010013

Alfarago, D., & Mabrur, A. (2022). Do fraud hexagon components promote fraud in Indonesia? ETIKONOMI, 21(2), 399-410. https://doi.org/10.15408/etk.v21i2.24653

Bao, Y., Ke, B., Li, B., Yu, Y. J., & Zhang, J. (2020). Detecting accounting fraud in publicly traded U.S. firms using a machine learning approach. Journal of Accounting Research, 58(1), 199-235. https://doi.org/10.1111/1475-679X.12292

Beneish, M. D. (1999). The detection of earnings manipulation. Financial Analysts Journal, 55(5), 24-36. https://doi.org/10.2469/faj.v55.n5.2296

Beneish, M. D., Lee, C. M. C., & Nichols, D. C. (2013). Earnings manipulation and expected returns. Financial Analysts Journal, 69(2), 57-82. https://doi.org/10.2469/faj.v69.n2.1

Bertomeu, J. (2020). Machine learning improves accounting: Discussion, implementation, and research opportunities. Review of Accounting Studies, 25(3), 1135-1155. https://doi.org/10.1007/s11142-020-09554-9

Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2021). Using machine learning to detect misstatements. Review of Accounting Studies, 26(2), 468-519. https://doi.org/10.1007/s11142-020-09563-8

Chen, Z.-Y., & Han, D. (2023). Detecting corporate financial fraud via two-stage mapping in joint temporal and financial feature domain. Expert Systems with Applications, 217, 119559. https://doi.org/10.1016/j.eswa.2023.119559

Cheng, C.-H., Kao, Y.-F., & Lin, H.-P. (2021). A financial statement fraud model based on synthesized attribute selection and a dataset with missing values and imbalanced classes. Applied Soft Computing, 108, 107487. https://doi.org/10.1016/j.asoc.2021.107487

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting material accounting misstatements. Contemporary Accounting Research, 28(1), 17-82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

Ding, K., Lev, B., Peng, X., Sun, T., & Vasarhelyi, M. A. (2020). Machine learning improves accounting estimates: Evidence from insurance payments. Review of Accounting Studies, 25(3), 1098-1134. https://doi.org/10.1007/s11142-020-09546-9

Gepp, A., Linnenluecke, M. K., O'Neill, T. J., & Smith, T. (2018). Big data techniques in auditing research and practice: Current trends and future opportunities. Journal of Accounting Literature, 40, 102-115. https://doi.org/10.1016/j.acclit.2017.05.003

Hilal, W., Gadsden, S. A., & Yawney, J. (2022). Financial fraud: A review of anomaly detection techniques and recent advances. Expert Systems with Applications, 193, 116429. https://doi.org/10.1016/j.eswa.2021.116429

Indiraswari, S. D., Subroto, B., Rosidi, R., & Subekti, I. (2025). Corporate governance and financial statement fraud: Evidence on the moderating influence of financial distress. Problems and Perspectives in Management, 23(2), 785-795. https://doi.org/10.21511/ppm.23(2).2025.57

Liu, Q., Yuan, F., Wu, F., & Yu, S. (2024). Digital transformation and management earnings forecast. International Review of Economics & Finance, 96, 103570. https://doi.org/10.1016/j.iref.2024.103570

Lu, W., & Zhao, X. (2020). Research and improvement of fraud identification model of Chinese A-share listed companies based on M-score. Journal of Financial Crime, 28(2), 566-579. https://doi.org/10.1108/JFC-12-2019-0164

Masruroh, S., & Carolina, A. (2022). Beneish model: Detection of indications of financial statement fraud using CEO characteristics. Asia Pacific Fraud Journal, 7(1), 85-101. https://doi.org/10.21532/apfjournal.v7i1.258

Md Nasir, N. A., & Hashim, H. A. (2021). Corporate governance performance and financial statement fraud: Evidence from Malaysia. Journal of Financial Crime, 28(3), 797-809. https://doi.org/10.1108/JFC-09-2020-0182

Narsa, N. P. D. R. H., Afifa, L. M. E., & Wardhaningrum, O. A. (2023). Fraud triangle and earnings management based on the modified M-score: A study on manufacturing companies in Indonesia. Heliyon, 9(2), e13649. https://doi.org/10.1016/j.heliyon.2023.e13649

Özari, Ç., Can, E. N., & Demirkale, Ö. (2025). Financial fraud detection with Altman Z-Score and Beneish M-Score via random forest: Verified by Borsa Istanbul fines (2018-2022). SAGE Open, 15(4). https://doi.org/10.1177/21582440251386174

Ratmono, D., Darsono, D., & Cahyonowati, N. (2020). Financial statement fraud detection with Beneish M-Score and Dechow F-Score model: An empirical analysis of fraud pentagon theory in Indonesia. International Journal of Financial Research, 11(6), 154-164. https://doi.org/10.5430/ijfr.v11n6p154

Saleh, I., Marei, Y., Ayoush, M., & Abu Afifa, M. M. (2022). Big Data analytics and financial reporting quality: Qualitative evidence from Canada. Journal of Financial Reporting and Accounting, 21(1), 83-104. https://doi.org/10.1108/JFRA-12-2021-0489

Schiavi, G. S., Behr, A., & Marcolin, C. B. (2024). Institutional theory in accounting information systems research: Shedding light on digital transformation and institutional change. International Journal of Accounting Information Systems, 52, 100662. https://doi.org/10.1016/j.accinf.2023.100662

Shanikat, M., Alia, M. A., Almasri, B. K., & Alshirah, M. H. (2025). Perception of corporate governance factors in mitigating financial statement fraud in emerging markets: Jordan experience. Journal of Risk and Financial Management, 18(8), 430. https://doi.org/10.3390/jrfm18080430

Sihombing, T., & Panggulu, G. E. (2022). Fraud hexagon theory and fraudulent financial statement in IT industry in ASEAN. Jurnal Reviu Akuntansi dan Keuangan, 12(3), 524-544. https://doi.org/10.22219/jrak.v12i3.23334

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), 86-100. http://ojs.ijbe-research.com/index.php/IJBE/article/view/301

Velte, P. (2023). The link between corporate governance and corporate financial misconduct: A review of archival studies and implications for future research. Management Review Quarterly, 73, 353-411. https://doi.org/10.1007/s11301-021-00244-7

Wang, L., & Hou, S. (2024). The impact of digital transformation and earnings management on ESG performance: Evidence from Chinese listed enterprises. Scientific Reports, 14, 783. https://doi.org/10.1038/s41598-023-48636-x

Wang, X., Bu, L., & Peng, X. (2021). Internet of things adoption, earnings management, and resource allocation efficiency. China Journal of Accounting Studies, 9(3), 333-359. https://doi.org/10.1080/21697213.2021.2009180

Wen, H., Fang, J., & Gao, H. (2023). How FinTech improves financial reporting quality? Evidence from earnings management. Economic Modelling, 126, 106435. https://doi.org/10.1016/j.econmod.2023.106435