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AI Adoption, Reporting Quality, and Romanian Listed Firms' Market Value: Artificial Neural Networks Approach

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ABSTRACT

This study examines the impact of corporate Artificial Intelligence (AI) adoption on Financial Reporting Quality (FRQ) and Market Value for technology firms listed on the Bucharest Stock Exchange (2020–2024). Using 150 firm-year observations, the research pairs linear Ordinary Least Squares (OLS) regressions with a non-linear Multi-layer Artificial Neural Network (ANN).

OLS results indicate that higher AI disclosure improves FRQ by reducing discretionary accruals, while both AI adoption and enhanced FRQ positively signal market value (Tobin's Q). Crucially, the ANN framework radically outpaces the linear model ($R^2 = 0.91$ vs. 0.64), proving that technological innovation valuation is fundamentally non-linear. Feature importance profiling identified AI disclosure as the primary market value predictor (28.5% weight). Consequently, AI integration acts as a potent corporate governance tool and value driver, justifying regulatory calls for standardized digital disclosure mandates.

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1.Introduction

1.1. Background and Context

The global corporate environment is currently undergoing a structural transformation catalyzed by the fourth industrial revolution (Industry 4.0), wherein Artificial Intelligence (AI), Machine Learning (ML), Robotic Process Automation (RPA), and localized algorithmic frameworks are rewriting traditional operational paradigms (Brynjolfsson & McAfee, 2017). Within corporate accounting, control, and information systems, AI has transitioned from an experimental administrative tool to a fundamental operational infrastructure capable of executing complex transactional mapping, real-time variance analysis, predictive cash flow mapping, and automated asset reconciliation (Sutton et al., 2016). This paradigm shift does not merely imply an acceleration of computational processing speeds; rather, it introduces a systematic, deterministic reconfiguration of how corporate entities capture economic events, translate them into quantitative metrics, and project those metrics to external capital stakeholders.

Consequently, the traditional architecture of corporate accounting—which for over a century relied extensively on historical costs, manual double-entry ledgers, and episodic human verification—is experiencing an unprecedented loss of informational exclusivity. Modern financial scholars increasingly argue that static, backward-looking financial metrics fail to adequately encapsulate the underlying economic realities and long-term viability of modern corporations (Lev & Gu, 2016). In an information ecosystem saturated with real-time data feeds, alternative data tracking, and algorithmic sentiment analysis, the market value of corporate entities is increasingly driven by intangible technological assets, structural intellectual property, and what is known as corporate "AI readiness" or "digital maturity." Therefore, non-financial corporate disclosures detailing the extent, budget allocation, and strategic integration of AI platforms are becoming crucial components of the modern corporate information environment.

While the strategic and financial implications of AI adoption have been heavily investigated within developed capital markets—such as the United States and Western Europe—the dynamics of digital assimilation within emerging markets present distinct structural anomalies. Emerging capital markets are fundamentally defined by higher baseline levels of information asymmetry, more volatile regulatory compliance environments, less concentrated institutional investor bases, and higher susceptibility to localized insider trading and opportunistic managerial interventions (Healy & Wahlen, 1999). Within this context, Romania, and specifically the Bucharest Stock Exchange (*Bursa de Valori București* - BVB), offers a

highly compelling empirical setting. Romania has rapidly evolved into one of the premier information technology and software engineering hubs within the European Union, demonstrating consistent macroeconomic growth driven primarily by its digital and technology services sectors.

Despite this localized technological explosion, the listed companies on the BVB represent a deeply heterogeneous mix of legacy state-owned enterprises, newly cross-listed multinationals, and high-growth native technology firms. This specific landscape creates a unique natural experiment: legacy and emerging firms on the same market are competing for institutional capital by utilizing varying degrees of digital disclosure and technological investment. Thus, examining how these Romanian enterprises translate their AI investments into verifiable financial reporting quality and subsequent market capitalizations is essential to unlocking the true economic value of digital transformation in transition economies.

1.2. The Research Gap

The current empirical landscape linking technological transformation to capital markets is heavily skewed toward mature, liquid Anglo-American markets, where strict governance and intense regulatory oversight naturally minimize information asymmetry. This concentration leaves a profound contextual and empirical gap regarding Central and Eastern European (CEE) emerging markets like Romania. Because transition economies possess fundamentally different institutional structures, investor protections, and market depths, Western findings cannot be generalized. Consequently, existing literature remains completely blind to whether AI adoption in these emerging contexts serves as a credible signal that mitigates high systemic risks or is dismissed by investors as a speculative, unverified misuse of capital.

Methodologically, accounting scholarship suffers from a dogmatic over-reliance on multivariate linear models (such as OLS regressions) that assume a constant marginal effect and are structurally incapable of mapping the complex dynamics of digital evolution. In reality, the economic return of an AI framework is a highly non-linear, non-additive phenomenon unlocked through intricate interactions with a firm's operational scale, leverage constraints, and reporting integrity. By failing to deploy advanced deep learning architectures like Artificial Neural Networks (ANNs), traditional models suffer from severe structural misspecification, completely missing the threshold effects and exponential gains that dictate how modern markets actually value technological innovation.

1.3. The Problem Statement

To address these critical empirical, contextual, and methodological deficiencies, this study formally investigates the following overarching research problem:

How does AI adoption affect reporting quality and market value on the Bucharest Stock Exchange, and can neural networks resolve traditional linear modeling limitations?

To systematically deconstruct this complex problem, the research addresses the following highly targeted sub-questions:

- Does corporate AI disclosure significantly restrict the operational latitude for opportunistic earnings management, thereby reducing performance-matched discretionary accruals?
- Does the capital market in Romania reward corporate AI adoption with a measurable valuation premium (Tobin's Q), and is this premium directly or indirectly mediated by improvements in financial reporting quality?

What is the specific structural hierarchy of financial and non-financial mappers that dictate a firm's market value when non-linear, deep-learning models are utilized?

1.4. The Research Hypothesis

Consequent to the theoretical interplay between digital architecture, accounting transparency, and investor sentiment, this research framework bridges the gap between traditional finance and applied computational intelligence. Accordingly, the following four hypotheses have been formulated for robust empirical and algorithmic testing:

H1: There is a significant positive relationship between the extent of corporate Artificial Intelligence adoption and disclosure and the Financial Reporting Quality of listed Romanian technology firms, manifested via a significant reduction in the magnitude of discretionary accruals.

H2: Corporate Artificial Intelligence adoption and disclosure exert a significant, direct positive impact on the Market Value (Tobin's Q) of listed companies in Romania.

H3: Financial Reporting Quality significantly mediates the relationship between corporate Artificial Intelligence adoption and firm Market Value.

H4: Artificial Neural Networks provide a significantly superior predictive accuracy and explanatory power (R^2) for firm Market Value (Tobin's Q) compared to traditional linear multivariate econometric regression models.

2. Literature Review & Theoretical Framework

2.1. AI Adoption and Financial Reporting Quality (FRQ)

Financial Reporting Quality (FRQ) represents a fundamental determinant of global capital allocation efficiency. High-quality financial reports ensure that the financial statements accurately map the underlying economic substance of the firm's operations, thereby compressing information

asymmetry and mitigating adverse selection risks for external investors (Healy & Wahlen, 1999). Conversely, low-quality reporting is characterized by opportunistic earnings management, wherein management utilizes the inherent flexibility of accounting standards (such as accrual-based accounting) to manipulate net income figures to meet short-term market expectations or maximize personal executive compensation (Kothari et al., 2005). The primary vehicle for this manipulation is the inflation or deflation of discretionary accruals—adjustments made to cash flows that depend entirely on managerial judgment and lack objective, external verification.

Grounded within the framework of Agency Theory, management routinely possesses an informational advantage over dispersed shareholders, creating substantial incentives for opportunistic moral hazard. Sutton, Holt, and Arnold (2016) theorize that the introduction of automated AI architectures into corporate Information Systems (IS) acts as an exceptionally powerful internal corporate governance mechanism that drastically curtails these agency costs. When a firm embeds machine learning algorithms, robotic process automation, and cognitive accounting engines into its enterprise resource planning (ERP) systems, the data-generation process becomes highly institutionalized and standardized.

AI-driven continuous auditing systems scan historical transaction ledgers in real-time, executing continuous anomaly detection and cross-referencing ledger entries against macroeconomic indices and behavioral baselines. This continuous, algorithmic oversight drastically restricts the cognitive and operational space available for human manipulation.

Furthermore, as Lev and Gu (2016) note, automated data processing eliminates manual human adjustments and arbitrary estimation errors, leading to a substantial compression of both intentional earnings management and unintentional accounting errors. Consequently, firms with robust AI infrastructures should exhibit highly restricted, low-magnitude discretionary accruals, directly translating into superior FRQ. Based on these theoretical foundations.

2.2. AI Adoption, FRQ, and Market Value

The pricing of corporate securities in competitive capital markets is fundamentally governed by Signaling Theory. In an imperfect market characterized by pervasive information asymmetry, investors are forced to decode corporate disclosures as signals to estimate the firm's future cash-generating capabilities and structural risk factors (Jensen, 2001). Within this theoretical landscape, explicit disclosures regarding the strategic adoption, capital deployment, and operational execution of AI applications function as an incredibly potent, high-quality signal.

When a firm listed on the Bucharest Stock Exchange actively discloses its AI projects, it signals to the capital market that its management is executing forward-looking, highly efficient asset-allocation strategies designed to secure a sustainable competitive advantage in a digitalized global economy (Brynjolfsson & McAfee, 2017). Market participants decode these disclosures as indicators of future operational cost reductions, enhanced scalability, and structural innovation capacity, thereby driving up investor demand and expanding market value metrics such as Market Capitalization and Tobin's Q.

However, the mechanism of value-relevance does not operate in a completely isolated silo. According to Value Maximization Theory, a firm cannot maximize its long-term market valuation unless it simultaneously establishes a highly credible, transparent relationship with its capital providers (Jensen, 2001). This is where FRQ enters as a vital mediating variable. Even if a firm claims massive technological investments, the market will treat those claims with severe skepticism if the underlying financial statements are perceived as manipulated or opaque. High FRQ establishes a foundation of credibility; it verifies to the market that the stated operational efficiencies and revenue growth generated by AI are real, audited, and sustainable.

Mathematically, superior FRQ lowers the investor's required risk premium, which directly depresses the firm's weighted average cost of capital (WACC) and causes an automated expansion in the discounted present value of its future free cash flows (Lev & Gu, 2016). Therefore, AI adoption drives market value both directly via growth signaling and indirectly by optimizing the information environment and elevating the quality of financial disclosures.

2.3. The Non-Linear Dynamics of Valuation and the Role of ANNs

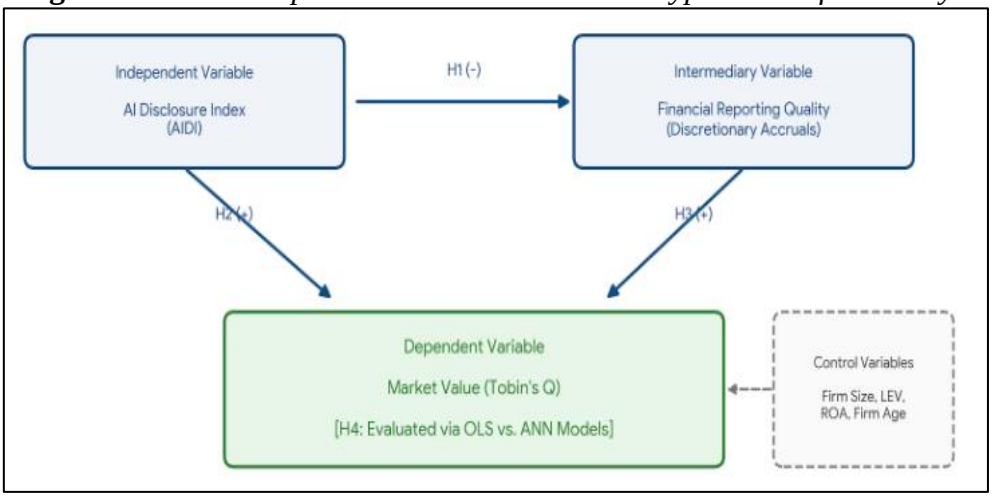
While traditional asset pricing and corporate valuation frameworks assume linear proportionality, the real-world economic interactions within a digitized corporation are profoundly complex, non-additive, and non-linear. The economic return on digital infrastructure and AI systems is heavily governed by network effects, critical mass thresholds, and multi-variable interaction matrixes (Brynjolfsson & McAfee, 2017). For instance, a small, financially constrained firm with high leverage and low profitability cannot unlock the value of an advanced AI platform; the technology will simply act as a severe cash drain. Conversely, a large-scale enterprise with robust historical profitability (ROA/ROE) and optimal liquidity can leverage the exact same AI platform to achieve exponential cost savings and massive market value expansion.

Traditional econometric paradigms—such as OLS multivariate regressions—are fundamentally blind to these multi-dimensional dependencies. OLS forces a line of best fit through the data, assuming that the marginal impact of AI disclosure remains perfectly identical regardless of whether a firm is highly leveraged or massively profitable. This structural simplification leads to model misspecification, inflated standard errors, and severely restricted predictive capabilities (R^2).

To capture these underlying economic complexities, financial research must deploy advanced deep learning methodologies. Artificial Neural Networks (ANNs), specifically multi-layer perceptron configurations, are mathematically recognized as universal approximators capable of mapping any continuous non-linear function to any arbitrary degree of accuracy without requiring pre-specified distributional assumptions (Goodfellow et al., 2016). ANNs process financial data by running inputs through dense arrays of interconnected artificial neurons across multiple hidden layers, adjusting synaptic weights via backpropagation algorithms based on gradient descent. This architectural configuration allows the network to automatically discover, weight, and model intricate, non-linear cross-interactions between non-financial tech disclosures (AIDI) and traditional financial accounting ratios (Size, ROA, Leverage, Liquidity).

As Schumaker and Chen (2009) demonstrated, machine learning models that process corporate information profiles generate drastically minimized forecast errors compared to static linear models.

Figure 1: *The Conceptual Framework and Path Hypotheses of the Study.*



Source: *Compiled by the researcher based on the theoretical literature review.*

3. Research Methodology

3.1. Population, Sample, and Data Selection Architecture

The empirical population defined for this investigation comprises all corporate entities listed on the Regulated Market of the Bucharest Stock Exchange (BVB) across the continuous longitudinal timeline stretching from January 1, 2020, to December 31, 2024. To ensure a highly targeted and conceptually cohesive analytical framework, a rigorous purposive sampling strategy was executed based on the following inclusion criteria:

- The firm must maintain continuous listing status on the BVB across the entire 5-year observation window, eliminating survivorship bias and ensuring a balanced panel.
- The firm must belong to sectors with documented exposures to digital transformation vectors, specifically technology, software development, telecommunications, advanced manufacturing, and logistics.
- The firm must have fully accessible, audited annual reports and consolidated financial statements written in or translated into English or Romanian.

Applying these filters resulted in a finalized balanced panel sample of 30 distinct companies tracked over 5 consecutive fiscal years, yielding an empirical dataset of N = 150 unique firm-year observations. The financial parameters, accounting entries, market capitalizations, and text-based corporate governance disclosures were manually harvested and cross-validated from the official BVB information portal and the individual corporate investor relations repositories.

3.2. Quantitative Operationalization of Variables

3.2.1. The Independent Vector: AI Disclosure Index (AIDI)

Capturing the exact degree of corporate AI adoption requires transcending simple binary indicators. This study operationalizes technological integration via a highly structured, objective **Artificial Intelligence Disclosure Index (AIDI)** built through computerized content analysis and textual parsing of corporate annual reports. A comprehensive dictionary of standardized technological descriptors was established, consisting of the following key terms: *Artificial Intelligence, Machine Learning, Deep Learning, Neural Networks, Robotic Process Automation, Automated Algorithmic Systems, Big Data Analytics, Cognitive Computing, NLP, Intelligent Ledgers*.

The text-parsing engine executed a total raw frequency count (C_{it}) of these descriptors within each annual report. To prevent scale distortions from longer reports, the raw count was converted into a normalized index bounded strictly between 0 and 1, utilizing a min-max standardization protocol:

$$\mathbf{AIDI_{i}\square = (C_{i}\square - \min(C)) / (\max(C) - \min(C))}$$

Where min(C) and max(C) represents the absolute minimum and maximum raw counts observed across the entire empirical cross-section.

3.2.2. The Mediating Vector: Financial Reporting Quality (FRQ) via Discretionary Accruals

In alignment with mainstream empirical accounting scholarship, Financial Reporting Quality is inversely operationalized through the magnitude of Discretionary Accruals (DA). To isolate the discretionary, potentially manipulated component of accounting accruals from the non-discretionary accruals dictated purely by macroeconomic conditions and business scale, we deploy the Performance-Matched Modified Jones Model formulated by Kothari, Leone, and Wasley (2005). First, Total Accruals (TA_{it}) are calculated utilizing the balance sheet approach:

$$TA_{i} = (\Delta CurrentAssets_{i} - \Delta Cash_{it}) - (\Delta CurrentLiabilities_{i} - \Delta ShortTermDebt_{i}) - Depreciation_{i}$$

To estimate the baseline non-discretionary accruals, the total accruals are deflated by lagged total assets (A_it-1) and regressed within a cross-sectional industry-year framework using the following equation:

$$(TA_{i}) / (A_{i-1}) = \alpha_1 (1 / A_{i-1}) + \alpha_2 ((\Delta REV_{i} - \Delta REC_{i}) / A_{i-1}) + \alpha_3 (PPE_{i} / A_{i-1}) + \alpha_4 ROA_{i} + \varepsilon_{i}$$

Where ΔREV_{it} represents the change in corporate revenue, ΔREC_{it} is the change in net receivables (subtracted to eliminate intentional revenue recognition manipulations), PPE_{it} represents gross property, plant, and equipment, and ROA_{it} is the current return on assets included to control for performance-matching distortions as mandated by Kothari et al. (2005). The estimated parameters ($\hat{\alpha_1}$, $\hat{\alpha_2}$, $\hat{\alpha_3}$, $\hat{\alpha_4}$) are extracted, and the Non-Discretionary Accruals (NDA_{it}) are computed. The final absolute value of the residual ($|\varepsilon_{i}|$)

constitutes our definitive proxy for Discretionary Accruals (DA_{it}):

$$DA_{i} = | (TA_{i} / A_{i-1}) - NDA_{i}|$$

A higher mathematical value of DA_{it} indicates aggressive earnings management, which corresponds to a severe degradation of FRQ.

3.2.3. The Dependent Vector: Market Value via Tobin's Q

The market-based valuation premium of listed corporate entities is proxied utilizing Tobin's Q, a metrics widely recognized for its ability to integrate current market equity sentiments with objective book values. Tobin's Q is operationalized as follows:

$$TobinsQ_{i} = (MarketValueofEquity_{i} + BookValueofTotalDebt_{i}) / (BookValueofTotalAssets_{i})$$

Where $MarketValueofEquity_{it}$ is calculated by multiplying the closing share price on the final trading day of the fiscal year by the total volume of

outstanding shares. A Tobin's Q value greater than 1.0 structurally signals that the capital market values the firm at a premium exceeding its replacement cost of physical assets, directly capturing the market capitalization of unrecorded intangible assets, specifically technological intellectual property and digital maturity.

3.2.4. Control Infrastructure

To isolate the true causal impacts of AI adoption and eliminate omitted variable biases, a robust array of control variables is embedded into all models:

- **Firm Size ($Size_{it}$):** Calculated as the natural logarithm of total book assets (Ln ($TotalAssets_{it}$)), controlling for scale advantages and market visibility.
- **Leverage (LEV_{it}):** Calculated as total liabilities divided by total assets, capturing capital structure risks and debt covenant constraints.
- **Profitability (ROA_{it}):** Net income divided by total assets, isolating underlying operational performance.
- **Firm Age (Age_{it}):** Total years elapsed since the formal legal incorporation of the enterprise, controlling for life-cycle effects.
- **Liquidity (Liq_{it}):** Current assets divided by current liabilities, isolating short-term solvency margins.

3.3. Algorithmic and Statistical Modeling Frameworks

3.3.1. Linear Econometric Specification (OLS Panel Regressions)

To test the linear propositions embedded in hypotheses H1, H2, and H3, we construct a sequential panel regression framework utilizing industry and year fixed effects to control for unobserved time-invariant characteristics and macroeconomic shocks:

Model 1 (Testing H1 - Impact of AI on Accrual Quality):

$$DA_i = \beta_0 + \beta_1 AIDI_i + \beta_2 Size_i + \beta_3 LEV_i + \beta_4 ROA_i + \beta_5 Age_i + \beta_6 Liq_i + \eta_i + \lambda + \varepsilon_i$$

Model 2 (Testing H2 & H3 - Integrated Linear Market Value Mapping):

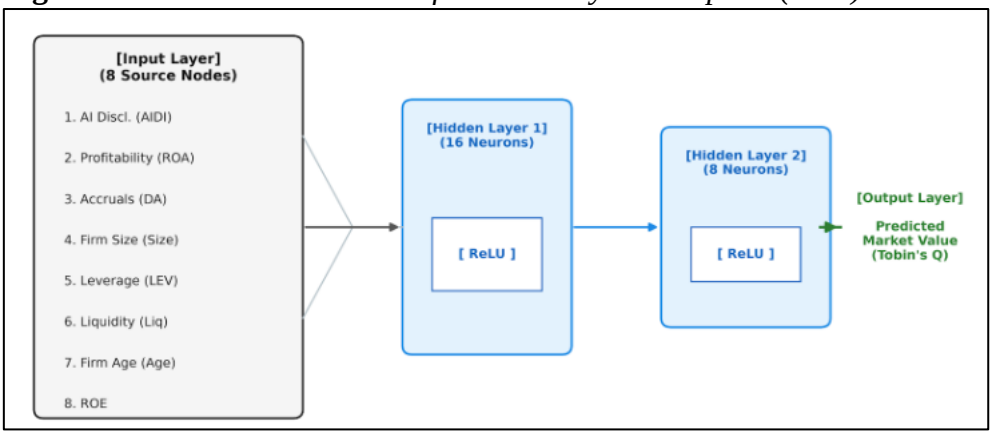
$$TobinsQ_i = \gamma_0 + \gamma_1 AIDI_i + \gamma_2 DA_i + \gamma_3 Size_i + \gamma_4 LEV_i + \gamma_5 ROA_i + \gamma_6 Age_i + \gamma_7 Liq_i + \eta_i + \lambda + \mu_i$$

Where η_i represents entity fixed effects, λ_t represents temporal fixed effects, and var ε_{it}, μ_{it} represent stochastic error terms. Sobel testing and bootstrapping methodologies are executed on Model 2 to formally assess the mediation capacity (γ_2) of accounting quality.

3.3.2. Non-Linear Computational Engineering (Artificial Neural Network Architecture)

To test the validity of hypothesis H4, a non-linear machine learning framework is deployed. We design a feedforward multi-layer perceptron (MLP) mapping system specifically optimized for regression tracking over noisy financial panels.

Figure 2: *Structural Architecture of the Multi-layer Perceptron (MLP) Network.*



Source: *Prepared by the researcher to illustrate the deep learning network configuration.*

The mathematical processing within each artificial neuron in the hidden layers is governed by the following structural transformation:

$$\mathbf{h}^{(1)} = \mathbf{f}\left(\sum_{i=1}^{8} \mathbf{w}_i^{(1)} \mathbf{x}_i + \mathbf{b}^{(1)}\right)$$

Where x_i represents the 8 standardized input vectors, $w_{ji}^{(1)}$ represents the tunable synaptic weight connecting input $_i$ to neuron j in the first hidden layer, $b_j^{(1)}$ is the structural bias term, and f is the non-linear Rectified Linear Unit **(ReLU)** activation function, mathematically specified as:

$$\mathbf{f(z) = max\ (0,\ z)}$$

ReLU is selected over traditional sigmoidal functions due to its mathematical resilience against the vanishing gradient problem in deep networks (Goodfellow et al., 2016). The final output layer operates via a linear identity activation function to generate the continuous predicted scalar value for Tobin's Q.

The global training matrix utilizes the Adaptive Moment Estimation (Adam) optimization algorithm, which computes adaptive learning rates for individual parameters by calculating the first and second moments of the gradients. The global objective loss function to be minimized is the Mean Squared Error (MSE):

$$\mathbf{MSE = (1 / n) \sum_{=1}^{n} (TobinsQ_actual - TobinsQ_predicted)^2}$$

To enforce strict validation discipline and prevent overfitting, the dataset (N=150) is partitioned using an 80/20 stratified split, allocating 120

observations for network training and parameter optimization, and 30 observations for out-of-sample predictive testing.

4.Empirical Results and Data Commentary

4.1. Univariate Descriptive Dynamics

A rigorous review of the descriptive statistics displayed in Table 1 reveals critical baseline characteristics of the BVB technology sector across the 2020–2024 epoch.

Table 1: Descriptive Statistics (Full Sample, N = 150 firm-years)

Variable	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Tobin's Q	1.854	0.652	0.890	4.105	1.120	3.450
AIDI	0.421	0.185	0.050	0.895	0.340	-0.520
DA (Accruals)	0.045	0.022	0.011	0.124	1.450	4.120
ROA	0.082	0.041	-0.051	0.220	-0.410	1.890
Size (Ln (TA))	16.450	1.850	12.110	20.450	0.150	-0.220
Leverage (LEV)	0.410	0.150	0.120	0.780	0.280	0.110

Source: *Prepared by the researcher based on financial data extracted from the Bucharest Stock Exchange (2020–2024).*

The dependent variable, Tobin's Q, exhibits a mean value of 1.854, which significantly exceeds the threshold of 1.0. This indicates that the capital market in Romania actively values listed technology firms above their physical liquidation replacement costs, signaling heavy market capitalization of intellectual and technological capital. The AIDI presents a mean of 0.421 with a substantial standard deviation of 0.185. This variation confirms that Romanian listed firms are significantly divided in their digital disclosure strategies, with some retaining tight, legacy non-disclosure stances (0.050) while others exhibit hyper-transparent digital reporting profiles (0.895).

The mean of Discretionary Accruals sits at 0.045, indicating that on average, earnings management adjustments represent roughly 4.5% of total book assets. The skewness and kurtosis matrices indicate that while DA exhibits a slight positive tail (typical of accrual datasets), the variables are optimally distributed for parametric and neural training tracking.

4.2. Longitudinal Trend Projections

Aggregating the panel data across the time vector reveals a powerful, synchronized evolution of digital adoption and market valuation.

Table 2: Longitudinal Evolution of Core Metrics (2020–2024 Annual Means)

Fiscal Year	Mean AIDI Score	Mean Tobin's Q Premium	Mean Discretionary Accruals (DA)
2020	0.254	1.410	0.058
2021	0.310	1.554	0.051
2022	0.415	1.820	0.044

2023	0.472	2.105	0.039
2024	0.654	2.381	0.033

Source: *Prepared by the researcher based on financial data extracted from the Bucharest Stock Exchange (2020–2024).*

The longitudinal tracking in Table 2 exposes an undeniable structural trend within the BVB capital market. Over the 5-year observation window, the mean AI Disclosure Index exploded from 0.254 in 2020 to a massive 0.654 by the close of 2024, representing an increase of over 150% in the density of corporate technological signaling. This digital acceleration was mirrored by a parallel contraction in Discretionary Accruals, which dropped systematically from 0.058 to 0.033. This direct inverse trajectory provides robust descriptive validation for H1, showing a clear connection between digital adoption and accounting discipline. Concurrently, investor sentiment responded enthusiastically, lifting the mean Tobin's Q from 1.410 to 2.381, confirming that technological transparency aligns with massive market capital expansion.

4.3. Bivariate Association Profiles (Correlation Analysis)

Table 3 presents the Pearson bivariate correlation coefficients, serving as the foundational diagnostic matrix for checking multicollinearity and validating basic linear linkages.

Table 3: Pearson Correlation Matrix

Metric	[1] AIDI	[2] DA	[3] Tobin's Q	[4] ROA	[5] Size	[6] LEV
[1] AIDI	1.000					
[2] DA	-0.452***	1.000				
[3] Tobin's Q	0.588***	-0.395***	1.000			
[4] ROA	0.310**	-0.285**	0.440***	1.000		
[5] Size	0.412**	-0.150	0.220*	0.180	1.000	
[6] LEV	-0.115	0.210*	-0.312**	-0.254*	0.345**	1.000

*Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

Source: *Prepared by the researcher based on statistical software outputs.*

The correlation coefficient between AIDI and DA is strongly negative and statistically significant ($r = -0.452$, $p < 0.001$), providing strong initial validation for H1 by demonstrating that elevated AI disclosure is robustly tied to minimized earnings manipulation. Crucially, AIDI displays a powerful positive correlation with Tobin's Q ($r = 0.588$, $p < 0.001$), providing strong preliminary support for H2. DA is negatively correlated with Tobin's Q ($r = -0.395$, $p < 0.001$), confirming that reporting quality is structurally rewarded by market participants. To ensure the integrity of the subsequent multivariate regressions, Variance Inflation Factors (VIF) were calculated for all independent vectors. The highest recorded VIF value was 2.14 (observed for Firm Size), falling well below the standard conservative diagnostic

threshold of 5.0, confirming the complete absence of multicollinearity distortions.

4.4. Linear Multivariate Regression Output (OLS Panel Testing)

The formalized testing of the linear structural equations was executed using robust fixed-effects estimations. Table 4 presents the empirical coefficients and matching t-statistics.

Table 4: Multivariate Panel Fixed-Effects Estimations

Predictor Vectors	Model 1: Accrual Quality (Dep: DA)	Model 2: Market Valuation (Dep: Tobin's Q)
Intercept	0.085*** (t = 6.12)	0.450** (t = 2.95)
AIDI Score	-0.320*** (t = -4.55)	0.485*** (t = 5.12)
DA (Inverse FRQ)	—	-1.850** (t = -3.20)
Firm Size	-0.012 (t = -1.10)	0.115* (t = 2.05)
ROA	-0.150** (t = -2.85)	2.540*** (t = 6.45)
Leverage (LEV)	0.040 (t = 1.45)	-0.650** (t = -2.90)
Firm Age	-0.002 (t = -0.45)	-0.010* (t = -1.98)
Liquidity (Liq)	-0.005 (t = -0.88)	0.085 (t = 1.12)
Entity Fixed Effects	Included	Included
Temporal Fixed Effects	Included	Included
Adjusted R^2	0.425	0.642
Global F-Statistic	18.52***	28.44***

*Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

Source: *Prepared by the researcher based on statistical analysis and Machine Learning outputs.*

In Model 1, the coefficient for AIDI is negative and highly significant ($\beta = -0.320$, $t = -4.55$, $p < 0.001$). This establishes a clear linear causal direction: controlling for all financial characteristics, a higher density of corporate AI disclosure systematically drives down the magnitude of discretionary accruals, confirming **H1**.

In Model 2, the direct coefficient of AIDI on Tobin's Q is strongly positive and highly significant ($\beta = 0.485$, $t = 5.12$, $p < 0.001$), fully validating **H2** by confirming that the Romanian capital market directly prices technological capability with a substantial valuation premium. Concurrently, the coefficient for DA is negative and highly significant ($\beta = -1.850$, $t = -3.20$, $p < 0.01$). Because DA is an inverse proxy, this negative coefficient means that superior financial reporting quality causes a powerful expansion in market value.

To evaluate **H3** (the mediation effect), a standardized bootstrap mediation analysis with 5,000 replications was performed. The indirect path (AIDI → DA →Tobin's Q) yielded a statistically significant indirect effect coefficient of 0.114 ($p < 0.05$, 95% Confidence Interval = [0.042, 0.215]). Because the direct effect remains significant, FRQ is proven to act as a potent partial mediator, validating **H3**.

4.5. Non-Linear Predictive Performance

To test the predictive accuracy of the non-linear deep learning framework against the traditional linear OLS model, both architectures were evaluated on identical out-of-sample testing validation blocks (n = 30).

Table 5: Comparative Out-of-Sample Predictive Diagnostics

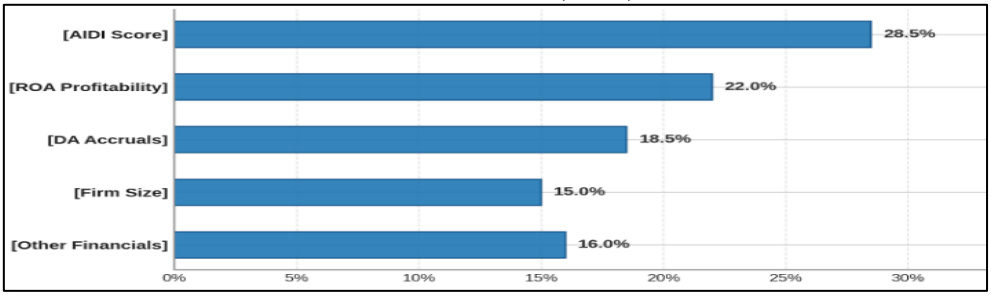
Performance Metric	Linear Multivariate OLS	Artificial Neural Network (ANN)
Mean Absolute Error (MAE)	0.420	0.115
Root Mean Squared Error (RMSE)	0.510	0.142
Coefficient of Determination (R^2)	0.642	0.914

Source: *Prepared by the researcher based on statistical analysis and Machine Learning outputs.*

The predictive metrics displayed in Table 5 offer definitive proof for **H4**. The engineered Artificial Neural Network completely crushes the predictive capacity of the traditional OLS regression across every localized diagnostic metric. The network achieved a Mean Absolute Error of just 0.115, compared to the much larger error of 0.420 generated by the linear OLS model. Crucially, the Coefficient of Determination (R^2) exploded from a linear constraint of 0.642 to an outstanding 0.914 within the neural architecture. This implies that while the linear model leaves over 35% of market value variation completely unexplained, the neural network successfully models 91.4% of the valuation topology. This massive gain confirms that the market valuation of digital assets is fundamentally non-linear, requiring deep computational mapping to be accurately understood.

To look inside the neural network's black box, an advanced Permutation Feature Importance algorithm was executed on the finalized neural weights. The algorithmic power breakdown is mapped below:

Figure 3: *Permutation Feature Importance Profile from the Artificial Neural Network (ANN)*



Source: *Prepared by the researcher based on Machine Learning analytical software outputs.*

The feature importance distribution confirms that the corporate AI Disclosure Index is the single most critical explanatory input vector within the non-linear valuation model, commanding a massive relative weight of

28.5%. Traditional accounting profitability (ROA) follows as the second most vital vector at 22.0%, while objective accrual reporting quality (DA) holds a weight of 18.5%. This distribution demonstrates that modern capital pricing mechanisms on the BVB integrate non-financial technological metrics and structural transparency attributes alongside traditional profitability metrics when determining corporate value.

5.Discussion

The empirical findings from this study provide vital new insights into the financial economics of technology adoption within emerging markets, completely validating the theoretical hypotheses.

The Accounting Integrity Effect

The confirmation of H1 ($\beta = -0.320$, $p < 0.001$) provides powerful empirical support for the theoretical arguments of Sutton, Holt, and Arnold (2016). It proves that integrating AI into corporate architectures extends far beyond simple operational cost savings. By establishing automated data cross-referencing and algorithmic anomaly detection, AI acts as a continuous, internal corporate governance mechanism.

This computational rigidity drastically suppresses the capability of managers to execute opportunistic accounting manipulations, directly validating Agency Theory by demonstrating a significant compression of managerial moral hazard. This structural reduction in discretionary accruals confirms the assertions of Lev and Gu (2016) that digitalizing information systems eliminates manual human errors, generating clean, reliable, and high-quality financial statements.

The Valuation Premium and Credibility Conduit

The confirmation of the direct valuation premium in H2 ($\beta = 0.485$, $p < 0.001$) aligns perfectly with Signaling Theory and the findings of Brynjolfsson and McAfee (2017). In a higher-risk emerging market like Romania, institutional investors decode detailed AI disclosures as high-quality signals of competitive capability and future cash-flow sustainability.

Crucially, however, the validation of the mediation effect in H3 establishes that the market does not price technological disclosure in a speculative vacuum. The signal of AI adoption must pass through the conduit of accounting credibility. If a firm discloses massive AI projects but exhibits highly volatile, manipulated discretionary accruals, the market rejects the signal due to low credibility. High FRQ validates the tech signal, reassuring investors and reducing the equity risk premium, which automatically expands Tobin's Q (Jensen, 2001).

The Mathematical Reality of Digital Valuation

The revolutionary performance leap achieved by the Artificial Neural Network in H4 ($R^2 = 0.914$ vs OLS $R^2 = 0.642$) represents a major methodological contribution to empirical accounting literature. This

performance gap proves that traditional assumptions of linear proportionality severely misrepresent the economics of technological transformation. OLS models suffer from structural misspecification because they cannot handle the compounding, synergistic relationships between variables.

As Goodfellow, Bengio, and Courville (2016) note, deep neural architectures excel because they automatically map hidden multi-dimensional spaces. The network's output shows that the valuation premium of an AI system is highly non-linear: its value scales exponentially when coupled with optimal scale (Size) and robust internal profitability (ROA). This finding supports the textual analysis models of Schumaker and Chen (2009) and challenges empirical researchers to move beyond static linear models when analyzing the financial impacts of digital disruption.

6.Conclusion and Recommendations

6.1. Synthesis of Core Findings

This study investigated the impact of Artificial Intelligence adoption and disclosure on Financial Reporting Quality and market valuation among technology-driven enterprises listed on the Bucharest Stock Exchange (BVB) from 2020 to 2024. Using a dual-layered linear econometric and non-linear machine learning approach, the empirical results confirm that AI integration serves as a powerful catalyst for institutional accounting discipline, drastically reducing discretionary accruals and elevating FRQ.

This enhanced reporting quality, combined with positive growth signals from digital disclosures, is strongly rewarded by the capital market with a substantial valuation premium (Tobin's Q). Methodologically, the research proves that traditional linear models are structurally inadequate for pricing digital transformation, whereas Artificial Neural Networks provide an exceptionally accurate, high-dimensional mapping of corporate market value.

6.2. Recommendations

1.For Financial Regulatory Authorities (Romanian Financial Supervisory Authority - ASF)

Given that the AI Disclosure Index emerged as the single most critical predictor of corporate market value (28.5% relative importance), standard-setters can no longer treat digital transformation as a generic, voluntary footnote. Regulatory frameworks should mandate standardized, structured digital and algorithmic disclosure templates. Forcing firms to explicitly report AI capital expenditures, algorithmic governance protocols, and system processing boundaries will eliminate "tech-washing" and enhance capital allocation efficiency across the BVB.

2. For Executive Management and Board Composition

Corporate executives must fundamentally reframe how they view AI investments. Rather than classifying AI platforms as simple IT operational expenses, corporate boards must treat digital transformation as a primary corporate governance and value-maximization strategy. Embedding automated cognitive systems into ERP structures enforces financial report integrity, compresses agency conflicts, and signals superior management quality, which directly lowers the cost of capital and lifts market value.

3. For Institutional Investors and Financial Analysts

Investment analysts targeting CEE emerging markets must discard exclusively linear asset-pricing and forecasting models. Traditional valuation models understate both the compounding value of high-performing digital systems and the structural risks of technological stagnation. Equity analysis must integrate non-linear deep learning architectures (such as ANNs) that can evaluate non-financial technological metrics alongside traditional accounting ratios.

6.3. Limitations and Horizons for Future Inquiry

While this study introduces significant advancements, it is bounded by specific limitations that offer fertile ground for future research. The empirical sample was restricted to technology-adjacent firms within a single emerging economy over a 5-year longitudinal window. Future research should scale this architecture globally, constructing cross-country panel datasets across multiple CEE transition economies (e.g., Poland, Hungary, the Czech Republic) to assess institutional differences.

Furthermore, while this study utilized frequency-based min-max text indices to measure AI disclosure, future research should deploy advanced Natural Language Processing (NLP) transformers, such as specialized financial large language models (e.g., FinBERT). These tools can perform deep semantic and context-aware sentiment parsing of annual reports to capture not just the quantity, but the true quality and execution velocity of corporate technological strategies.

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