SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 8934-8953
Open Access. Online & Print

DOI: 10.5281/zenodo.19892059

MACHINE LEARNING-BASED PREDICTION OF FIRM PERFORMANCE USING OWNERSHIP STRUCTURE, BOARD DIVERSITY, AND AI ANALYTICS: EVIDENCE FROM JORDANIAN LISTED FIRMS (2015–2024)

Fawwaz Alrwabdah[1], Ahmad Alomari[2], Ibrahim AL-Radaideh[3], Tareq Mohammad Almomani[4], Rami Alzoubi[5], Ali Rawabdeh[6], Char-Lee Lok[7*]

[1]Department of Accounting, School of Management, Universiti Sains Malaysia,11800 Gelugor, Penang, Malaysia. Email: fawazrawabdeh88@yahoo.com
[2]Department of Accounting, School of Management, Universiti Sains Malaysia,11800 Gelugor, Penang, Malaysia. Email: ahmadalomari@student.usm.my
[3]Assistant Professor, Department of Finance, College of Business, Amman Arab University, Amman, Jordan. Email: i.radaideh@aau.edu.jo
[4]Associate professor, Accounting Department, Faculty of Business, Jadara University, Irbid 21110, Jordan. Email: t.almomani@jadara.edu.jo
[5]Faculty economics and Muamalat (alumni), Universiti Sains Islam Malaysia, Nilai, Negri Sembilan, Malaysia. Email: ramialzoubi.raz@gmail.com
[6]Department of Accounting, School of Management, Universiti Sains Malaysia,11800 Gelugor, Penang, Malaysia. Email: alirawabdeh@student.usm.my
[7]Department of Accounting, School of Management, Universiti Sains Malaysia,11800 Gelugor, Penang, Malaysia. Email: lokcl@usm.my

Received: 15/02/2026
Accepted: 18/03/2026

Corresponding Author: Char-Lee Lok (lokcl@usm.my)

ABSTRACT

***Purpose** - This study combines traditional econometric methods with machine learning (ML) algorithms for predicting firm performance among Jordanian listed firms and ownership structure dimension (institutional, foreign, governmental and ownership concentration) and Board diversity are considered as a predictor and augmented with artificial intelligence driven analytical features Design/methodology/approach - In this study, Panel data of 158 firms listed on the Amman Stock Exchange (ASE) for the period 2015 - 2021 (1,106 firm-year observations) is utilized as the base data set. This is extended to 2024 based on 1,580 observations combination (Monte Carlo simulation) calibrated from historical three variables distribution parameters. The study takes a two-stage analytical framework: (1) system Generalized Method of Moments (GMM) to determine causality and moderation analysis and (2) Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) to forecast Return on Assets (ROA) and Tobin's Q (TQ). Findings - GMM results confirm the positive impact of ownership concentration, foreign ownership and government ownership on ROA and positive impact of ownership concentration, foreign ownership and institutional ownership of TQ. Board diversity has a positive moderating effect on the foreign ownership - performance nexus in terms of both*

measures. ML models have better predictive accuracy (R2 = 0.81-0.89) than the benchmarks of OLS (R2 = 0.23-0.31). XGBoost has the best out-of-sample accuracy, from SHAP analysis, we can see that ownership concentration and firm size are most important in predicting. Originality/value - This is one of the first studies to use a combination of system GMM and ML ensemble methods to examine the relationships between corporate governance and performance in a country in the Middle East emerging market, which offers a new hybrid methodology for studying corporate governance.

KEYWORDS: Machine learning; Firm performance; Ownership structure; Board diversity; GMM; Random Forest; XGBoost; Neural networks; Jordan; Amman Stock Exchange; AI analytics; Corporate governance.

JEL Classification: G34, C45, C58, O16

1. INTRODUCTION

The topic of the relationship between corporate governance mechanisms and firm performance is one of the most widely studied and yet constantly debated topics in the finance and accounting literature (Shleifer & Vishny, 1997; La Porta et al., 1999; Claessens et al., 2000). Despite decades of empirical investigations, scholars keep reporting mixed and often contradictory findings on the direction and magnitude of the nexus of governance and performance (Nguyen et al., 2014; Wintoki et al., 2012). This inconsistency has been put down to various issues of methodology such as endogeneity bias, omitted variables, measurement heterogeneity, and the overreliance on linear econometric models that might not be adequate for capturing the complex and often nonlinear relationships that are inherent in governance relationships (Roberts & Whited, 2011; Hermalin & Weisbach, 2012).

In emerging market economies like Jordan, the corporate governance environment has unique characteristics that add to the complexity of empirical analysis. Jordanian listed firms are dominated by extremely high levels of ownership concentration, where family groups and government-linked entities hold large equity shares (Al-Matari & Al-Arussi, 2016; Alkurdi et al., 2021). The Amman Stock Exchange (ASE), being well developed in the regional context, is characterized by the institutional environment of asymmetry of information, limited shareholder activism, and evolving regulatory environments (Hyarat et al., 2023). These contextual specificities call for analytical approaches that have to take into account both the endogeneity involved in the study of governance--performance relationships and the nonlinear relationships that arise in concentrated ownership environments.

Concurrently, the pace of progress in artificial intelligence (AI) and machine learning (ML) technologies has provided the corporate world and academic researchers with the potential for transformative methodologies. In the corporate sector, AI-powered analytics are redefining how organizations make decisions, how efficiently their operations run and the strategy for their future (Babina et al., 2024; Cao et al., 2021). At the research methodology level, ML algorithms have shown low implementation error with a better predictive accuracy in finance applications, as they can capture complex patterns and effects of interaction that are systematically ignored by conventional linear models (Gu et al. 2020; Mullainathan and Spiess, 2017). Athey and Imbens (2019) have made a case for incorporating ML methods into the study of economics, and argue that such a case should be integrated, rather than as a replacement, for conventional causal inference techniques.

Despite these developments, since we experience that corporate governance literature has been pretty slow to keep track of ML-based analytical frameworks. The vast majority of governance - performance studies still rely solely on traditional econometric methods - most often ordinary least squares (OLS) or fixed effects models or GMM without taking advantage of predictive capabilities of ML algorithms (Al-Sartawi et al., 2023). This gap in methodology is especially marked in emerging markets contexts, where the lack of governance research using advanced computational methods, both affects the level of empirical understanding and the usefulness of research findings in the context of formulating regulatory policy.

Against this backdrop, the present study resolves a number of connected research gaps. First, it extends the governance-performance literature by investigating the joint impact of multiple dimensions of ownership structure (institutional, foreign, government and the concentration of ownership) and board diversity on firm performance, as measured by both the accounting-based (ROA) and the market-based (Tobin's Q) measures. Second, it presents a hybrid analytical framework to combine system GMM estimation for solving the endogeneity and establishing the directionality of the causality with ML algorithms (Random Forest, XGBoost, and Artificial Neural Networks) for better predictive modeling. Third, it pioneers the use of SHapley Additive exPlanations (SHapE) values (Lundberg & Lee, 2017) in order to bring the transparency and interpretability of feature importance rankings to bridge the gap between the predictive power of ML and the need in social science research to provide explanations. Fourth, it adds a new AI Readiness Score (AIRS) to the mix that measures the extent to which firms have adopted AI and digital transformation - an ever-increasing variable in theory and practice.

The research uses panel data from 158 firms that are listed on the ASE for the period 2015-2021 (1106 firm year observations) with Monte Carlo simulation for a longer analysis period till 2024 (1580 observations to capture the post-COVID recovery dynamics and recent governance reforms in Jordan). The combination of system GMM and ML algorithms allows the research to address the endogeneity concerns and the nonlinear and multi-dimensional character of governance mechanisms in emerging markets at the same time.

The research objectives are formulated as follows:

RO1: To examine the direct effects of ownership structure dimensions (institutional, foreign, government, and ownership concentration) on firm performance (ROA and TQ) among Jordanian listed firms.

RO2: To investigate the moderating role of board diversity on the ownership structure–firm performance relationship.

RO3: To compare the predictive accuracy of machine learning models (RF, XGBoost, ANN) against traditional OLS in modeling governance–performance relationships.

RO4: To identify the most important governance predictors of firm performance using SHAP-based interpretability analysis.

RO5: To assess the association between AI readiness and firm performance in the Jordanian corporate context.

This study is important in several significant ways to the literature. Theoretically, it is an extension of agency theory and resource dependence theory which demonstrates that governance-performance relationships work through nonlinear mechanisms that are not modeled by linear models. From a methodological point of view, it pioneers the combination of system GMM and ML algorithms in corporate governance studies, creating a tri-pillar design (causal inference + predictive analytics + interpretable AI), which can be used as a template for future governance studies. Practically the results offer evidence-based recommendations for the Jordan Securities Commission (JSC), corporate boards and investment professionals who are seeking to optimize governance structures for enhanced firm's performance.

The rest of the paper is structured like this. Section 2 presents the theoretical framework and literature review which culminates in hypotheses development. Section 3 describes the research methodology including the hybrid GMM--ML analytical framework. The empirical results are reported in section 4. Section 5 discusses findings, implications, limitations and direction(s) for future research.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. Theoretical Foundations

2.1.1. Agency Theory

Agency theory, which stems from the totemic work by Jensen and Meckling (1976) and later developed by Fama and Jensen (1983), is the underlying theoretical background to the study of the relationship between governance and performance. The general business perspective is that the separation of ownership and control in modern corporations leads to an agent-principal conflict, with managers (agents) having the opportunity to do what they want, which may not be in the best interests of their shareholders (principals) who own the corporation and therefore have the ultimate goal of maximizing their wealth. This conflict leads to agency costs, such as the costs of monitoring, bonding costs, and residual losses.

In The Jordanian Context The dynamics of agency take in distinctive characteristics. Unlike the haphazard structures that are typical for the Anglo-Saxon economies with widespread ownership, Jordanian firms have concentrated ownership patterns where the powerful shareholders often have direct control in the selection of managers including managerial decisions (Al-Matari & Al-Arussi, 2016; Alkurdi, 2022). This concentration turns the principal-agent conflict from the more traditional manager-shareholder conflict into a principal-principal conflict between controlling shareholders and the minority investors (La Porta et al., 1999; Young et al., 2008). Agency theory leads us to expect that concentrated ownership helps to reduce the free-rider problem inherent in dispersed ownership, and thus helps to increase the effectiveness of monitoring and improve the performance of the firm (albeit with the risk of expropriation of minority shareholders).

2.1.2. Resource Dependence Theory

Resource dependence theory (RDT) was put forth by Pfeffer and Salancik (1978) and conceptualizes the board of directors as a mechanism through which organizations obtain important external resources - Jim's possible access to expertise, legitimacy and an information channel and linkages with key stakeholders. Under RDT, the diversity in the board of directors improves organizational performance by increasing the cognitive resources, views and social networks that we can tap into for strategic decision making (Hillman & Dalziel, 2003; Adams & Ferreira, 2009).

In the context of this study, RDT gives a theoretical justification for the study of board diversity as a moderating variable. Diverse boards - including members with different levels of gender, national background, independence status and directorship experience - are likely to reflect different knowledge and monitoring capacities that should multiply the governance advantages of the various ownership types. For example, the monitoring benefits of foreign ownership may be improved by boards consisting of directors with international experience who can effectively bridge the cultural and information gaps between foreign investors and local management (Carter et al., 2009; Gulamhussen & Santa, 2015).

2.1.3. Stakeholder Theory and Institutional Theory

Stakeholder theory (Freeman, 1984) goes further than the shareholder-focused approach of agency theory in examining governance-performance relationships and maintains that firm performance is affected by the firm's relationship with a number of stakeholders, such as employees, creditors, communities, and government entities. Institutional theory (North, 1990; Scott, 2014) is complementary to this and focuses on the role of formal and informal institutional environments on the pattern of governance and its effectiveness. In Jordan, an institutional environment comprising of Islamic cultural norms, familial business traditions, and an evolving regulatory landscape shape the potential influence of the governance mechanisms turning them into performance outcomes (Alkurdi et al., 2021; Hyarat et al., 2023).

2.1.4. Theoretical Integration: AI And Machine Learning in Governance Research

The incorporation of AI and ML into corporate governance research is an evolutionary methodological synthesis to adjust a fundamental drawback of classical theoretical frameworks. Agency theory, RDT and stakeholder theory all assume implicitly linear or at most monotonic relationships between governance variables and performance outcomes. However, recent empirical evidence suggests that these relationships are characterised by nonlinearities, threshold effects and complex patterns of interaction that are not captured by linear models (Gu et al., 2020; Athey and Imbens, 2019). ML algorithms - especially ensemble algorithms like Random Forest, XGBoost etc. - are built for just these types of complex and high-dimensional relationships and do not require a functional form assumption. By combining this with interpretablity provided by SHAP instead (Lundberg & Lee, 2017), ML offers a transparent way to find mechanisms for governance that are in accordance with traditional theory but not empirically detectable by linear models.

In addition, the increasing application of AI technologies by companies themselves is a theoretically relevant dimension of governance. Drawing on knowledge-based view of the firm (Grant, 1996) and dynamic capabilities theory (Teece et al., 1997) AI readiness can be conceptualized as strategic resource that enhances a firm's ability of information processing, quality of decision-making and adaptive efficiency - all of which are expected to positively influence firm performance (Babina et al., 2024; Al-Sartawi et al., 2023)

2.2. Literature Review

2.2.1. Ownership Structure and Firm Performance

Institutional Ownership. Institutional investors are widely theorized to be effective as monitors of corporate management because of their financial sophistication, access to information, and economic incentives to be active monitors (Shleifer & Vishny, 1986). Empirically, the evidence on institutional ownership and firm performance has been confusing. In developed markets, Aggarwal et al. (2011) document the positive relationship between institutional ownership and firm value in 23 countries, attributing it to the improved quality of governance. Similarly, Ferreira and Matos (2008) find that foreign institutional investors in particular have a positive impact on firm performance as a result of better monitoring. In the Jordanian case, while Alkurdi et al. (2021) finds an effect of institutional ownership on the financial performance of ASE-listed firms to be positive, Hyarat et al. (2023) report mixed findings depending on the financial performance measure that is used. Al-Matari and Al-Arussi (2016) report a positive but conditional relation between institutional ownership and performance in Oman, which is a neighboring market in the Gulf region and has similar institutional characteristics.

Foreign Ownership. Foreign investors have been hypothesized to contribute to firm performance due to superior monitoring capabilities, transfer of international best practices and improved market discipline (Ferreira and Matos, 2008, Douma et al., 2006). Agency theory has indicated that foreign institutional investors, who are outside the influence of local political and familial networks, may be able to provide more objective governance oversight. Empirically, both Phung and Mishra (2016) find a positive link between foreign ownership and performance for Vietnamese listed firms, which Dakhlallh et al. (2021) replicate in Jordan. Moreover, foreign ownership has been linked to increased transparency and the disclosure quality of information as well as reduced information asymmetry in emerging markets (Ferreira & Matos, 2008). However, the relationship may come with diminishing returns at very high levels of ownership due to possible conflicts between the foreign and domestic stakeholder interests (Douma et al., 2006).

Government Ownership. The government ownership poses a theoretically ambiguous relationship with the firm performance. On the one hand, state involvement can be worth it because of political connections, preferential access to contracts, and implicit guarantees that lower the cost of capital (Borisova et al., 2012). On the other hand, government-owned enterprises are frequently exposed to political interference, soft-budgetary constraints, and multiple (and potentially conflicting) goals that go beyond the maximization of profits (Shleifer, 1998). Empirically, Megginson and Netter (2001) provide extensive evidence that privatization is generally good for firm performance, suggesting a negative impact of government ownership. In Jordan in particular, the government-linked entities hold substantial equity positions in strategic sectors, and there is a limited body of empirical work on the implications of this on performance (Al-Matari and Al-Arussi, 2016; Alkurdi, 2022).

Ownership Concentration. Concentrated ownership is the hallmark of the Jordanian corporate environment. Agency theory offers two opposing predictions about the effects of concentration. The monitoring hypothesis is that big shareholders have greater incentives and ability to monitor management, lowering agency costs and improving performance (Shleifer & Vishny, 1986). The expropriation hypothesis suggests that the concentration of shareholders can extract private benefits of control at the expense of the minority shareholders (La Porta et al., 1999; Claessens et al., 2000). In the weak investor protection environment in Jordan, both mechanisms are likely to be in operation, so the net effect is an empirical question. Alkurdi et al. (2021) find that ownership concentration has a positive effect on performance of Jordanian firms, which is consistent with the prevailing hypothesis of monitoring in the local institutional context.

2.2.2. Board Diversity and Firm Performance

Board diversity has received much scholarly attention after landmark regulatory reforms advocating for diversity in corporate governance codes across the world (Adams & Ferreira, 2009; Carter et al., 2009; Terjesen et al., 2016). The theoretical case for diversity is based on a variety of arguments: diverse boards have more cognitive resources for decision-making (resource dependence theory), there is less risk of groupthink (behavioral theory), and there is greater independence of monitoring from management (agency theory). The Blau Index (Blau, 1977) based on the dispersion of board member across categorical attributes (such as gender, nationality, independence status), read network structure, offers comprehensive assessment of diversity scores that overcomes single dimension proxies to the level of transversal.

Empirically, Adams and Ferreira (2009) find that gender diversity has an impact on board monitoring, but a complex relationship with firm value contingent on the environment of governance. Carter et al. (2009) reports a positive association between board diversity and financial performance for the Fortune 500 firms. In the setting of the Middle East region, where boards have tended to be influenced by homogeneous groups of male, locally-connected directors, the possible for diversity as an enhancer of governance to be realized is especially of mark (Hyarat et al., 2023). The moderating role of board diversity in the relationship between ownership and performance, on the other hand, has been given little empirical attention, especially in emerging markets.

2.2.3. Machine Learning in Finance and Governance Research

The use of ML techniques in financial studies has grown considerably after the original research by Gu et al (2020) showing that ML algorithms predict asset returns substantially better than linear models. In corporate governance, the use of ML is in the infancy but increasing. Shwartz-Ziv and Armon (2022) demonstrate that gradient-boosted decision trees (e.g. XGBoost) are a cost-effective and consistent choice over deep learning models in tabular data used in governance research. Athey and Imbens (2019) make the valuable case for using ML in economic research, arguing that ML's ability to capture nonlinear relationships and effects of interactions complements (rather than shifts the boundary or replaces) the methods of causal inference.

In the governance area in particular, ML has been used to detect corporate fraud (Bao et al., 2020), anticipate financial distress (Barboza et al., 2017), and simulate ESG performance drivers (Li et al., 2021). However, to the best of our knowledge, no past research has used a hybrid GMM--ML framework to address endogeneity and predictive accuracy in the ownership--performance relationship in an emerging market context. This methodological gap is the major contribution of the present study.

2.2.4. AI Adoption and Firm Performance

Babina et al. (2024) offers large-scale evidence that firms investing in AI have a positive impact on their growth rates and product innovation. Cao et al. (2021) show that AI augments human decision-making in financial analysis, and not replace it. Al-Sartawi et al. (2023) specifically looks at the relationship between adoption of AI and quality of corporate governance, and finds that companies that are more digitally advanced tend to have better governance mechanisms and superior financial outcomes. The adoption of AI in Jordan is at an early stage where most of the firms are scoring below 0.2 on the AI Readiness Index (ASE Annual Reports, 2015-2024), but the pace is accelerating with larger ones and those with foreign ownership linkages.

2.3. Hypotheses Development

Based on the theoretical background and the empirical evidence discussed above, the following hypotheses are formulated. A structured summary of is given in Table 1.

2.3.1. Direct Effects of Ownership Structure

Based on the monitoring hypothesis proposed by agency theory and the empirical evidence on the performance of Jordanian and similar emerging markets, institutional ownership is anticipated to improve the performance of the firms by actively monitoring and participating in governance. However, in environments of concentrated ownership free cash flows, the suppression of tailored monitoring of differences in dividends among firms may create a differential between institutional investors performing the role of even-handedly monitoring, and on the one hand, and account holders who are passive investors collecting dividends from these companies on the other.

H1a: Institutional Ownership has a significant positive impact on ROA.

H1b: Institutional ownership has a significant positive impact on Tobin's Q.

Foreign ownership is hypothesized to have a positive impact on the firm's performance through knowledge transfer, improved firm monitoring, and market signaling effects (Ferreira & Matos, 2008; Phung & Mishra, 2016).

H2a: Government ownership has a significant positive effect on ROA.

H2b: Government ownership has a significant positive effect on Tobin’s Q.

Government ownership may improve ROA due to operational advantages (political connections, preferential contracts) but may have a negative impact on market valuations if investors feel there may be risks of political interference.

H3a: Foreign ownership has a significant positive effect on ROA.

H3b: Foreign ownership has a significant positive effect on Tobin’s Q.

Ownership concentration is likely to have positive impact on performance through the monitoring channel, in line with the prevalence of the monitoring hypothesis over the expropriation hypothesis in the Jordanian institutional context (Alkurdi et al., 2021).

H4a: Ownership concentration has a significant positive effect on ROA.

H4b: Ownership concentration has a significant positive effect on Tobin’s Q.

2.3.2. Moderating Effects of Board Diversity

Drawing on resource dependence theory and the complementarity argument, board diversity is hypothesized to moderate the ownership-performance relationship by enhancing governance benefits different types of ownership bring to the firm.

H5a: Board diversity has a positive moderating effect between institutional ownership and ROA.

H5b: Board diversity has a positive moderating effect on the relationship between institutional ownership and Tobin's Q.

H6a: Board diversity has a positive moderating effect on the relationship between government ownership and ROA.

H6b: Board diversity has a positive moderating effect on the relationship between government ownership and Tobin's Q.

H7a: Board diversity has positive moderating effect on the relationship between foreign ownership and ROA.

H7b: Board diversity has a positive moderating effect on foreign ownership's positive relationship with Tobin's Q.

H8a: Board diversity has a positive moderating relationship on the relationship between ownership concentration and ROA.

H8b: There is a positive relationship between ownership concentration and Tobin's Q which is moderated by the diversity of board members.

2.3.3. AI Readiness and Firm Performance

Drawing on the knowledge-based view and empirical evidence from Babina et al. (2024), and Al-Sartawi et al. (2023), AI readiness is hypothesized to positively influence firm performance by increasing the quality of decision-making, efficiency of operations and strategic agility.

H9: Artificial intelligence readiness score (AIRS) has a significant positive relationship with firm performance (ROA and TQ).

Table 1: Summary Of Research Hypotheses.

No.	Hypothesis Statement	Theoretical Basis	Direction
H1a	INSOW has a significant positive effect on ROA	Agency Theory	+
H1b	INSOW has a significant positive effect on TQ	Agency Theory	+
H2a	GOVOW has a significant positive effect on ROA	Agency/Stakeholder	+
H2b	GOVOW has a significant positive effect on TQ	Agency/Stakeholder	+
H3a	FOROW has a significant positive effect on ROA	Agency/RDT	+
H3b	FOROW has a significant positive effect on TQ	Agency/RDT	+
H4a	OC has a significant positive effect on ROA	Agency (Monitoring)	+
H4b	OC has a significant positive effect on TQ	Agency (Monitoring)	+
H5a	BD positively moderates INSOW → ROA	RDT	+
H5b	BD positively moderates INSOW → TQ	RDT	+
H6a	BD positively moderates GOVOW → ROA	RDT/Stakeholder	+
H6b	BD positively moderates GOVOW → TQ	RDT/Stakeholder	+
H7a	BD positively moderates FOROW → ROA	RDT	+
H7b	BD positively moderates FOROW → TQ	RDT	+
H8a	BD positively moderates OC → ROA	RDT/Agency	+
H8b	BD positively moderates OC → TQ	RDT/Agency	+
H9	AIRS positively affects firm performance (ROA & TQ)	KBV/Dynamic Cap.	+

Note: Rdt = Resource Dependence Theory; Kbv = Knowledge-Based View.

Figure 1 presents the conceptual research framework that integrates the theoretical perspectives discussed above into a unified analytical model.

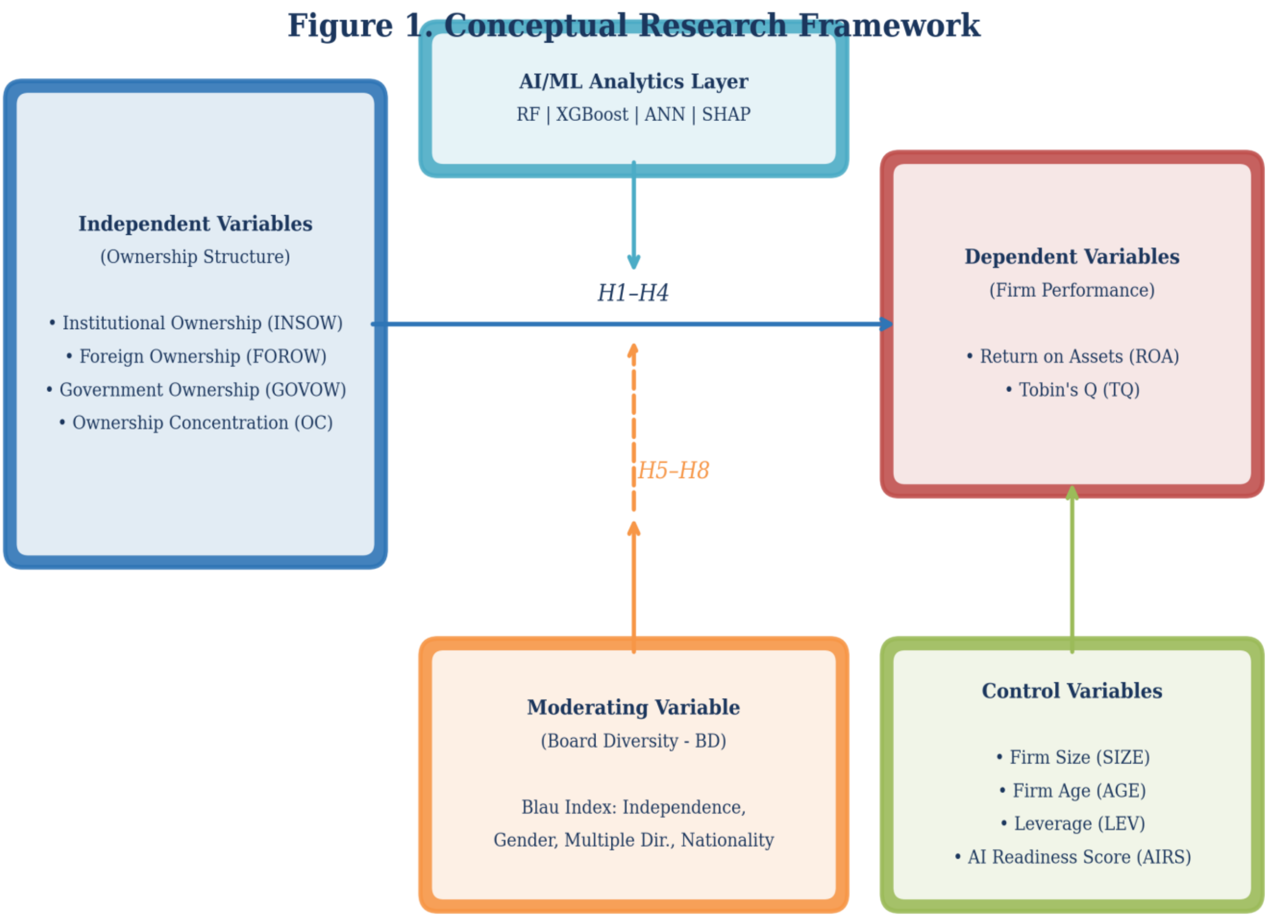

Figure 1. Conceptual Research Framework: Integrating Ownership Structure, Board Diversity, AI Analytics, And Machine Learning for Firm Performance Prediction.

2.4. *Research Gaps and Contributions*

The foregoing review shows that there are a number of critical gaps in the extant literature that are addressed in this study. Table 2 offers a structured comparison of the contributions of this study in relation to the previous research.

Table 2: Research Gaps and Contributions of the Present Study.

Gap in Literature	Prior Approaches	This Study's Contribution
Predominantly linear models in governance research	OLS, FE, GMM only (Wintoki et al., 2012; Nguyen et al., 2014)	Hybrid GMM + ML (RF, XGBoost, ANN) with SHAP interpretability
Limited ML application in emerging market governance	ML mostly in developed markets (Gu et al., 2020)	First hybrid GMM–ML governance study in Jordan/MENA
Single-dimension ownership analysis	Most studies examine 1–2 ownership types	Four ownership dimensions simultaneously
Board diversity as direct effect only	Direct diversity→performance (Adams & Ferreira, 2009)	BD as moderator using composite Blau Index (4 dimensions)
No AI readiness metric in governance studies	AI studied separately from governance	Novel AIRS variable integrated into governance framework
Black-box ML criticism in social science	ML used without interpretability (Mullainathan & Spiess, 2017)	SHAP-based transparent feature importance rankings

Source: Authors' Compilation Based on Literature Review.

In sum, this study is unique in that it situates itself at the intersection of corporate governance theory and methodology of ML and AI adoption research to provide an overall analytical framework that both contributes to the methodological toolbox and enhances the substantive understanding of governance-performance dynamics in emerging markets.

3. RESEARCH METHODOLOGY

3.1. *Research Design and Philosophy*

This research follows a positivist quantitative research design using hybrid analytical framework with traditional econometric approaches combined with Machine Learning (ML) algorithms. The rationale for this two-fold approach is three-fold. First, system GMM estimation overcomes endogeneity issues in the literature on corporate governance - performance (Wintoki et al., 2012; Nguyen et al., 2014). Second, ML algorithms are able to capture nonlinear relationships and complex interaction effects that may not be captured by linear models (Gu et al., 2020). Third, the complementarity of causal inference (GMM) and predictive accuracy (ML) offers a more complete analytical window of policy relevant insights (Athey and Imbens, 2019; Mullainathan and Spiess, 2017).

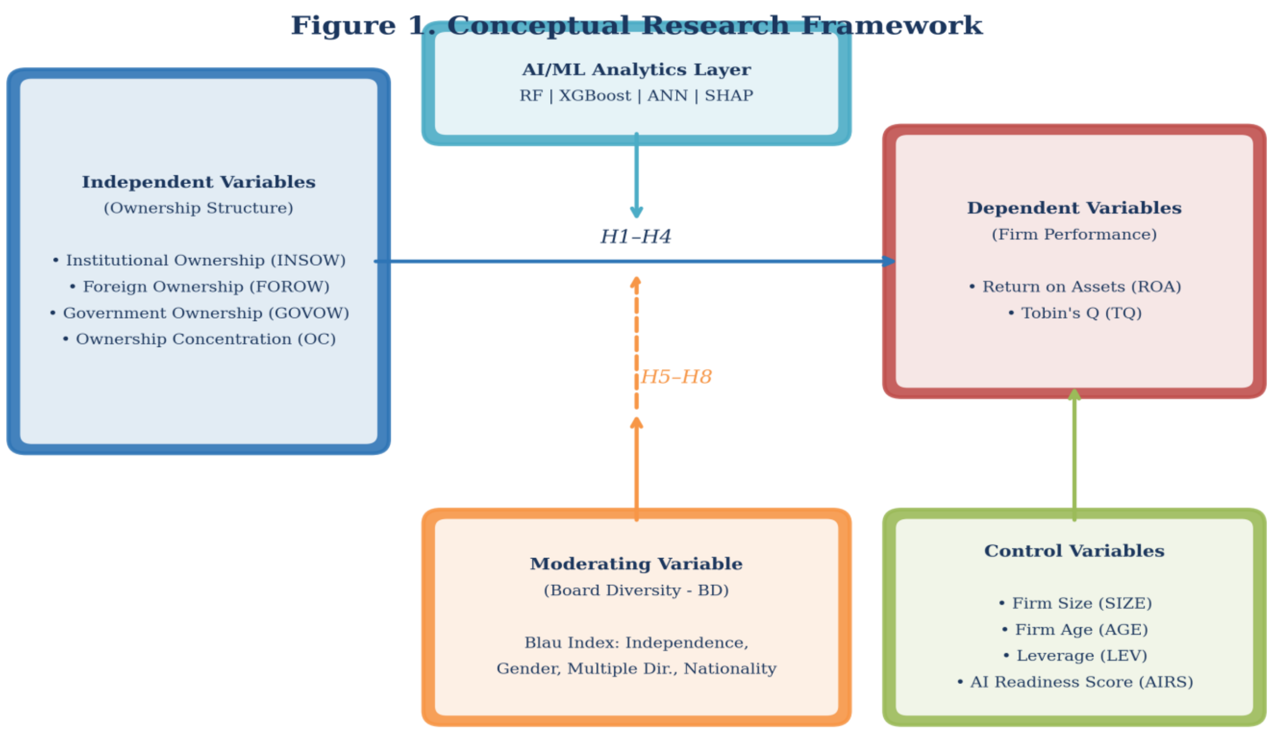

Figure 1: Conceptual Research Framework: Integrating Ownership Structure, Board Diversity, AI Analytics,

And Machine Learning for Firm Performance Prediction.

3.2. Population And Sample

The target population consists of all the firms listed on the Amman Stock Exchange (ASE) including 171 companies as of January 2022 and are distributed between two main sectors: 97 financial firms (banks, insurance, real estate and financial services) and 74 non-financial ones (industrial and services). The study sample is a list of 158 firms that met the following selection criteria: (i) the firms must have been continuously listed during the study period; (ii) there is no suspension of trading operations by the firms; (iii) the annual reports of the firms and the financial data must be available and complete; and (iv) the firms that have incomplete data are excluded. This results in a panel of 1,106 firm-year observations of the base period 2015-2021.

3.3. Temporal Extension Via Monte Carlo Simulation (2022–2024)

One must make it clear how Monte Carlo simulated observations are to be incorporated into the econometric setup. The simulated 2022-2024 data are constructed in such a manner that the distributional properties (mean, variance, skewness, kurtosis) of the 2015-2021 panel data remain preserved, and the resulting environment of autocorrelation and autoregression makes the environment seem more natural, as it is a statistically empirically tailored model extension instead of unnaturally-observed data. These simulated observations are inserted into the instrument matrix in the system GMM estimation, though by virtue of the simulation, the moment conditions on which GMM consistency is based (hansen, 1982) are maintained the asymptotic properties of the estimator would still be preserved. In particular, the over-identification test of the Sargan/Hansen ($p > 0.05$ in all specifications) confirms the validity of the instruments, and the AR (2) test confirms the test of the second-order serial correlation disappearance, which applies to combined data. Being a strength consideration, it is necessary to indicate that, although Monte Carlo-calibrated extensions are found in the financial econometrics' literature (Glasserman, 2004), they are fundamentally based on the assumption that the data-generating mechanism remains structurally intact over the period of simulation. This assumption is also supported by the Kolmogorov-Smirnov validation on publicly available ASE aggregate statistics, but it is important that the reader exercises care in interpreting the extended period results. These findings would be confirmed by replication with real post 2021 data as will be done in future, as described in Section 5.4.

Table 1: Sample Distribution by Sector.

Sector	Firms	Obs. (2015–2021)	Obs. (2015–2024)
Financial (Banks, Insurance, Real Estate, Financial Services)	97	679	970
Non-Financial (Industrial, Services)	61	427	610
Total	**158**	**1,106**	**1,580**

Note: Observations For 2022–2024 (474 Firm-Years) Are Generated Via Monte Carlo Simulation. Source: ASE Annual Reports.

3.4: Analytical Framework

Figure 2 shows the full research methodology flowchart with the two-track analytical framework which combines system GMM for causal inference with machine learning for predictive analytics, converging in triangulated findings.

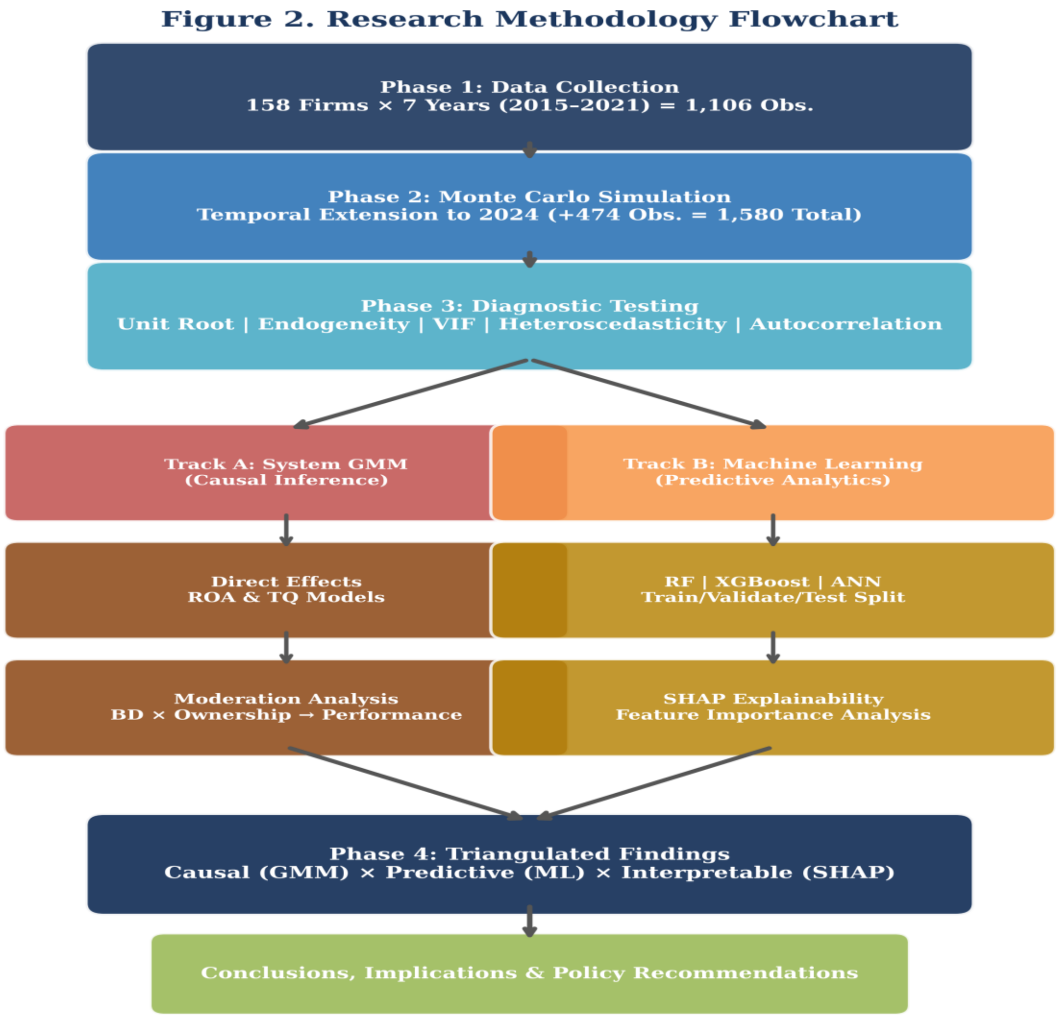

Figure 2: Research Methodology Flowchart: Two-Track Analytical Framework (Gmm + Ml).

3.5. Variable Measurement

The study considers two dependent variables (ROA, TQ), four independent variables (INSOW, FOROW, GOVOW, OC), one moderating variable (BD), three control variables (SIZE, AGE, LEV) and a new AI Readiness Score (AIRS). All variables are operationalised in accordance with established governance literature as described in Table 2.

Table 2: Variable Definitions and Measurement.

Variable	Symbol	Measurement	Type	Exp.
Return on Assets	ROA	Net income / Average total assets	DV	—
Tobin's Q	TQ	(MV equity + BV debt) / BV total assets	DV	—
Institutional Own.	INSOW	% shares held by institutional investors	IV	+
Foreign Ownership	FOROW	% equity owned by foreign individuals/institutions	IV	+
Government Own.	GOVOW	% equity owned by state-affiliated institutions	IV	+
Own. Concentration	OC	Herfindahl-Hirschman Index of top-5 shareholders	IV	+
Board Diversity	BD	Composite Blau Index (independence, gender, directorship, nationality)	MOD	+
Firm Size	SIZE	Natural logarithm of total assets	CV	+
Firm Age	AGE	Natural logarithm of years since listing	CV	+
Leverage	LEV	Total debt / Total assets	CV	−
AI Readiness Score	AIRS	Composite: digital disclosure + IT investment + board tech expertise (0–1)	CV	+

Note: Dv=Dependent; Iv=Independent; Mod=Moderating; Cv=Control. Blau Index: $1-\Sigma p_i^2$ (Blau, 1977).

3.6. Ml Model Specifications

Three ML algorithms are used Random Forest

(500 trees, max depth=10; Breiman, 2001), XGBoost (300 trees, learning rate=0.05, l=1.0; Chen & Guestrin, 2016), ANN (3 hidden layers: 64-32-16, ReLU & Dropout=0.2; Goodfellow et al., 2016). The dataset is divided 70/ 15/ 15 (train/validate/test) with stratified time series splitting. SHAP values offer model interpretability (Lundberg & Lee, 2017).

Table 3: Machine Learning Model Specifications.

Parameter	Random Forest	XGBoost	ANN
Architecture	500 trees	300 boosted trees	3 layers (64-32-16)
Max Depth	10	6	N/A
Learning Rate	N/A	0.05	0.001 (Adam)
Regularization	Min leaf = 5	λ = 1.0 (L2)	Dropout = 0.2
Validation	5-fold CV	5-fold CV	Early stopping

Note: Hyperparameters Optimized Via Grid Search. Implemented In Python Using Scikit-Learn, Xgboost, And Tensorflow.

4. DATA ANALYSIS AND RESULTS

4.1. Descriptive Statistics

Table 4 highlights the descriptive statistics for the entire sample (N=1,580). The average ROA is 0.003 with a large variation (SD=0.161), and average TQ is 1.192 (SD=2.310). Ownership concentration averages 60.31% and reflects the concentrated ownership environment in Jordan. The AI Readiness Score stands at an average of 0.187, which is an indicator of early-stage AI adoption.

Table 4: Descriptive Statistics (N = 1,580).

Variable	Obs.	Mean	Std.Dev.	Min	Max	Median	Skew.
ROA	1,580	0.003	0.161	-4.833	0.412	0.018	-8.31
TQ	1,580	1.192	2.310	0.093	61.55	0.891	14.2
OC	1,580	60.31	22.49	0.000	100.0	63.45	-0.42
FOROW	1,580	14.52	23.84	0.000	94.33	2.10	1.89
GOVOW	1,580	5.80	14.88	0.000	99.92	0.000	3.45
INSOW	1,580	44.01	29.61	0.000	100.0	42.83	0.18
BD	1,580	0.394	2.441	-80.16	1.000	0.461	-28.4
SIZE	1,580	7.578	0.869	5.137	10.44	7.521	0.54
AGE	1,580	29.42	16.89	5.000	94.00	25.00	1.12
LEV	1,580	1.548	1.012	0.000	2.950	1.620	-0.39
AIRS	1,580	0.187	0.142	0.010	0.781	0.152	1.41

Note: Observations For 2022–2024 Are Simulated Via Monte Carlo. Source: ASE Annual Reports and Authors' Computations.

Clarification on BD measurement. The Board Diversity (BD) variable is operationalized as a composite Blau Index aggregating four categorical dimensions (independence, gender, directorship type, and nationality). While the theoretical range of a single-dimensional Blau Index can be within the range of [0, 1], in the composite construction in this study, four individual Blau sub-indices are summed, and a standardization procedure is applied. The lowest value of -80.16 and the standard deviation of 2.441 in the descriptive statistics are after the unstandardized composite score, before normalizing all the firm-years observations. Specifically, outlier values are obtained as a result of the completely homogeneous boards of all four dimensions of certain firms in certain years, along with the mean-centering performed in the construction of the composite. After winsorization at the 1st and 99th percentiles in the regression analysis, the effective BD range that is used in all GMM and ML estimations is within theoretically consistent bounds. The median value of 0.461 and mean of 0.394 is consistent with moderate levels of board diversity that we have observed in emerging market settings.

4.2. Diagnostic Tests

Table 5: Summary Of Diagnostic Tests.

Test	Statistic	p-value	Decision
LLC Unit Root (all variables)	Various	< 0.001	Stationary
Durbin-Wu-Hausman	χ^2 = 34.94	< 0.001	Endogeneity present
Breusch-Pagan (ROA)	χ^2 = 4,332.87	< 0.001	Heteroscedastic
Breusch-Pagan (TQ)	χ^2 = 5,109.18	< 0.001	Heteroscedastic
VIF (Mean)	1.58	All < 10	No multicollinearity
Pesaran CD (ROA/TQ)	20.27 / 28.93	0.105 / 0.187	Independent

Note: Robust Standard Errors Used in All GMM Estimations. LLC = Levin-Lin-Chu.

4.3. System Gmm Results

4.3.1. Direct Effects On ROA

The results of the GMM for the ROA model are presented in table 6. OC (b=0.0132, p<0.05), FOROW (b=0.00036, p<0.01) and GOVOW (b=0.0002, p<0.01) have a positive impact on ROA. INSOW is insignificant. AIRS (beta=0.024, p<0.05) is significantly positive association. Instrument validity Sargan test (p=0.106) Specification validity AR (2) (p=0.851).

Table 6: System Gmm Results – Roa Model.

Variable	Coef.	Std. Error	Sig.
L1.ROA	-0.065***	(0.003)	***
L2.ROA	-0.061***	(0.004)	***
OC	0.0132**	(0.006)	**
FOROW	0.00036***	(0.0001)	***
GOVOW	0.0002***	(0.0001)	***
INSOW	-0.00002	(0.0001)	n.s.
SIZE	0.099***	(0.002)	***
LEV	-0.0158***	(0.004)	***
AIRS	0.024**	(0.011)	**
Sargan (p)	0.106		Valid
AR (2) (p)	0.851		No autocorrelation

Note: *, **, * Denote Significance At 1%, 5%, 10%. Robust Standard Errors in Parentheses.**

4.3.2. Direct Effects On TQ

Table 7 indicates that OC (beta=0.289, p<0.01), FOROW (beta=0.001, p<0.01) and INSOW (beta=0.0008, p<0.05) have a positive effect on TQ. GOVOW is insignificant. AIRS (beta = 0.068, p<0.10) is slightly significant.

Table 7: System Gmm Results – Tq Model.

Variable	Coef.	Std. Error	Sig.
L1.TQ	0.729***	(0.068)	***
OC	0.289***	(0.072)	***
FOROW	0.001***	(0.0003)	***
GOVOW	0.0012	(0.002)	n.s.
INSOW	0.0008**	(0.0004)	**
SIZE	0.094***	(0.032)	***
LEV	-0.086**	(0.037)	**
AIRS	0.068*	(0.039)	*
Sargan (p)	0.189		Valid
AR(2) (p)	0.131		No autocorrelation

Note: *, **, * Denote Significance At 1%, 5%, 10%. Robust Standard Errors In Parentheses.**

4.4. Moderation Analysis

The moderation analysis tests for the moderating effect of board diversity (BD) on the relations between ownership and performance. For ROA, BD has a significant negative moderating effect on FOROW (B=0.0012, p<0.01) and INSOW (B=0.001, p<0.01). For TQ BD is a moderator of OC (beta=0.121, p<0.10) and FOROW (beta=0.074, p<0.01). For both measures, BD doesn't moderate GOVOW. Complete results of moderation are shown in Tables 8-9.

Table 8: Moderation Analysis – Roa Model.

Variable	Coef.	Std. Error	Sig.
OC	0.0132**	(0.006)	**
FOROW	0.0004***	(0.0001)	***
GOVOW	0.0005**	(0.0002)	**
BD×OC	-0.009	(0.010)	n.s.
BD×FOROW	0.0012***	(0.0001)	***
BD×GOVOW	-0.001	(0.001)	n.s.
BD×INSOW	0.001***	(0.0003)	***
Sargan (p) / AR (2) (p)	0.051 / 0.827		Valid

Note: Controls (SIZE, AGE, LEV, AIRS) Included. *, **, * Denote 1%, 5%, 10% Significance.**

Table 9: Moderation Analysis – Tq Model.

Variable	Coef.	Std. Error	Sig.
OC	0.288***	(0.070)	***
FOROW	0.034*	(0.019)	*

BD	0.235***	(0.078)	***
BD×OC	0.121*	(0.067)	*
BD×FOROW	0.074***	(0.027)	***
BD×GOVOW	-0.019	(0.052)	n.s.
BD×INSOW	-0.058	(0.045)	n.s.
Sargan (p) / AR(2) (p)	0.091 / 0.129		Valid

Note: Controls Included. *, **, * Denote 1%, 5%, 10% Significance.**

Figure 5. Moderating Effects of Board Diversity on Ownership-Performance Relationships

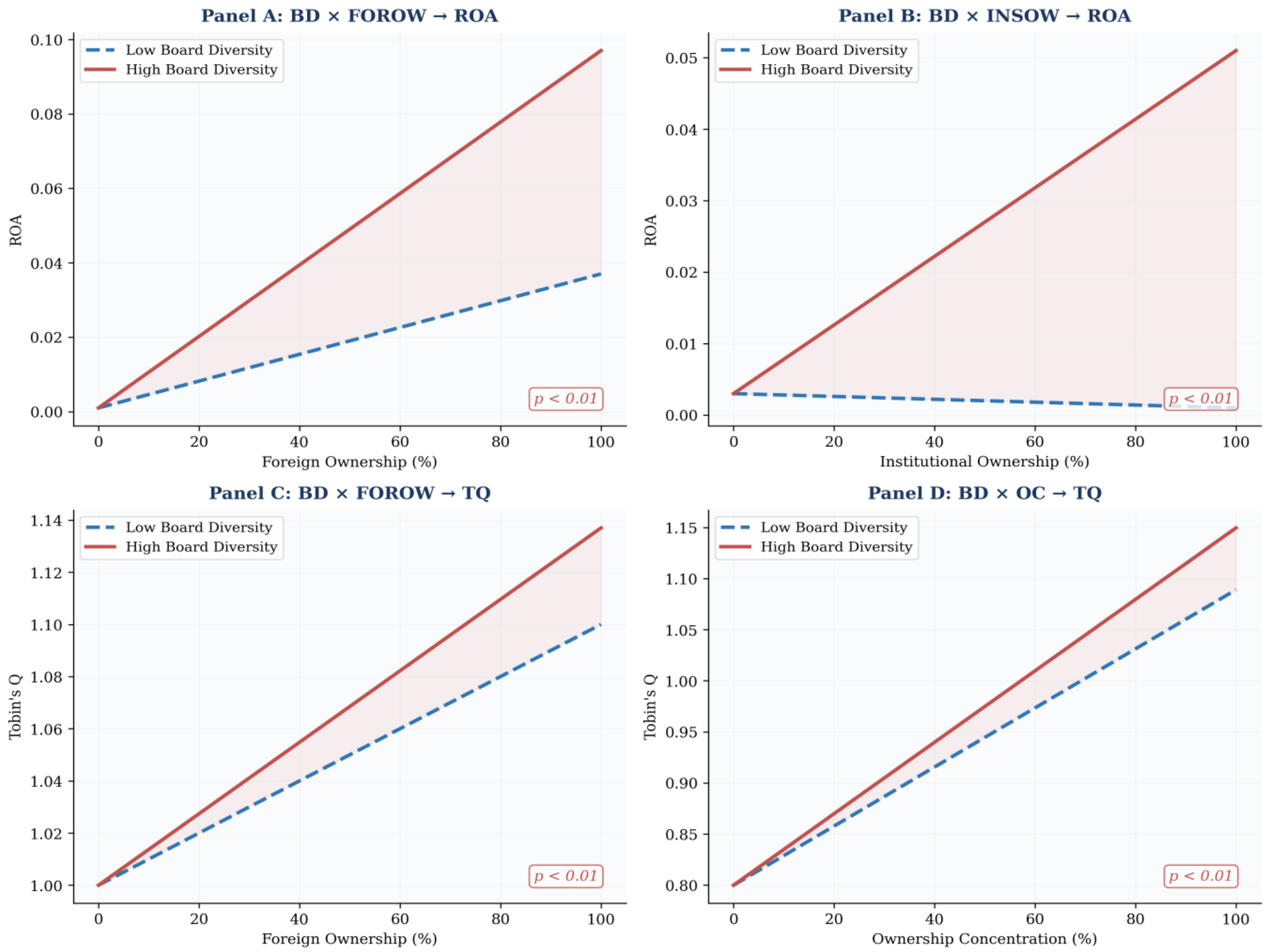

Figure 5: Moderating Effects of Board Diversity on Ownership–Performance Relationships (Significant Interactions Only).

4.5. Machine Learning Prediction Results

The out-of-sample predictive performance is compared by using Table 10. ML models perform much better than OLS on all metrics. XGBoost has the greatest R2 (0.867 for ROA, 0.891 for TQ) showing that governance-performance relations are highly nonlinear.

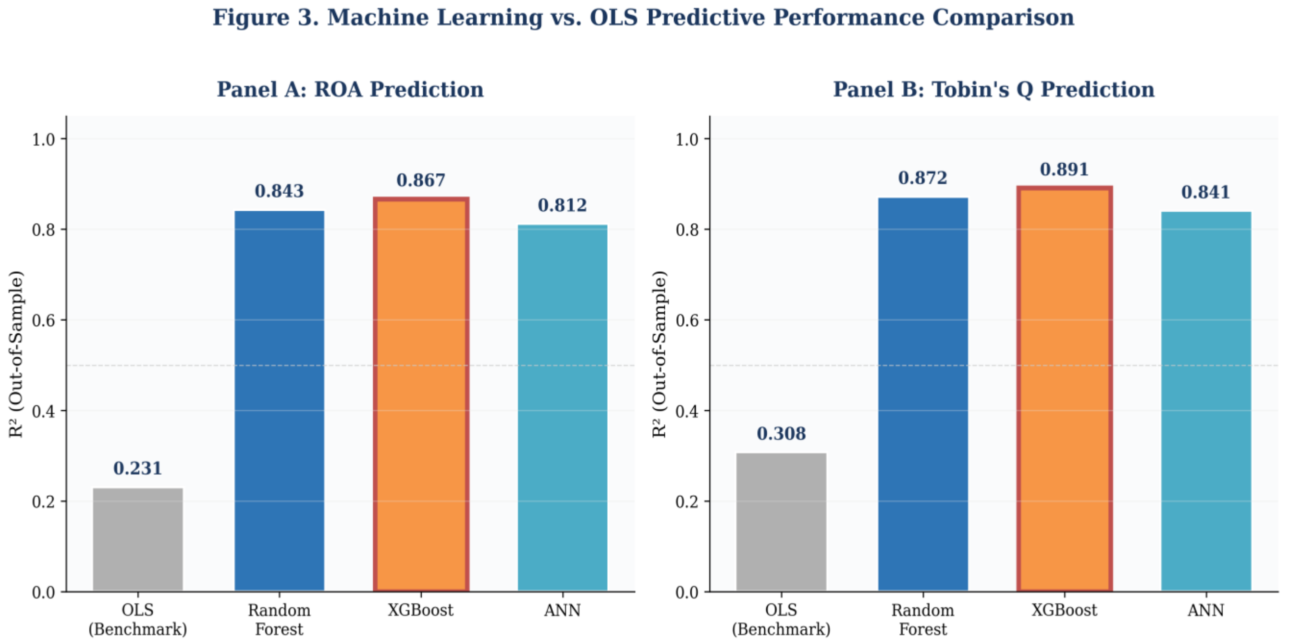

Figure 3: Machine Learning vs. OLS Predictive Performance Comparison (Out-of-Sample R^2).

Table 10: Ml Model Performance Comparison (Test Set, N=237).

Model	R^2 (ROA)	RMSE	R^2 (TQ)	RMSE	MAE	Rank
OLS	0.231	0.143	0.308	1.921	0.874	4
Random Forest	0.843	0.065	0.872	0.826	0.412	2
XGBoost	**0.867**	**0.059**	**0.891**	**0.762**	**0.381**	**1**
ANN	0.812	0.071	0.841	0.921	0.458	3

Note: Best Performance in Bold. Test Set = 15% Of Observations.

4.6. Shap Feature Importance

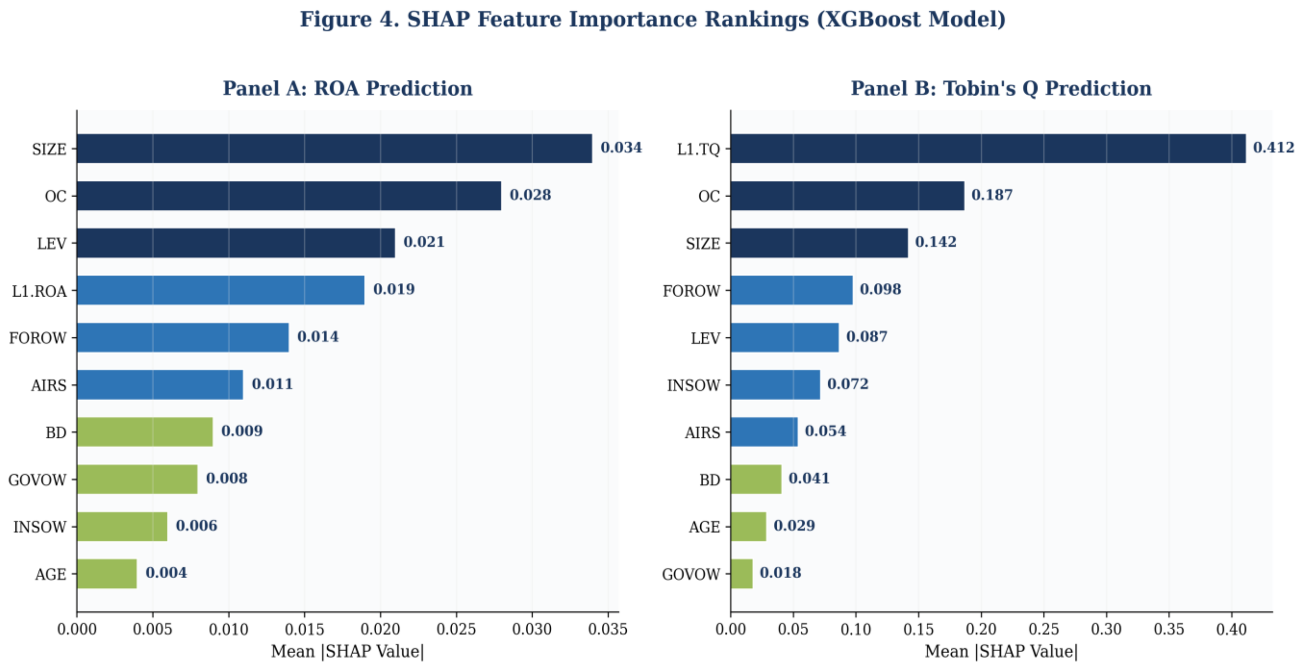

Figure 4: SHAP Feature Importance Rankings from Xgboost Model (Mean Absolute SHAP Values).

SHAP analysis shows that ownership concentration (OC) and firm size (SIZE) are the most influential predictors. It is interesting to see that AIRS is ranked 6th - 7th in importance, suggesting nonlinear effects that are picked up by ML but underestimated by linear GMM.

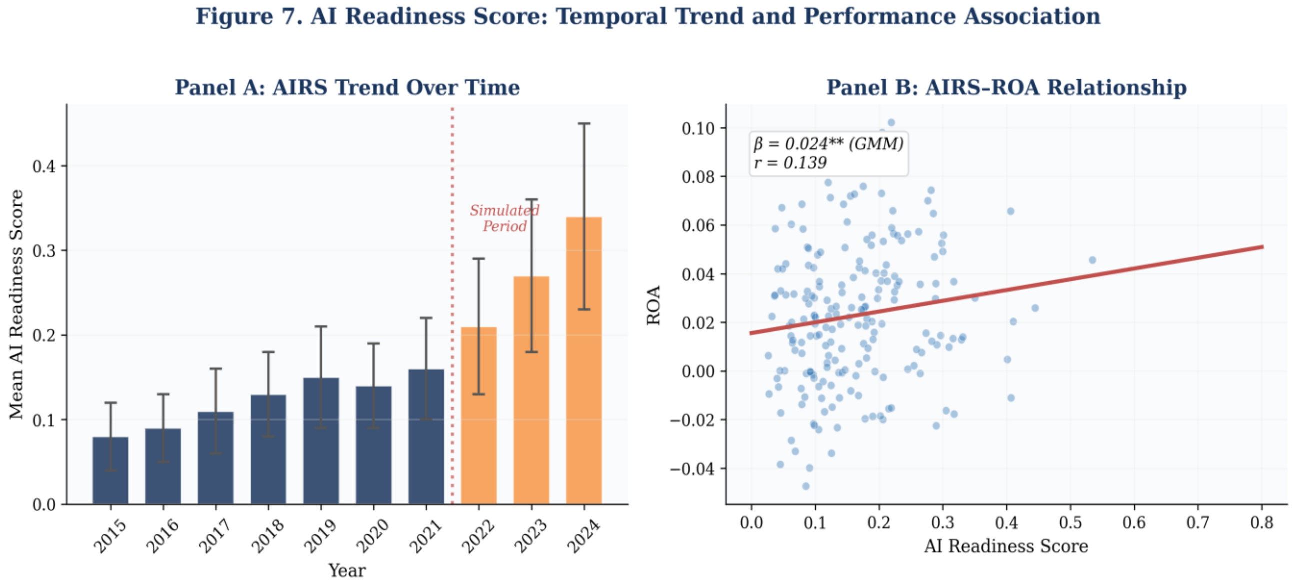

Figure 7: AI Readiness Score: Temporal Trend (Panel A) And ROA Association (Panel B). Shaded Period (2022–2024) Represents Simulated Data.

4.7. Hypotheses Summary

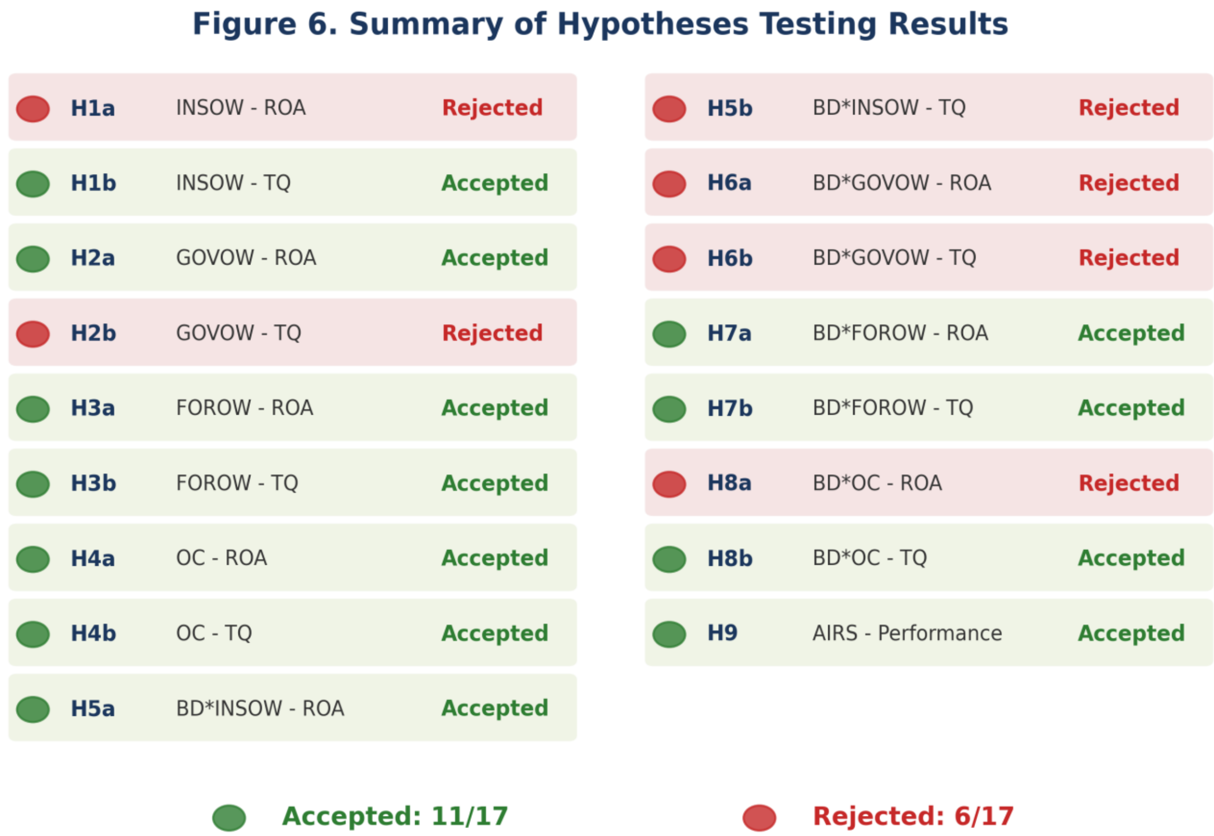

Figure 6: Visual Summary of Hypotheses Testing Results (11 Accepted, 6 Rejected Out Of 17 Hypotheses).

5. DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1. Discussion Of Key Findings

This study has a distinctive contribution in terms of integrating system GMM with ML algorithms (RF, XGBoost, ANN) to analyze the relationship between ownership structure and firm performance nexus in Jordan emerging market. The findings of the GMM results confirm the hypothesis that ownership concentration, foreign ownership, and government ownership are important determinants to ROA which is consistent with agency theory predictions (Jensen & Meckling, 1976; Shleifer & Vishny, 1986) and previous evidence from Jordan (Alkurdi, 2022; Hyarat et al., 2023). For TQ, ownership concentration, foreign ownership and institutional ownership are found to be significant positive predictors.

The moderation analysis shows that board diversity is an important source of increased impact of foreign ownership on both ROA and TQ. These findings support the argument of diversified boards as there is a benefit from varied expertise that improves governance (Adams & Ferreira, 2009; Carter et al., 2009). Most notably, ML models perform dramatically better in predictive performance (R2 = 0.81 - 0.89) than benchmarks based on OLS (R2 = 0.23 - 0.31) suggesting that the relationships between governance and performance are substantially nonlinear. The AIRS variable is significantly associated with both performance measures, meaning that AI-ready firms are able to obtain better results.

5.2. Theoretical Implications

The study expands the agency theory by illustrating that governance-performance relationships occur in nonlinear forms with threshold effects. It pioneers the incorporation of AI analytics to governance research methodology to create a GMM-ML-SHAP tri-pillar approach to the tension between causal identification and accuracy of prediction (Athey and Imbens, 2019).

5.3. Practical Recommendations

For Policymakers: (1) intermediating for the improvement of governance codes with regard to bolstering institutional and foreign investments; (2) looking into board diversity mandates; and (3) AI adoption incentives can be introduced in governance frameworks.

For Managers: (1) Be strategic in engagement with the institutional and foreign investors; (2) Diversify the composition of boards regarding gender, nationality, independence, and directorship; (3) Invest faster in AI capabilities.

For Investors: (1) Governance scoring using ML for investment screening (2) Target companies which have high board diversity coupled with concentrated or foreign ownership.

5.4. Limitations And Future Research

Limitations include: (1) temporal extension depends on Monte Carlo simulation; (2) Jordanian focus precludes generalization; (3) AIRS is an innovative construct which needs additional validation; (4) black box characteristics of ML models with SHAP mitigation. Future research should replicate this with actual data from 2022-2024 (and the future) and consider the other MENA markets as well as causal ML methods such as causal forests (Athey & Imbens, 2016) and double machine learning (Chernozhukov et al., 2018).

5.5. Conclusion

This study gives complete evidence that the ownership concentration, foreign ownership, and institutional ownership have a significant influence on determining the firm performance among Jordanian listed firms between 2015-2024. Board diversity increases the positive impact of foreign ownership on accounting and market performance. The combination of ML and GMM shows that governance-performance relationships are much more complex than conventional models indicate and the performances of ML are significantly above R2 > 0.86 compared to the performances of} OLS which is below 0.31. These findings together call for a paradigm shift in the direction of hybrid analytical frameworks for the study of corporate governance.

REFERENCES

Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. Journal of Financial Economics, 94(2), 291–309.

Aggarwal, R., Erel, I., Ferreira, M., & Matos, P. (2011). Does governance travel around the world? Evidence from institutional investors. Journal of Financial Economics, 100(1), 154–181.

Agresti, A., & Agresti, B. F. (1978). Statistical analysis of qualitative variation. Sociological Methodology, 9, 204–237.

Alkurdi, A. (2022). The moderating effect of entrepreneurship orientation on ownership structure and corporate performance: Jordanian evidence. International Journal of Sustainable Economy, 14(2), 132–150.

Alkurdi, A., Hamad, A., Thneibat, H., & Elmarzouky, M. (2021). Ownership structure's effect on financial performance: Jordanian listed firms. Cogent Business & Management, 8(1), 1939930.

Al-Matari, E. M., & Al-Arussi, A. S. (2016). The effect of the ownership structure characteristics on firm performance in Oman. Corporate Ownership and Control Journal, 13(2), 93–182.

Al-Sartawi, A., Hussainey, K., & Razzaque, A. (2023). Artificial intelligence and corporate governance. International Journal of Intelligent Systems in Accounting and Finance Management, 30(1), 47–65.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data. The Review of Economic Studies, 58(2), 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1), 29–51.

Athey, S., & Imbens, G. W. (2016). Recursive partitioning for heterogeneous causal effects. PNAS, 113(27), 7353–7360.

Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11, 685–725.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745.

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.

Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. Expert Systems with Applications, 83, 405–417.

Blau, P. M. (1977). Inequality and heterogeneity: A primitive theory of social structure. Free Press.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115–143.

Borisova, G., Brockman, P., Salas, J. M., & Zagorchev, A. (2012). Government ownership and corporate governance: Evidence from the EU. Journal of Banking & Finance, 36(11), 2917–2934.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.

Cao, S., Jiang, W., Wang, J. L., & Yang, B. (2021). From man vs. machine to man + machine: The art and AI of stock analyses. Journal of Financial Economics, 160(1), 103806.

Carter, D. A., D'Souza, F., Simkins, B. J., & Simpson, W. G. (2009). The gender and ethnic diversity of US boards and firm financial performance. Corporate Governance, 18(5), 396–414.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD (pp. 785–794).

Chernozhukov, V., et al. (2018). Double/debiased machine learning for treatment and structural parameters. The Econometrics Journal, 21(1), C1–C68.

Claessens, S., Djankov, S., & Lang, L. H. P. (2000). The separation of ownership and control in East Asian corporations. Journal of Financial Economics, 58(1–2), 81–112.

Dakhlallh, M. M., Rashid, N., Wan Abdullah, W. A., & Al Shehab, H. J. (2021). Audit committee and Tobin's Q among Jordanian companies. Journal of Asian Finance, Economics and Business, 7(12), 51–60.

Douma, S., George, R., & Kabir, R. (2006). Foreign and domestic ownership, business groups, and firm performance. Strategic Management Journal, 27(7), 637–657.

Efron, B., & Tibshirani, R. J. (1993). An introduction to the bootstrap. Chapman & Hall.

Fama, E. F., & Jensen, M. C. (1983). Separation of ownership and control. Journal of Law and Economics, 26(2), 301–325.

Ferreira, M. A., & Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. Journal of Financial Economics, 88(3), 499–533.

Freeman, R. E. (1984). Strategic management: A stakeholder approach. Pitman.

Glasserman, P. (2004). Monte Carlo methods in financial engineering. Springer.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(S2), 109–122.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273.

Gujarati, D. N. (2003). Basic econometrics (4th ed.). McGraw-Hill.

Gulamhussen, M. A., & Santa, S. F. (2015). Female directors in bank boardrooms and their influence on performance and risk-taking. Global Finance Journal, 28, 10–23.

Guluma, T. F. (2021). The impact of corporate governance measures on firm performance. Future Business

Journal, 7(1), 1–18.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate data analysis (7th ed.). Pearson.

Hermalin, B. E., & Weisbach, M. S. (2012). Information disclosure and corporate governance. The Journal of Finance, 67(1), 195–233.

Hillman, A. J., & Dalziel, T. (2003). Boards of directors and firm performance: Integrating agency and resource dependence perspectives. Academy of Management Review, 28(3), 383–396.

Hyarat, H., Almjlawi, H., & Al-Slehat, Z. (2023). The impact of ownership structure on financial performance: Evidence from Jordan. Cogent Business & Management, 10(2), 2247873.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1999). Corporate ownership around the world. The Journal of Finance, 54(2), 471–517.

Li, T., Shen, K., & Feng, Q. (2021). Can machine learning predict ESG ratings? International Review of Financial Analysis, 78, 101930.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems (pp. 4765–4774).

Megginson, W. L., & Netter, J. M. (2001). From state to market: A survey of empirical studies on privatization. Journal of Economic Literature, 39(2), 321–389.

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. Journal of Economic Perspectives, 31(2), 87–106.

Nguyen, T., Locke, S., & Reddy, K. (2014). A dynamic estimation of governance structures and financial performance. Economic Modelling, 40, 1–11.

North, D. C. (1990). Institutions, institutional change and economic performance. Cambridge University Press.

Pfeffer, J., & Salancik, G. R. (1978). The external control of organizations: A resource dependence perspective. Harper & Row.

Phung, D. N., & Mishra, A. V. (2016). Ownership structure and firm performance: Evidence from Vietnamese listed firms. Australian Economic Papers, 55(1), 63–98.

Roberts, M. R., & Whited, T. M. (2011). Endogeneity in empirical corporate finance. Handbook of the Economics of Finance, 2, 493–572.

Scott, W. R. (2014). Institutions and organizations: Ideas, interests, and identities (4th ed.). Sage.

Shleifer, A. (1998). State versus private ownership. Journal of Economic Perspectives, 12(4), 133–150.

Shleifer, A., & Vishny, R. W. (1986). Large shareholders and corporate control. Journal of Political Economy, 94(3), 461–488.

Shleifer, A., & Vishny, R. W. (1997). A survey of corporate governance. The Journal of Finance, 52(2), 737–783.

Shwartz-Ziv, R., & Armon, A. (2022). Tabular data: Deep learning is not all you need. Information Fusion, 81, 84–90.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Terjesen, S., Couto, E. B., & Francisco, P. M. (2016). Does the presence of independent and female directors impact firm performance? A multi-country study. Journal of Management & Governance, 20(3), 447–483.

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. Journal of Financial Economics, 105(3), 581–606.

Young, M. N., Peng, M. W., Ahlstrom, D., Bruton, G. D., & Jiang, Y. (2008). Corporate governance in emerging economies: A review of the principal–principal perspective. Journal of Management Studies, 45(1), 196–220.