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ARTIFICIAL INTELLIGENCE IN DETECTING FINANCIAL AND TAX REPORTING ANOMALIES: EVIDENCE FROM ALBANIAN ENTERPRISES

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Abstract

The increasing digitalization of accounting systems and tax administration has created new opportunities for applying Artificial Intelligence (AI) in financial and tax risk assessment. This study investigates the effectiveness of Machine Learning techniques in detecting anomalies in financial and tax reporting among Albanian enterprises.

The analysis is based on a sample of 100 enterprises operating in the trade, manufacturing, construction, and service sectors. Financial and fiscal indicators were examined using descriptive statistics, multiple linear regression, Random Forest classification, and Isolation Forest anomaly detection.

The results show that the regression model explains 83.6% of the variation in Fiscal Risk Score ($R^2 = 0.836$). Profit Margin and Operating Cash Flow exhibit significant negative effects on fiscal risk, while the Debt-to-Assets Ratio demonstrates a positive relationship. Furthermore, the Random Forest model achieved an accuracy rate of 86.7% and an AUC value of 0.98, whereas the Isolation Forest algorithm identified 19 enterprises with anomalous reporting characteristics.

The findings demonstrate that Artificial Intelligence can significantly improve anomaly detection and fiscal risk assessment, providing valuable support for auditors, tax authorities, and policymakers.

Keywords: *Artificial Intelligence; Machine Learning; Anomaly Detection; Fiscal Risk Assessment; Financial Reporting; Tax Reporting; Random Forest; Isolation Forest*

1. Introduction

The rapid digital transformation of accounting and taxation has significantly increased the volume and complexity of financial and fiscal information. Consequently, traditional audit and compliance procedures face growing challenges in identifying irregular reporting patterns and assessing fiscal risk efficiently (OECD, 2023).

Artificial Intelligence (AI) and Machine Learning techniques provide new opportunities for analyzing large datasets and detecting anomalies that may indicate reporting irregularities, fraud, or tax non-compliance (Russell & Norvig, 2021). Previous studies suggest that Machine Learning algorithms can improve risk assessment, fraud detection, and compliance monitoring by identifying patterns that remain difficult to detect using conventional statistical methods (Bolton & Hand, 2002; Phua et al., 2010).

Despite increasing international interest in AI applications, empirical evidence from emerging economies remains limited. In Albania, the implementation of fiscalization reforms and digital reporting systems has expanded substantially, creating favorable conditions for the application of Artificial Intelligence in financial and tax risk management.

Therefore, this study aims to evaluate the effectiveness of Machine Learning techniques in identifying anomalies in financial and tax reporting among Albanian enterprises. The research combines econometric analysis with Random Forest and Isolation Forest algorithms to assess fiscal risk determinants and anomaly detection performance.

2. Research method

This study employs a quantitative research design to evaluate the effectiveness of Artificial Intelligence techniques in detecting anomalies in financial and tax reporting among Albanian enterprises. The analytical framework combines conventional statistical methods with Machine Learning algorithms to identify fiscal risk determinants and anomalous reporting patterns.

The empirical analysis is based on a sample of 100 enterprises operating in the trade, manufacturing, construction, and service sectors. Financial and tax-related data for the fiscal year 2024 were obtained from the database of the General Directorate of Taxes (GDT) of Albania. The dataset was processed and validated to ensure consistency, accuracy, and comparability across all observations.

The dependent variable is Fiscal Risk Score (RF), while the explanatory variables include Operating Cash Flow (CF), VAT-to-Turnover Ratio (TVSHR), Profit Margin (MF), Debt-to-Assets Ratio (DA), and Employee Productivity (PP). These indicators were selected based on previous research examining financial performance, tax compliance, and fiscal risk assessment (Bolton & Hand, 2002; James & Alley, 2004; Kirchler, 2007).

Table 1. *Definition of Variables*

Variable	Description	Type
RF	Fiscal Risk Score	Dependent
CF	Operating Cash Flow	Independent
TVSHR	VAT-to-Turnover Ratio	Independent
MF	Profit Margin	Independent
DA	Debt-to-Assets Ratio	Independent
PP	Employee Productivity	Independent

Note. Source: Author's calculations

The study tests the following hypotheses:

H1: Financial and fiscal indicators significantly influence Fiscal Risk Score.

H2: Operating Cash Flow negatively affects Fiscal Risk Score.

H3: The VAT-to-Turnover Ratio negatively affects Fiscal Risk Score.

H4: Profit Margin negatively affects Fiscal Risk Score.

H5: Artificial Intelligence techniques effectively identify anomalies and classify fiscal risk.

To evaluate the determinants of fiscal risk, a multiple linear regression model was estimated:

$$RF = \beta_0 + \beta_1 CF + \beta_2 TVSHR + \\ + \beta_3 MF + \beta_4 DA + \beta_5 PP + \varepsilon$$

In addition, two Machine Learning algorithms were employed. Random Forest was used as a supervised learning model for fiscal risk classification (Breiman, 2001), while Isolation Forest was applied as an unsupervised anomaly detection technique (Liu et al., 2008). These algorithms were selected because of their ability to identify complex relationships and unusual observations within financial datasets.

The validity of the regression model was assessed using Variance Inflation Factor (VIF), Shapiro–Wilk, Jarque–Bera, Breusch–Pagan, and Durbin–Watson tests. The predictive performance of the Machine Learning models was evaluated through Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC) metrics.

3. Results analysis

3.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the study variables. The results indicate considerable variation among enterprises regarding financial performance, tax reporting behavior, and fiscal risk exposure. Fiscal Risk Score has a mean value of 28.77 and ranges from 0.20 to 79.50, suggesting substantial differences in risk profiles across the sample. Similarly, Cash Flow and Employee Productivity exhibit relatively high dispersion, reflecting heterogeneous operational and financial conditions among enterprises.

Table 2. *Descriptive Statistics of the Study Variables*

Variable	Mean	Std. Dev.	Min	Max
Fiscal Risk Score	28.77	19.29	0.20	79.50
Cash Flow	14.86	29.99	–47.50	139.20
VAT-to-Turnover Ratio	10.09	5.09	1.00	20.00
Profit Margin	5.80	5.97	–11.00	22.91
Debt-to-Assets Ratio	54.87	21.62	11.22	99.00
Employee Productivity	21.47	32.57	0.22	199.20

Note. Source: Author's calculations

3.2 Determinants of Fiscal Risk

The Random Forest model was used to identify the variables that contribute most significantly to fiscal risk classification. As presented in Table 3, Cash Flow (0.341) and Profit Margin (0.243) emerge as the most influential predictors, highlighting the importance of liquidity and profitability in explaining fiscal risk.

Table 3. *Variable Importance in the Random Forest Model*

Variable	Importance Score	Rank
Cash Flow	0.341	1
Profit Margin	0.243	2
Employee Productivity	0.168	3
VAT-to-Turnover Ratio	0.143	4
Debt-to-Assets Ratio	0.105	5

Note. Source: Author's calculations

The correlation analysis further confirms these relationships. Fiscal Risk Score is negatively associated with Cash Flow (r = –0.36), VAT-to-Turnover Ratio (r = –0.51), and Profit Margin (r = –0.63), while a positive relationship is observed with Debt-to-Assets Ratio (r = 0.54). The strongest negative correlation is identified between Fiscal Risk Score and Profit Margin, suggesting that more profitable enterprises generally exhibit lower fiscal risk.

Table 4. *Pearson Correlation Matrix*

Variable	RF	CF	TVSHR	MF	DA	PP
RF	1.000	–0.36	–0.51	–0.63	0.54	0.44

Note. Source: Author's calculations

To evaluate the simultaneous effects of the explanatory variables, a multiple linear regression model was estimated. The results indicate that Cash Flow, VAT-to-Turnover Ratio, and Profit Margin negatively affect Fiscal Risk Score, whereas Debt-to-Assets Ratio and Employee Productivity exert positive effects. Profit Margin appears as the strongest predictor ($\beta = -1.417$), emphasizing the importance of profitability in reducing fiscal risk.

Table 5. *Multiple Regression Results*

Variable	Coefficient	Std. Error	t-Statistic	p-value
Cash Flow	–0.165	0.031	–5.339	<0.001
VAT-to-Turnover Ratio	–1.105	0.173	–6.401	<0.001
Profit Margin	–1.417	0.151	–9.403	<0.001
Debt-to-Assets Ratio	0.299	0.039	7.661	<0.001
Employee Productivity	0.192	0.028	6.774	<0.001

Note. Source: Author's calculations

Model Statistics: $R^2 = 0.836$; Adjusted $R^2 = 0.827$; F = 95.97; Durbin–Watson = = 2.122.

The model explains 83.6% of the variation in Fiscal Risk Score, indicating strong explanatory power. Diagnostic tests confirmed the validity of the regression assumptions, with no evidence of serious multicollinearity, heteroskedasticity, or autocorrelation.

3.3 Artificial Intelligence Performance and Anomaly Detection

The effectiveness of Artificial Intelligence techniques was assessed through Random Forest classification and Isolation Forest anomaly detection. The Random Forest model achieved an accuracy rate of 86.7% and an AUC value of 0.98, indicating excellent classification performance. In addition, the Isolation Forest algorithm identified 19 anomalous enterprises, representing 19% of the sample.

Table 6. *Artificial Intelligence Performance Metrics*

Indicator	Value
Random Forest Accuracy	86.7%
AUC	0.98
Detected Anomalies	19
Anomaly Rate	19.0%

Note. Source: Author's calculations

These findings demonstrate that Machine Learning techniques can effectively support fiscal risk assessment and anomaly detection. The high classification accuracy and the successful identification of anomalous observations provide strong evidence regarding the practical applicability of Artificial Intelligence in financial and tax reporting analysis.

4. Conclusion and discussion

This study examined the application of Artificial Intelligence techniques in detecting anomalies in financial and tax reporting among Albanian enterprises. By integrating econometric analysis with Machine Learning algorithms, the study developed a framework for fiscal risk assessment and anomaly detection.

The empirical findings confirm that financial and fiscal indicators significantly influence Fiscal Risk Score. The regression model explained 83.6% of the variation in fiscal risk ($R^2 = 0.836$), indicating strong explanatory power. Profit Margin, Operating Cash Flow, and the VAT-to-Turnover Ratio were negatively associated with fiscal risk, while the Debt-to-Assets Ratio exhibited a positive relationship, suggesting that highly leveraged enterprises are more exposed to fiscal risk.

The Artificial Intelligence models demonstrated high predictive performance. The Random Forest algorithm achieved an accuracy rate of 86.7% and an AUC value of 0.98, while the Isolation Forest algorithm identified 19 anomalous enterprises, representing 19% of the sample. In addition, Cash Flow and Profit Margin emerged as the most influential predictors of fiscal risk within the Random Forest model.

These findings provide strong empirical evidence that Artificial Intelligence can effectively support anomaly detection, fiscal risk assessment, and risk-based monitoring systems. The integration of Machine Learning techniques into auditing and tax administration processes may improve risk profiling, enhance compliance monitoring, and contribute to more efficient allocation of control resources.

Despite its contributions, the study is limited by its sample of 100 enterprises and its focus on the Albanian business environment. Future research may expand the sample size, incorporate longitudinal data, and evaluate additional Artificial Intelligence techniques such as XGBoost, Gradient Boosting, and Deep Learning models.

Overall, the study demonstrates that Artificial Intelligence represents a valuable tool for modern financial and tax risk management, with significant potential to strengthen auditing practices and support the digital transformation of tax administration.

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