Artificial Intelligence Exposure and Corporate Dividend Policy: Evidence from Egyptian Listed Firms

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Abstract

This study examines the association between documented corporate artificial intelligence (AI) exposure and three dimensions of cash-dividend policy: conditional dividend persistence, the payout ratio, and the decision to make a positive payment. The analysis uses a retrospective panel of 12 Egyptian companies, including four banks and eight non-bank firms, over 2017–2025; 2016 serves exclusively as the base year for lagged variables. The empirical analysis examines dividend persistence through the interaction between lagged dividends and lagged AI exposure in a modified Lintner model, payout intensity through cash dividends relative to positive net income, and payment incidence through a linear probability model. All benchmark specifications include firm and year fixed effects, company-clustered standard errors, and restricted wild-cluster inference. Each full model uses 99 complete observations, with partially different membership in the payout-ratio sample. The dividend-persistence interaction is positive but statistically insignificant ($\beta = 0.5884$; $p = 0.1704$; wild-cluster $p = 0.4060$). Lagged AI exposure is also not significantly associated with the payout ratio ($\beta = -0.0520$; $p = 0.7037$; wild-cluster $p = 0.7070$) or the payment decision ($\beta = -0.0505$; $p = 0.7315$; wild-cluster $p = 0.7144$). Listing-year eligibility checks leave all three hypothesis decisions unchanged. This study links documented corporate AI exposure to three distinct dividend-policy outcomes in Egyptian firms, distinguishing payout levels, persistence, and payment incidence while separating technological engagement from realized financial benefits.

Keywords: Artificial intelligence exposure; Dividend smoothing; Dividend payout ratio; Payout decision; Egyptian listed firms.

1. Introduction

Artificial intelligence (AI) has become an increasingly important dimension of corporate technological transformation, with applications in information processing, forecasting, operational efficiency, and managerial decision-making. Growing evidence associates corporate AI investment with innovation and firm growth, although observable AI engagement does not necessarily translate into immediate financial returns (Babina, Fedyk, He, & Hodson, 2024); (Laviola, Renzi, Taragoni, & Vagnani, 2026). Dividend policy provides a relevant setting for examining the financial implications of this transformation because it reflects firms' decisions concerning shareholder distributions and the retention of resources for internal use.

The relationship between corporate AI engagement and dividend policy may operate through competing financial channels. Improvements in information quality, forecasting, and operational efficiency could support more informed payout planning, whereas technological investment

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requirements, implementation uncertainty, and precautionary liquidity considerations may encourage firms to retain financial resources. Consistent with this trade-off, (Fan, Chen, & Chen, 2026) document a negative association between AI application intensity and cash-dividend distributions among Chinese firms. However, documented AI exposure, application intensity, and realized economic benefits are distinct constructs, and their associations with different aspects of dividend policy need not be identical.

Dividend policy itself encompasses several related but conceptually distinct decisions. Dividend smoothing concerns the conditional persistence of historical payments, the dividend payout ratio reflects the proportion of earnings distributed, and payout incidence captures whether a positive cash-dividend payment occurs. These distinctions are established in the corporate-finance literature (Lintner, 1956); (Fama & French, 2001). Egyptian evidence has also examined payout decisions separately from payout ratios (Abdel-Gawad, Sakr, & Abdou, 2021), but without incorporating corporate AI exposure. An important question therefore remains: whether documented AI engagement is associated with these three payout dimensions within a common empirical framework, particularly when changes in dividend levels do not necessarily imply corresponding changes in payment persistence or incidence.

Egypt offers a relevant empirical setting for this investigation. The study period encompasses substantial macroeconomic and financing developments, including inflationary pressures and exchange-rate adjustments, with the March 2024 reforms marking a further shift toward exchange-rate flexibility (International Monetary Fund, 2024). These conditions form part of the financial environment in which firms balance investment requirements, liquidity, and shareholder distributions. Institutional attention to technological transformation is also reflected in Egypt's National Artificial Intelligence Strategy 2025–2030 (National Council for Artificial Intelligence, 2025). Nevertheless, national policy initiatives are not treated as evidence of AI adoption by individual firms; company-level exposure is established through dated, attributable corporate documentation.

Against this background, the present study examines the association between corporate AI exposure and three dimensions of cash-dividend policy using a panel of 12 Egyptian companies listed by the end of the study period, with an estimation window covering 2017–2025. AI exposure is measured through an evidence-graded, stage-based firm-year index that distinguishes awareness and planning from capability development, operational implementation, and strategic integration. By examining conditional dividend persistence, payout intensity, and payment incidence separately, the study extends emerging AI-related corporate-finance research while preserving the conceptual distinctions among these outcomes. Section 2 develops the theoretical foundations, critically synthesizes the relevant literature, and establishes the research gap and hypotheses guiding the empirical analysis.

2. 2. Literature Review, Research Gap and Hypotheses

2.1. Corporate AI exposure and financial channels

Corporate AI exposure, operational adoption, and realized economic benefits are related but conceptually distinct. (Babina, Fedyk, He, & Hodson, 2024) develop a firm-level AI-investment measure using employee-resume data and document positive associations with sales, employment, and market-valuation growth, primarily through product innovation. From a disclosure perspective,

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(Barrios, Campbell, Johnson, & Liu, 2025) find that corporate AI disclosures convey information about underlying investments and subsequent operational outcomes, although their informativeness varies across disclosure contexts. These findings underscore the importance of distinguishing documented technological engagement from investment intensity, operational implementation, and realized financial returns. Accordingly, the present study employs an evidence-graded company-year index rather than treating generic AI references as equivalent to demonstrated adoption.

The economic implications of AI engagement also depend on how investments are undertaken. (Laviola, Renzi, Taragoni, & Vagnani, 2026) find that standalone AI-investment announcements do not generate significant abnormal stock returns, whereas investments associated with strategic alliances elicit positive market responses. Their evidence suggests that the financial implications of AI cannot be inferred uniformly from investment announcements alone.

Beyond growth and valuation, AI engagement may influence corporate liquidity and resource allocation. (Damle & Sinha, 2025) find that AI investment is associated with higher cash holdings among US firms, identifying reduced dividend payouts among the sources used to finance these reserves. (Aram, 2026), using an industry-level AI-exposure measure, reports specification-dependent associations with corporate cash holdings in a working paper. From a conceptual perspective, (Mertzanis, 2026) identifies information processing, forecasting, monitoring, and automation as potential channels through which AI may affect financial decisions, alongside model-related risks.

Collectively, this literature suggests competing financial channels. Improvements in information quality and operational efficiency may support financial planning and payout continuity, whereas technological investment requirements and precautionary liquidity considerations may encourage cash retention. Whether these considerations are differently associated with dividend persistence, payout intensity, and payment incidence remains an empirical question.

2.2. Corporate AI exposure and dividend smoothing (H1)

Dividend smoothing represents a dynamic dimension of corporate payout policy, reflecting the relationship between current distributions, previous dividends, and earnings. (Lintner, 1956) established the partial-adjustment framework, proposing that managers target sustainable payout levels and adjust dividends gradually rather than responding fully to short-term earnings fluctuations.

Subsequent research reinforces the importance of payout stability. (Brav, Graham, Harvey, & Michaely, 2025), drawing on executive surveys and interviews, document managers' reluctance to reduce regular dividends and their preference for accommodating investment and liquidity requirements before increasing distributions. (Leary & Michaely, 2011) further demonstrate that smoothing varies systematically across firms. Younger, smaller firms and those with more volatile earnings tend to smooth less, whereas firms with lower growth prospects and greater financial flexibility generally exhibit stronger smoothing.

Evidence from technology-intensive firms adds a relevant perspective. Examining US technology companies, (Barros, Verga Matos, Miranda Sarmento, & Rino Vieira, 2023) find that stronger ESG performance is associated with a higher likelihood of dividend payments and greater stability in the amounts distributed, while R&D intensity constrains dividend policy. Although their study does not measure corporate AI exposure, it illustrates the relevance of competing investment requirements and financial-policy considerations to payout stability.

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Recent AI-related evidence introduces a more direct financial connection. (Fan, Chen, & Chen, 2026) document a negative association between AI application intensity and cash-dividend distributions among Chinese firms, while (Damle & Sinha, 2025) identify reduced payouts as one source of increased cash reserves among US firms investing in AI. Nevertheless, lower distributions or greater cash retention do not necessarily imply a corresponding change in dividend persistence. Conceptually, improved information processing and forecasting may support more predictable financial planning, whereas technological investment requirements and implementation uncertainty may alter firms' reliance on historical payouts (Mertzanis, 2026). The expected direction of the relationship is therefore ambiguous.

Accordingly, H1 examines whether prior-year corporate AI exposure moderates the conditional association between lagged and current dividends per share within a modified Lintner specification. The interaction coefficient captures model-based conditional dividend persistence rather than an independently identified structural speed of adjustment.

2.3. Corporate AI exposure and the dividend payout ratio (H2)

The cash-dividend payout ratio (DPR) measures annual cash distributions relative to positive net income, capturing payout intensity rather than dividend persistence or the binary payment decision. It reflects how firms allocate earnings between shareholder distributions and internally retained resources. Corporate AI exposure may influence this allocation through competing channels: improvements in information processing and operational efficiency may support distributions, whereas technological investment requirements and uncertainty surrounding future returns may encourage earnings retention.

Recent empirical evidence highlights this trade-off. (Fan, Chen, & Chen, 2026), using an annual-report-based measure of AI application intensity constructed through Latent Dirichlet Allocation (LDA), document a negative association between AI applications and cash-dividend distributions among Chinese firms. Their analysis identifies innovation-related investment crowding-out, operating risk, and increased cash holdings as relevant mechanisms. Similarly, (Damle & Sinha, 2025) find that AI investment is associated with higher corporate cash holdings among US firms, with reduced dividend payouts identified among the sources used to finance these reserves. However, these findings do not directly establish the relationship between documented AI exposure and the proportion of positive earnings distributed to shareholders.

Evidence from related strategic investments provides a useful comparison. (Gyamfi, Yadav, Arhinful, & Khudoykulov, 2026) associate green bond issuance with lower dividend payouts, while improvements in emission efficiency and environmental performance are associated with higher payout ratios. Although their study does not examine AI, it illustrates why investment commitments and realized performance may have different implications for corporate distributions.

From a methodological perspective, (El Khayati & Saidi, 2026) employ explainable machine-learning techniques to predict dividend payout ratios among Moroccan firms, identifying profitability, firm size, and historical payout behavior as influential predictors. In their research, AI serves as a forecasting method rather than a measure of corporate technological exposure. Within Egypt, (Abdel-Gawad, Sakr, & Abdou, 2021) distinguish dividend-payment decisions from payout ratios and identify free cash flow, profitability, and managerial ownership as significant determinants of the latter.

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Taken together, these studies motivate examining payout intensity as a distinct outcome without assuming that documented technological engagement immediately generates distributable financial benefits. Accordingly, H2 investigates the association between prior-year corporate AI exposure and the annual ratio of total cash dividends to positive net income, conditional on the specified financial controls and firm and year fixed effects.

2.4. Corporate AI exposure and the cash-dividend payout decision (H3)

The cash-dividend payment decision represents a distinct dimension of payout policy, capturing whether a firm makes a positive distribution rather than the proportion of earnings distributed. (Fama & French, 2001) highlight the importance of payout propensity by documenting a decline in dividend-paying firms that cannot be fully explained by changes in firm characteristics, including size, profitability, and investment opportunities.

Corporate life-cycle research provides further insight into this decision. (DeAngelo, DeAngelo, & Stulz, 2006) establish a strong association between dividend payment and the proportion of retained earnings in total equity, consistent with the greater payout propensity of mature, internally financed firms. (Denis & Osobov, 2008) extend this evidence across six countries, finding that larger, more profitable firms with greater accumulated retained earnings exhibit a higher propensity to distribute dividends.

Evidence from technological and financial transformation adds a complementary perspective. (Song, Lee, & Wang, 2025), examining Chinese listed firms, find that regional digital-finance development is positively associated with both the likelihood and level of dividend payments. Their findings identify reduced information asymmetry and financing constraints as relevant channels. Although digital finance is conceptually distinct from firm-level AI exposure, this evidence illustrates how changes in the financial-information environment may be associated with the decision to distribute cash.

More directly related to AI, (Fan, Chen, & Chen, 2026) document a negative association between AI application intensity and cash-dividend distributions, while (Damle & Sinha, 2025) identify reduced payouts among the sources of increased cash reserves in AI-investing firms. These results provide relevant financial evidence but do not, by themselves, establish whether documented corporate AI exposure is associated with the occurrence of a positive payment. Within Egypt, (Abdel-Gawad, Sakr, & Abdou, 2021) separately examine dividend-payment decisions and payout ratios, identifying profitability and investment opportunities as significant determinants of payment decisions without incorporating corporate AI exposure.

The expected association remains theoretically ambiguous. Improved information quality and cash-flow forecasting may strengthen firms' capacity to maintain or initiate payments, whereas technological investment requirements, implementation uncertainty, and precautionary liquidity needs may discourage distributions. Accordingly, H3 examines whether prior-year corporate AI exposure is associated with the subsequent occurrence of a positive cash-dividend payment, conditional on previous payout status, current earnings per share, the specified financial controls, and firm and year fixed effects.

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2.5. Critical Synthesis and Research Gap

The reviewed literature establishes growing evidence of the financial implications of corporate AI engagement, but important distinctions remain between AI disclosures, investment, operational adoption, and realized economic benefits. (Barrios, Campbell, Johnson, & Liu, 2025) highlight the information conveyed by corporate AI disclosures, while Fan et al. (2026); (Damle & Sinha, 2025) provide direct evidence linking AI applications or investment to cash distributions and corporate liquidity. These studies advance understanding of AI-related financial decisions without fully resolving how documented corporate AI exposure relates to distinct dimensions of dividend policy.

Related research demonstrates that payout behavior cannot be adequately represented by a single outcome. (Barros, Verga Matos, Miranda Sarmento, & Rino Vieira, 2023) examine dividend payment and stability in technology-intensive firms, while (Song, Lee, & Wang, 2025) distinguish payment likelihood from dividend levels in the context of digital-finance development. Within Egypt, (Abdel-Gawad, Sakr, & Abdou, 2021) separately investigate payout decisions and payout ratios. However, these studies do not jointly examine corporate AI exposure, conditional dividend persistence, payout intensity, and payment incidence within a common empirical framework.

The remaining research gap therefore concerns the potentially differentiated associations between documented corporate AI engagement and these three dividend-policy outcomes. This distinction is economically relevant because improvements in information processing and operational efficiency, technological investment requirements, and precautionary liquidity considerations need not have identical implications for maintaining previous distributions, allocating earnings to shareholders, and deciding whether to distribute cash.

The present study addresses this gap using an evidence-graded firm-year AI-exposure index for Egyptian listed firms. It examines whether lagged exposure moderates conditional dividend persistence within a modified Lintner specification and whether it is associated with the cash-dividend payout ratio and the occurrence of a positive payment. Its contribution lies in integrating these distinct outcomes while separating documented technological engagement from application intensity and realized financial benefits, without presuming a uniform direction of association.

2.6. Research Hypotheses

The proposed relationships are examined using corporate AI exposure measured in the preceding year, in accordance with the operational definitions and empirical models presented in Section 3.

Accordingly, the following non-directional hypotheses are proposed:

H1: Corporate AI exposure is associated with dividend smoothing, as reflected in the conditional persistence of dividend payments.

H2: Corporate AI exposure is associated with the cash dividend payout ratio.

H3: Corporate AI exposure is associated with the likelihood of a firm making a cash dividend payment.

3. Research Methodology

3.1. Research Design and Sample

This quantitative longitudinal panel study examines corporate AI exposure in relation to conditional dividend smoothing (H1), the cash-dividend payout ratio (H2), and the cash-dividend payment decision (H3). It covers 12 Egyptian firms listed by the end of the study period—four banks

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and eight non-bank companies (ADIB, ALCN, CIB, CIEB, EFIG, ETEL, FWRY, GBCO, HRHO, QNBA, RAYA, and TALM).

The sample was constructed through a purposive review of historical financial statements, annual reports, and official corporate disclosures, guided by the longitudinal measurement requirements of the study. Firm selection was primarily based on the availability of dated and verifiable historical evidence sufficient to construct a consistent annual AI Exposure Index, together with the financial and dividend data required for the empirical analysis. High AI exposure or advanced AI implementation was not a prerequisite for inclusion. Rather, the key consideration was the ability to reliably measure and trace firm-level AI exposure over time. As inclusion depended partly on historical disclosure availability, the findings are interpreted within the selected sample rather than as population-wide estimates for all EGX-listed firms.

The approved source panel contains 120 firm-year records for 2016–2025. The year 2016 supplies lagged variables only; the main descriptive and estimation window is 2017–2025 (108 potential records). Historical pre-listing records are retained in the benchmark. Appendix Table A3 reports two listing-eligibility sensitivity analyses: eligibility of the outcome year, and eligibility of both the outcome and preceding AI-exposure years.

Descriptive statistics use variable-specific available observations, while regressions rely on specification-specific complete cases without missing-value imputation. Detailed estimation sample sizes and cross-model overlap are reported in Section 4.2.1 (Table 4).

3.2. Variable Definitions and Measurement

3.2.1. Firm-Level AI Exposure

AI_SCORE is an ordinal firm-year index (0–5) representing the highest stage substantiated by dated, firm-attributable evidence in annual reports, governance disclosures, or official company publications. A score of zero requires a completed eligible-source review without qualifying evidence; incomplete or unavailable source coverage is coded as missing.

Table M1. Firm-level AI exposure coding rubric

Score	Stage	Coding criterion
0	No qualifying evidence	Review of eligible sources completed without firm-specific qualifying evidence.
1	Awareness	Explicit firm-specific reference to AI.
2	Discussion or planning	An identifiable initiative or plan without evidence of operational deployment.
3	Capability or investment	Evidence of dedicated AI capability or identifiable AI investment.
4	Implementation	Dated evidence of AI application in operations, products, or services.
5	Strategic integration	AI embedded in corporate strategy or the business model, supported by organizational or strategic evidence.

Coding reflects the highest documented stage, not keyword frequency; later disclosures are not assigned retrospectively unless they date the underlying activity. The normalized measure is:

$AI_EXPOSURE_{it} = AI_SCORE_{it} / 5.$

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AI_EXPOSURE ranges from 0 to 1; one AI_SCORE stage equals 0.2 normalized units. All benchmarks use prior-year exposure ($AI_EXPOSURE_{i,t-1}$). This index measures documented engagement, not deployment intensity or realized AI-related financial returns.

3.2.2. Dependent Variables

H1 – Dividend smoothing. The outcome is annual cash dividends per share (DPS); its lag enters the modified Lintner model to estimate conditional dividend persistence.

H2 – Cash-dividend payout ratio. The primary DPR is recorded annual total cash dividends (DIV_TOTAL) divided by recorded net income (NET_INCOME) when net income is strictly positive:

$DPR_{it} = DIV_TOTAL_{it} / NET_INCOME_{it}$, for $NET_INCOME_{it} > 0$.

An observed zero dividend yields DPR = 0 when net income is positive. The ratio is undefined if either input is missing or net income is non-positive. Values above one are retained in the primary measure; DPS/EPS, where EPS is positive and inputs are observed, is examined only as a measurement sensitivity.

H3 – Cash-dividend payment decision. $PAYOUT_{it}$ equals one for recorded $DPS_{it} > 0$ and zero for observed $DPS_{it} = 0$; missing DPS remains missing. Lagged payout status is constructed analogously from previous-year DPS.

3.2.3. Control Variables

The five common financial controls are defined as follows:

Variable	Operational definition
SIZE	Natural logarithm of total assets
LEV	Debt divided by total assets
CASH_RATIO	Cash and cash equivalents divided by total assets
GROWTH	Annual change in revenue divided by preceding-year revenue
CAPEX_RATIO	Capital expenditure divided by revenue

Current earnings per share (EPS) is included in H1 and H3, but not in the primary H2 model (an EPS-augmented H2 specification is examined separately). Ratios and growth rates require valid inputs and denominators. Although calculated consistently, the financial ratios may differ in economic meaning between banks and non-bank firms.

3.3. Econometric Specifications

All benchmark models include firm fixed effects (μ_i) and year fixed effects (λ_t). Let $A_{i,t-1}$ denote lagged AI_EXPOSURE and X_{it} the five financial controls defined above.

3.3.1. Conditional Dividend Smoothing (H1)

$$DPS_{it} = \alpha + \beta_1 DPS_{i,t-1} + \beta_2 EPS_{it} + \beta_3 A_{i,t-1} + \beta_4 (DPS_{i,t-1} \times A_{i,t-1}) + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}.$$

H1 tests the interaction coefficient β_4. At AI-exposure level A = a, estimated conditional persistence is:

$$\rho(a) = \beta_1 + \beta_4 a.$$

Thus β_4 measures variation in the lagged-DPS association across AI-exposure levels; it is not an independently identified structural adjustment-speed parameter.

3.3.2. Cash-Dividend Payout Ratio (H2)

$$DPR_{it} = \alpha + \delta_1 A_{i,t-1} + \theta' X_{it} + \mu_i + \lambda_t + u_{it}.$$

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H2 tests δ_1, the conditional within-firm association between lagged AI exposure and DPR among observations with a defined ratio.

3.3.3. Cash-Dividend Payment Decision (H3)

$$PAYOUT_{it} = \alpha + \varphi_1 PAYOUT_{i,t-1} + \varphi_2 A_{i,t-1} + \varphi_3 EPS_{it} + \psi' X_{it} + \mu_i + \lambda_t + \nu_{it}.$$

The benchmark H3 estimator is a two-way fixed-effects linear probability model (LPM). Its focal coefficient, φ_2, gives the conditional linear probability-point difference for a one-unit increase in lagged AI exposure; one AI_SCORE stage corresponds to 0.2 of this unit.

3.4. Estimation, Inference, and Sensitivity Analysis

Inference uses company-clustered CR1 standard errors and two-sided t(G − 1) tests (G = 12; df = 11). For the focal coefficients, null-imposed, firm-level Rademacher restricted wild-cluster tests supplement conventional inference: 9,999 draws for H1 and exhaustive enumeration of 2^{12} = 4,096 sign assignments for H2 and H3.

Descriptive distributions, Pearson correlations, and VIFs (including the centered H1 interaction) are reported with the results. Archived Breusch–Pagan checks and residual summaries are preliminary or exploratory, not formal Pesaran CD or Wooldridge panel tests.

Sensitivity analyses comprise H1 conditional slopes and firm exclusions; H2 alternative estimators and covariance, outcome-only winsorization on a separate derived series, a positive-payout subsample, DPS/EPS, and an EPS-augmented model; and H3 alternative LPM specifications, a DIV_TOTAL-based coding check, firm exclusions, and pooled year-effects Logit/Probit with average marginal effects. The nonlinear checks do not estimate the same firm-within parameter as the benchmark LPM.

The dynamic fixed-effects models in H1 and H3 may exhibit finite-T bias; inference with 12 clusters also depends on the maintained cross-firm error assumptions. H3 LPM fitted values are not invariably within [0, 1]. Results are therefore interpreted as conditional associations, not causal effects or proof of a zero population relationship.

3. 4. Empirical Results and Discussion

4.1 Descriptive Statistics and Preliminary Analysis

Table 1 reports the variable-specific descriptive profile for the 2017–2025 outcome window. Sample construction and regression-specific complete cases are defined in Sections 3.2 and 4.2.

Table 1. Descriptive statistics for the analysis period, 2017–2025

Variable	N	Mean	SD	Min	P25	Median	P75	Max	Skew.	Excess kurt.
AI Exposure (t)	108	0.463	0.359	0	0	0.600	0.800	1	-0.229	-1.570
AI Exposure (t−1)	108	0.381	0.357	0	0	0.400	0.800	1	0.082	-1.725
DPS (t)	103	0.579	0.878	0	0	0.143	0.953	4.240	2.125	4.817
DPS (t−1)	100	0.526	0.820	0	0	0.138	0.782	4.240	2.410	6.834
EPS (t)	105	3.198	3.670	-0.610	0.410	1.700	4.800	18.250	1.701	3.104
DPS (t−1) × AI (t−1)	100	0.256	0.528	0	0	0	0.303	3.392	3.391	14.528
DPR (primary)	100	0.221	0.296	0	0	0.116	0.291	1.380	1.706	2.644

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Variable	N	Mean	SD	Min	P25	Median	P75	Max	Skew.	Excess kurt.
Payout indicator (t)	103	0.612	0.490	0	0	1	1	1	-0.465	-1.820
Payout indicator (t−1)	100	0.600	0.492	0	0	1	1	1	-0.414	-1.866
SIZE	106	10.470	1.878	6.893	8.920	10.680	11.856	14.182	-0.106	-0.895
LEV	105	0.138	0.168	0	0.013	0.037	0.240	0.592	1.104	-0.071
CASH_RATIO	106	0.196	0.161	0.010	0.072	0.147	0.276	0.707	1.382	1.568
GROWTH	106	0.289	0.248	-0.210	0.124	0.259	0.427	1.023	0.574	0.195
CAPEX_RATIO	105	0.136	0.244	0.001	0.027	0.046	0.147	1.864	4.553	26.811

Notes: SD is the sample standard deviation; P25 and P75 are the 25th and 75th percentiles; skewness and excess kurtosis reproduce the final master statistics. N is variable-specific rather than the common regression N. DPR uses approved DIV_TOTAL/NET_INCOME when NET_INCOME > 0. The payout indicator equals one for positive recorded DPS and zero for recorded DPS equal to zero. All figures refer to 2017–2025; 2016 is excluded as an outcome year.

Mean current-year AI exposure is 0.463 (N = 108), versus 0.381 for its lag. Mean DPS is 0.579 (N = 103; median = 0.143); the primary DPR averages 0.221 (N = 100). A positive cash-dividend decision is observed in 63 of 103 available cases (61.2%). These are sample descriptions, not AI-effect estimates. DPS, the interaction and capital-investment intensity show right skewness. IQR flags are descriptive only: zero dividends and all recorded original values remain in the baseline, and undefined DPR observations are not coded as zero.

4.1.1 Bivariate associations

Table 2 presents the Pearson correlation matrix for the H1 baseline-eligible sample. Current DPS is positively correlated with lagged DPS (r = 0.626), consistent with descriptive payout persistence, and with EPS (r = 0.376). The highest correlation among predictors is observed between the interaction term and lagged DPS (r = 0.816), partly reflecting the mechanical construction of the interaction term, followed by the correlation between EPS and SIZE (r = 0.734). These associations are descriptive; hypothesis testing relies on the specified panel regression models.

Table 2. Pearson correlation matrix: H1 baseline-eligible sample

Variable	1	2	3	4	5	6	7	8	9	10
1 DPS	1.000									
2 EPS	0.376***	1.000								
3 DPS (t−1)	0.626***	0.211**	1.000							
4 AI (t−1)	0.157	0.106	0.136	1.000						
5 Interaction	0.578***	0.232**	0.816***	0.416***	1.000					

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Variable	1	2	3	4	5	6	7	8	9	10
6 SIZE	0.230 **	0.734 ***	0.161	0.304 ***	0.201 **	1.000				
7 LEV	-0.255 **	-0.322 ***	-0.226 **	-0.067	-0.221 **	-0.111	1.000			
8 CASH	0.112	-0.152	0.105	0.035	0.047	-0.388 ***	-0.445 ***	1.000		
9 GROWTH	-0.245 **	0.073	-0.294 ***	0.198 **	-0.200 **	0.031	-0.011	0.172 *	1.000	
10 CAPEX	-0.104	-0.164	-0.090	-0.134	-0.097	-0.258 ***	0.021	-0.174 *	0.110	1.000

Correlation coefficients are reproduced from the approved archived H1 baseline output. Pairwise N = 100 for variables 1–9 and N = 99 for pairs involving CAPEX_RATIO. ***p < 0.01; **p < 0.05; *p < 0.10 (conventional two-sided, unclustered Pearson tests). Interaction = DPS(t−1) × AI(t−1); CASH = CASH_RATIO; CAPEX = CAPEX_RATIO. Significance markers are exploratory and do not account for within-firm or cross-firm dependence.

4.1.2 Multicollinearity assessment

Table 3 presents the variance inflation factors (VIFs) for the H1 regressors. The maximum VIF decreased from 4.485 for the original interaction term to 3.542 (SIZE) after mean-centering, while the interaction VIF declined to 1.152. All reported values are below the conventional threshold of 5, indicating no substantial multicollinearity among the assessed regressors.

Table 3. Variance inflation factors for H1 regressors

Regressor	Original VIF	Centered interaction VIF
EPS	2.7572	2.7572
DPS(-1)	3.8697	1.3369
AI(-1)	1.8747	1.2851
Interaction	4.4849	1.1520
SIZE	3.5421	3.5421
LEV	1.6718	1.6718
CASH	2.1963	2.1963
GROWTH	1.3417	1.3417
CAPEX_RATIO	1.3063	1.3063

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VIFs are calculated for the economic regressors, excluding firm and year fixed effects. Mean-centering reparameterizes the interaction and its constituent terms without altering the underlying data. Reported values are reproduced from the approved diagnostic output.

4.2 Model Diagnostics and Estimation Strategy

4.2.1 Analytical samples and model comparability

Complete-case samples are constructed separately for each model. The full-control specifications contain 99 observations each; H1 and H3 share identical firm-year observations, while their overlap with H2 comprises 96 observations. Table 4 summarizes the estimation coverage across specifications.

Table 4. Sample construction and estimation coverage

Sample definition	Firm-years	Scope / interpretation
Original source panel	120	2016–2025; 12 firms × 10 years
Potential outcome observations	108	2017–2025; 12 firms × 9 years
H1 baseline complete cases	100	Modified Lintner baseline
H1 with all controls	99	Two-way fixed-effects benchmark
H2 primary DPR defined	100	Positive net income and available numerator
H2 with all controls	99	Two-way fixed-effects benchmark
H3 observed binary payout	103	Indicator defined from observed DPS
H3 with all controls	99	Two-way fixed-effects LPM benchmark
Common H1 ∩ H2 ∩ H3 cases	96	Comparison subsample; not substituted for the three benchmarks

The estimation period is 2017–2025; 2016 provides lagged variables only. DPR = DIV_TOTAL/NET_INCOME for strictly positive net income, with zero recorded dividends assigned DPR = 0. PAY = 1 for positive recorded DPS and 0 for recorded DPS = 0. Missing values are not imputed. The 96 common observations are retained as a comparison subsample rather than replacing the model-specific estimation samples.

4.2.2 Preliminary heteroskedasticity diagnostics

The preliminary Breusch–Pagan tests for H1 yield LM statistics of 33.6947 ($p = 0.0697$) for the baseline specification and 31.8091 ($p = 0.2823$) for the full-control specification (Table 5). Neither test rejects the null hypothesis of homoskedasticity at the 5% level, although the baseline result provides marginal evidence of heteroskedasticity at the 10% level. These findings are limited to the preliminary H1 specifications.

Table 5. Archived preliminary heteroskedasticity diagnostics (H1)

Statistic	Baseline H1	Full-control H1
Complete-case observations	100	99
Breusch–Pagan auxiliary regression R^2	0.336947	0.321304
Breusch–Pagan LM	33.6947	31.8091
Breusch–Pagan p-value	0.0697	0.2823

Results are reproduced from the approved preliminary H1 diagnostic output. $LM = N \times R^2_aux$. The tests are specification-specific and do not determine the standard-error treatment in the final panel regressions.

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4.2.3 Exploratory dependence and serial-correlation checks

Table 6 reports archived exploratory residual diagnostics for the preliminary H1 specifications. The cross-sectional residual statistics are 0.8591 and −0.8078 for the baseline and full-control models, respectively, while pooled adjacent-residual correlations are small (0.0517 and 0.0461). As the computational basis of these statistics is not fully documented, they are retained as descriptive diagnostics rather than formal tests of panel dependence.

Table 6. Archived exploratory residual summaries (H1 only)

Archived quantity	Baseline H1	Full-control H1
Approximate cross-sectional residual statistic	0.8591	−0.8078
Approximate associated p-value	0.3903	0.4192
Pooled adjacent-residual correlation	0.0517	0.0461

Values are reproduced from the approved preliminary H1 output. The reported quantities are not validated Pesaran CD or Wooldridge test statistics and do not establish cross-firm independence or the absence of within-firm serial correlation.

4.2.4 Benchmark estimators and finite-cluster inference

All three benchmark models incorporate firm and year fixed effects to account for time-invariant firm heterogeneity and common annual shocks. H1 estimates a modified Lintner specification incorporating lagged DPS, EPS, lagged AI exposure, their interaction, and five financial controls. H2 examines the relationship between lagged AI exposure and DPR, while H3 employs a two-way fixed-effects linear probability model incorporating lagged payout status, lagged AI exposure, EPS, and the five controls.

Standard errors are clustered at the firm level using the CR1 correction, with conventional two-sided inference based on t(11), reflecting the 12 firm clusters. To complement conventional inference in this small-cluster setting, restricted, null-imposed wild-cluster bootstrap tests with Rademacher weights are conducted for each hypothesis. H1 uses 9,999 bootstrap draws, whereas H2 and H3 employ complete enumeration of all 4,096 sign combinations. Table 7 summarizes the estimation and inferential framework.

Table 7. Estimation and inferential design for the three hypotheses

Hypothesis	Benchmark outcome and estimator	Target parameter	Firm-cluster bootstrap
H1	DPS; two-way FE-OLS	DPS(t−1) × AI(t−1)	Restricted wild; 9,999 draws
H2	DPR; two-way FE-OLS	AI(t−1)	Restricted wild; exact 4,096 signs
H3	Payout indicator; two-way FE LPM	AI(t−1)	Restricted wild; exact 4,096 signs

All full-control specifications use N = 99 and G = 12 firm clusters, with model-specific complete-case samples. CR1 denotes the finite-sample-adjusted firm-clustered covariance estimator. Wild-cluster tests use firm-level Rademacher weights. Neither inference procedure automatically accommodates residual dependence across firms. Complete sign enumeration removes bootstrap simulation error but does not establish exact finite-sample inference.

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4.2.5 Specification limitations and robustness scope

The inclusion of lagged dependent variables in H1 and H3 introduces potential finite-T dynamic-panel bias under firm fixed effects. Lagged AI exposure establishes temporal ordering but does not eliminate endogeneity concerns. Furthermore, firm-clustered inference assumes independence across companies, while the linear probability specification in H3 may generate fitted probabilities outside the unit interval. Robustness analyses examine alternative H2 specifications, firm exclusions, and Logit/Probit functional-form sensitivities for H3. The findings are therefore interpreted as conditional associations, with due consideration of the sample size and these specification limitations.

4.3 AI Exposure and Dividend Smoothing (H1)

Hypothesis H1 examines whether lagged AI exposure moderates dividend persistence in a modified Lintner framework. The hypothesis is evaluated through the interaction between lagged DPS and lagged AI exposure, using the two-way fixed-effects benchmark.

4.3.1 Benchmark regression results

Table 8 reports the benchmark estimates for H1, based on 99 firm-year observations from 12 companies over 2017–2025.

Table 8. AI exposure and dividend persistence: two-way fixed-effects estimates (Panel A: benchmark coefficients)

Regressor	Coefficient	Clustered SE	t(11)	p-value	95% confidence interval
Lagged DPS	-0.1095	0.2636	-0.4156	0.6857	[-0.6897, 0.4706]
Current EPS	0.1190	0.0480	2.4805	0.0305	[0.0134, 0.2247]
Lagged AI exposure	-0.1925	0.5277	-0.3647	0.7222	[-1.3538, 0.9689]
Lagged DPS × lagged AI exposure	0.5884	0.4011	1.4670	0.1704	[-0.2944, 1.4712]
SIZE	0.3968	0.3542	1.1202	0.2865	[-0.3828, 1.1763]
LEV	0.6558	1.1569	0.5668	0.5822	[-1.8906, 3.2022]
CASH_RATIO	-1.2399	1.2786	-0.9698	0.3530	[-4.0541, 1.5742]
GROWTH	-0.5497	0.5857	-0.9387	0.3681	[-1.8388, 0.7393]
CAPEX_RATIO	0.1503	0.3495	0.4300	0.6755	[-0.6189, 0.9195]

Dependent variable: current-year cash DPS. Firm and year fixed effects are included but not reported. N = 99; G = 12; R^2 = 0.7002; adjusted R^2 = 0.5802. Standard errors are firm-clustered (CR1), with two-sided inference based on t(11). ADIB and 2017 are the reference categories.

The estimated interaction coefficient is positive (β = 0.5884), but statistically insignificant (p = 0.1704; 95% CI: [−0.2944, 1.4712]). Thus, the benchmark provides insufficient evidence that AI exposure moderates dividend persistence, and H1 is not supported by the conventional firm-clustered inference.

The lagged DPS coefficient (β = −0.1095; p = 0.6857) represents the conditional persistence slope at zero AI exposure. Current EPS is positively associated with DPS (β = 0.1190; p = 0.0305), whereas the standalone AI coefficient and the five financial controls are statistically insignificant at the 5% level. The conditional persistence estimates across observed AI-exposure levels are presented in Panel B.

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Table 8 (continued). Panel B: conditional lagged-DPS slopes at observed AI-exposure levels

Lagged AI exposure	Observations at level	Conditional slope	Clustered SE	95% confidence interval
0.0	36	-0.1095	0.2636	[-0.6897, 0.4706]
0.2	4	0.0081	0.1866	[-0.4027, 0.4189]
0.4	10	0.1258	0.1142	[-0.1256, 0.3773]
0.6	16	0.2435	0.0643	[0.1019, 0.3851]
0.8	31	0.3612	0.0900	[0.1631, 0.5592]
1.0	2	0.4788	0.1579	[0.1314, 0.8263]

Conditional slopes are calculated as $\beta_1 + a\beta_4$, where a denotes the observed lagged AI-exposure level. Clustered standard errors and 95% confidence intervals are obtained using the delta method, incorporating the full covariance between β_1 and β_4, with t(11) critical values. Level counts sum to N = 99; the highest exposure level contains only two observations.

The estimated conditional lagged-DPS slope increases from −0.1095 at zero AI exposure to 0.4788 at full exposure. Although the conventional confidence intervals exclude zero at exposure levels of 0.6, 0.8, and 1.0, these estimates do not establish significant moderation. The hypothesis-defining interaction remains statistically insignificant under both conventional clustered inference (p = 0.1704) and the restricted wild-cluster bootstrap (p = 0.4060). Accordingly, H1 is not supported.

4.3.2 Finite-cluster inference and sensitivity to HRHO

The restricted wild-cluster bootstrap yields a p-value of 0.4060 for the full-sample interaction, providing no evidence of statistically significant moderation under the complementary finite-cluster procedure. Table 9 also assesses the sensitivity of the interaction estimate to excluding HRHO.

Table 9. Inference on the H1 interaction and influential-firm sensitivity

Specification	N	Firms	Interaction β	Clustered SE	t-based p	Wild-bootstrap p
All firms	99	12	0.5884	0.4011	0.1704	0.4060
Excluding HRHO	90	11	-0.0147	0.3497	0.9673	0.9686

Both specifications retain the same regressors and two-way fixed-effects structure. Restricted wild-cluster inference uses firm-level Rademacher weights, with 9,999 draws for the full sample. The HRHO-exclusion bootstrap p-value is reproduced from the approved archived output. Full leave-one-firm-out results are reported in Appendix Table A1.

Excluding HRHO reduces the interaction coefficient from 0.5884 to −0.0147, indicating substantial sensitivity of the positive benchmark estimate to this firm's inclusion. None of the 12 leave-one-firm-out specifications produces a significant interaction at the 5% level. The largest exclusion estimate occurs when QNBA is omitted (β = 0.7620; p = 0.0649), while HRHO is the only exclusion that reverses the coefficient's sign. These results indicate limited robustness of the positive moderation estimate without warranting any change to the prespecified sample.

4.3.3 Hypothesis decision and interpretation

The benchmark interaction is statistically insignificant under both conventional firm-clustered inference (p = 0.1704) and the restricted wild-cluster bootstrap (p = 0.4060). Moreover, the positive coefficient is sensitive to HRHO's inclusion, and none of the leave-one-firm-out specifications yields

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a significant interaction at the 5% level. Accordingly, H1 is not supported. The findings provide insufficient evidence that AI exposure systematically moderates dividend persistence within the observed sample. Given the associational design and potential dynamic-panel bias, the estimated relationships should not be interpreted as causal or as evidence of a structural dividend-adjustment mechanism.

4.4 AI Exposure and Dividend Payout Ratio (H2)

H2 examines the association between lagged AI exposure and the cash dividend payout ratio (DPR), using the fully controlled two-way fixed-effects specification.

4.4.1 Benchmark payout-ratio regression

Table 10 reports the benchmark estimates based on 99 complete firm-year observations.

Table 10. AI exposure and dividend payout ratio: benchmark two-way fixed-effects estimates

Regressor	Coefficient	Clustered SE	t(11)	p-value	95% confidence interval
Intercept	-0.0961	0.9091	-0.1057	0.9177	[-2.0970, 1.9048]
Lagged AI exposure	-0.0520	0.1332	-0.3904	0.7037	[-0.3451, 0.2411]
Firm size	0.0314	0.0917	0.3424	0.7385	[-0.1704, 0.2332]
Leverage	0.1514	0.2806	0.5394	0.6003	[-0.4663, 0.7690]
Cash ratio	-0.4342	0.4877	-0.8904	0.3923	[-1.5076, 0.6391]
Revenue growth	-0.0427	0.1552	-0.2749	0.7885	[-0.3844, 0.2990]
Capital-expenditure ratio	-0.0389	0.0662	-0.5886	0.5680	[-0.1846, 0.1067]

Dependent variable: DPR = DIV_TOTAL/NET_INCOME, defined for positive net income. Firm and year fixed effects are included but not reported (reference categories: ADIB and 2017). N = 99; G = 12; R^2 = 0.6781; adjusted R^2 = 0.5678. Standard errors are firm-clustered (CR1), with two-sided inference based on t(11). No missing values are imputed.

Lagged AI exposure has a negative but statistically insignificant coefficient ($\beta = -0.0520$; p = 0.7037; 95% CI: [−0.3451, 0.2411]). Thus, the benchmark provides insufficient evidence of an association between AI exposure and the dividend payout ratio, conditional on the financial controls and two-way fixed effects. None of the five financial controls is statistically significant at the 5% level.

4.4.2 Finite-cluster inference and alternative specifications

Table 11 examines the sensitivity of the H2 benchmark to alternative estimators, covariance specifications, payout-ratio measurements, and sample restrictions.

Table 11. H2 benchmark and alternative specifications

Specification	N	Firms	AI coefficient	SE	p-value	R^2
Two-way FE (benchmark)	99	12	-0.0520	0.1332	0.7037	0.6781
Pooled OLS	99	12	0.0950	0.1280	0.4735	0.3072
Firm FE only	99	12	-0.1067	0.1274	0.4200	0.6374
Two-way FE; HC3 SE	99	12	-0.0520	0.1094	0.6362	0.6781
DPR winsorized (1/99)	99	12	-0.0436	0.1263	0.7362	0.7017
Positive dividends only	60	10	0.1212	0.1499	0.4397	0.8217

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Specification	N	Firms	AI coefficient	SE	p-value	R^2
Per-share DPR (DPS/EPS)	99	12	-0.1967	0.1943	0.3331	0.4293
Two-way FE; add EPS	99	12	-0.0244	0.1226	0.8457	0.6865

All specifications retain the five benchmark financial controls, except where otherwise indicated. Standard errors follow the archived specifications (firm-clustered CR1, except for the HC3 sensitivity). Winsorization is applied exclusively to the benchmark DPR outcome at the 1st and 99th percentiles (0 and 1.190688), affecting only HRHO in 2017. Original data and benchmark values remain unchanged. The positive-dividend specification is conditional on observed payouts; DPS/EPS and the additional EPS control are measurement and specification sensitivities, respectively.

The estimated AI coefficient remains statistically insignificant across all alternative specifications (Table 11). Its sign varies across estimators and sample restrictions, while winsorizing DPR, adopting the per-share payout measure, and adding EPS do not alter the baseline inference. The positive-dividend subsample also yields an insignificant coefficient, although its interpretation is conditional on payout occurrence. Overall, the robustness analyses provide no statistically reliable evidence of an association between lagged AI exposure and dividend payout intensity.

Table 12. H2 finite-cluster inference for the benchmark AI coefficient

To assess finite-cluster inference for H2, the benchmark AI coefficient is additionally evaluated using the restricted wild-cluster bootstrap (Table 12).

Inference method	AI estimate / |t|	SE	Two-sided p	Details
Firm-cluster CR1; t(11)	-0.0520	0.1332	0.7037	99 observations; 12 firm clusters
Restricted wild-cluster bootstrap	0.3904	—	0.7070	4,096 Rademacher assignments; 2,896 exceedances

The bootstrap row reports the absolute null-restricted test statistic (|t| = 0.3904), not a separate coefficient estimate. The p-value is obtained by complete enumeration of firm-level Rademacher sign assignments (2,896/4,096 = 0.7070).

The restricted wild-cluster bootstrap yields p = 0.7070, consistent with the insignificant benchmark estimate (β = −0.0520; p = 0.7037). Although the coefficient's direction and magnitude vary across alternative specifications (Table 11), none produces a statistically significant association at the 5% level. Accordingly, H2 is not supported: the results provide insufficient evidence that lagged AI exposure is systematically associated with the dividend payout ratio.

4.4.3 Firm influence and hypothesis decision

The leave-one-firm-out analysis (Appendix Table A2) yields no statistically significant AI coefficient at the 5% level across the 12 exclusion specifications. Excluding HRHO reverses the benchmark coefficient's sign (β = 0.0489; p = 0.6360), while excluding CIEB produces the most negative estimate (β = −0.1319; p = 0.2155). Thus, although the coefficient's direction is sensitive to firm composition, its statistical insignificance persists.

Taken together, the benchmark estimates, restricted wild-cluster inference, alternative specifications, and firm-exclusion checks do not support H2. The findings provide insufficient evidence of a systematic association between lagged AI exposure and dividend payout intensity

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within the study sample, without establishing the absence of an economically meaningful relationship.

4.5 AI Exposure and the Dividend Payout Decision (H3)

H3 examines the association between lagged AI exposure and the cash dividend payout decision. PAYOUT equals one for positive recorded DPS and zero for recorded DPS = 0, with missing values retained as missing. The alternative DIV_TOTAL-based indicator yields identical classifications wherever both measures are observed.

The benchmark employs a two-way fixed-effects linear probability model (LPM), incorporating lagged payout status, lagged AI exposure, current EPS, and five financial controls. Estimation uses 99 complete firm-year observations from 12 firms, with firm-clustered CR1 standard errors and complementary restricted wild-cluster inference. As four firms exhibit no within-firm payout variation, pooled year-effects Logit and Probit models are used as non-equivalent functional-form sensitivity checks.

4.5.1 Payout incidence and benchmark estimates

Table 13 presents the annual incidence of cash-dividend payments across firm-years with observed payout status during 2017–2025.

Table 13. Annual cash-dividend payout incidence, 2017–2025

Year	Observed	Payers	Nonpayers	Payout rate (%)
2017	10	7	3	70.0
2018	11	7	4	63.6
2019	11	9	2	81.8
2020	11	7	4	63.6
2021	12	4	8	33.3
2022	12	8	4	66.7
2023	12	6	6	50.0
2024	12	7	5	58.3
2025	12	8	4	66.7
Total	103	63	40	61.2

Figures are based on 103 observed PAYOUT values out of 108 potential firm-years. Five missing payout statuses are excluded rather than classified as nonpayments. The overall payout rate is calculated as 63/103 = 61.2%.

Cash dividends were paid in 63 of the 103 observed firm-years (61.2%), with annual payout incidence ranging from 33.3% in 2021 to 81.8% in 2019. Unlike DPR, the binary payout indicator remains defined for non-positive earnings: RAYA distributed cash dividends in 2019 and 2020, whereas GBCO recorded no payout in 2017. Consequently, H2 and H3 measure distinct dimensions of payout policy, with 100 defined DPR observations versus 103 observed payout decisions and 96 common observations across their fully controlled regression samples.

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Table 14 presents the benchmark two-way fixed-effects linear probability model for the cash-dividend payout decision, estimated using 99 complete firm-year observations.

Table 14. AI exposure and cash-dividend payout decision: benchmark two-way FE LPM

Regressor	Estimate	Cluster SE	t(11)	p-value	95% CI
Lagged payout indicator	−0.0396	0.1284	−0.308	0.7635	[−0.3223, 0.2431]
Lagged AI exposure	−0.0505	0.1433	−0.352	0.7315	[−0.3660, 0.2650]
EPS	0.0406	0.0185	2.199	0.0501	[−0.0000, 0.0812]
SIZE	−0.3460	0.2029	−1.705	0.1162	[−0.7926, 0.1005]
LEV	−0.1812	0.6117	−0.296	0.7725	[−1.5277, 1.1652]
CASH_RATIO	−1.0550	0.7618	−1.385	0.1935	[−2.7317, 0.6216]
GROWTH	0.3880	0.3462	1.121	0.2863	[−0.3740, 1.1501]
CAPEX_RATIO	0.0790	0.1632	0.484	0.6379	[−0.2802, 0.4381]

Dependent variable: PAYOUT (1 = positive recorded cash DPS; 0 = recorded zero DPS). N = 99; G = 12. Firm and year fixed effects are included but not reported. Standard errors are firm-clustered (CR1), with two-sided inference based on t(11). Coefficients represent conditional changes in fitted payout probability within the linear probability specification.

Lagged AI exposure has a negative but statistically insignificant coefficient (β = −0.0505; p = 0.7315; 95% CI: [−0.3660, 0.2650]). Thus, the benchmark provides insufficient evidence of an association between AI exposure and the subsequent cash-dividend payout decision. EPS exhibits a positive, borderline association (β = 0.0406; p = 0.0501), narrowly missing the conventional 5% significance threshold. The remaining regressors are statistically insignificant at this level.

4.5.2 Finite-cluster inference and model sensitivity

Table 15 examines the sensitivity of the H3 benchmark to alternative control specifications, fixed-effects structures, payout definitions, and binary-response models.

Table 15. H3 alternative specifications: coefficient on lagged AI exposure

Specification	N	AI coefficient	Cluster SE	p-value
Two-way FE LPM (benchmark)	99	−0.0505	0.1433	0.7315
No lagged payout indicator	99	−0.0519	0.1440	0.7254
Reduced controls, two-way FE	99	−0.0336	0.1456	0.8217
Firm FE only	99	0.0034	0.1567	0.9831
Pooled LPM with year effects	99	0.2596	0.1944	0.2086
DIV_TOTAL-based outcome	99	−0.0505	0.1433	0.7315
Pooled year-effects Logit[1]	99	1.9795	1.4866	0.1830

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Specification	N	AI coefficient	Cluster SE	p-value
Pooled year-effects Probit[1]	99	1.0190	0.7550	0.1771

Unless otherwise specified, regressors follow the benchmark. FE-LPM models use firm-clustered CR1 standard errors and t(G−1) inference. Pooled Logit and Probit use company-clustered score-sandwich covariance with finite-cluster correction [G/(G−1)] × [(N−1)/(N−K)] (N = 99, G = 12, K = 17) and asymptotic z-tests; the Probit covariance uses the observed Hessian. [1]Nonlinear link coefficients are not directly comparable with LPM coefficients, and the pooled models do not include firm fixed effects.

Table 16 reports the average marginal effects from the pooled binary-response models and the restricted wild-cluster inference for the benchmark LPM, including the HRHO-exclusion sensitivity.

Table 16. Binary-model average marginal effects and exact wild-cluster inference

Sensitivity / inference	Estimate / |t|	SE	p-value	95% CI or details
Logit: AI average marginal effect	0.2823	0.1957	0.1491	[−0.1013, 0.6659]
Probit: AI average marginal effect	0.2502	0.1812	0.1674	[−0.1050, 0.6055]
Restricted wild-cluster, full sample	0.3520	—	0.7144	2,926 / 4,096 assignments
Restricted wild-cluster, omit HRHO	0.3408	—	0.7031	1,440 / 2,048 assignments

Logit and Probit average marginal effects are computed as sample means of the fitted probability derivatives with respect to lagged AI exposure. Delta-method standard errors incorporate the full corresponding firm-clustered coefficient covariance matrix, with asymptotic z-inference. Wild-cluster rows report absolute null-restricted t statistics rather than coefficient estimates. Reported bootstrap p-values are obtained by complete enumeration of firm-level Rademacher sign assignments.

The alternative specifications yield no statistically significant association between lagged AI exposure and payout incidence. Although the pooled Logit and Probit models produce positive average marginal effects (0.2823 and 0.2502, respectively), both are statistically insignificant and differ in their estimands from the benchmark FE-LPM.

The restricted wild-cluster bootstrap also confirms non-significant benchmark inference (p = 0.7144), with a similar result after excluding HRHO (p = 0.7031). Overall, the results provide insufficient evidence of a systematic association between lagged AI exposure and the dividend payout decision, while offering no stable directional conclusion across specifications.

4.5.3 Firm influence, limitations, and hypothesis assessment

The leave-one-firm-out analysis (Appendix Table A2) yields no statistically significant AI coefficient at the 5% level across the 12 exclusion specifications. Excluding HRHO changes the coefficient to 0.0454 (p = 0.7403), whereas excluding RAYA produces −0.1252 (p = 0.2748), indicating sensitivity in the direction and magnitude of the estimate. Furthermore, the benchmark LPM generates 20 fitted values outside the unit interval (seven below zero and 13 above one), limiting their interpretation as individual probabilities.

Taken together, the benchmark estimates, restricted wild-cluster inference, alternative specifications, and firm-exclusion checks do not support H3. The findings provide insufficient evidence of a systematic association between lagged AI exposure and the subsequent cash-dividend

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payout decision within the study sample. Given the associational design and potential dynamic-panel bias, no causal interpretation is warranted.

4.6 Discussion of Findings in Relation to Prior Literature

This section discusses the findings across the three dimensions of dividend policy and considers their implications in relation to prior literature, accounting for differences in outcome measurement and empirical design.

4.6.1 Overall pattern: three distinct payout outcomes

None of the three benchmark AI parameters is statistically significant at the 5% level under either conventional firm-clustered inference or the restricted wild-cluster bootstrap. However, the estimates represent distinct economic relationships: dividend persistence (H1), payout intensity (H2), and payout incidence (H3). Table 17 translates the coefficients into comparable changes in AI exposure equivalent to one point on the original AI_SCORE scale (0.2 standardized units).

Table 17. Economic-scale translation of the benchmark AI parameters (one AI_SCORE point = 0.2 AI_EXPOSURE units)

Hypothesis	Interpretation of a 0.2-unit exposure difference	Point estimate	95% CR1 t(11) CI
H1	Change in fitted lagged-DPS persistence slope	+0.1177	[−0.0589, +0.2942]
H2	Cash dividends / positive net income, in percentage points	−1.04 pp	[−6.90, +4.82] pp
H3	LPM fitted payout probability, in percentage points	−1.01 pp	[−7.32, +5.30] pp

Estimates and confidence intervals are linear rescalings of the benchmark coefficients and firm-clustered CR1 t(11) intervals, not additional regressions. H1 refers to the conditional lagged-DPS slope; H2 and H3 are expressed in percentage points (pp). The interpretation assumes equal spacing between successive levels of the ordinal AI measure. All intervals include zero.

The estimates indicate no statistically established association between AI exposure and any of the three examined payout dimensions. Nevertheless, their confidence intervals encompass potentially meaningful positive and negative relationships, precluding conclusions of economic equivalence to zero. Moreover, H2 and H3 capture related but distinct payout outcomes using partially overlapping samples and should not be interpreted as independent replications of the same effect.

4.6.2 H1: dividend smoothing versus the traditional persistence literature

The traditional dividend-smoothing literature emphasizes the role of previous payouts and sustainable earnings in corporate distribution decisions (Lintner, 1956); (Brav, Graham, Harvey, & Michaely, 2025). (Leary & Michaely, 2011) further demonstrate that smoothing varies systematically with firm characteristics, including size, earnings volatility, and growth opportunities.

Extending this literature, H1 examines whether corporate AI exposure moderates the association between past and current dividends. Although the interaction coefficient is positive in the benchmark specification, it is statistically insignificant under both conventional and wild-cluster inference. Its sensitivity to HRHO's inclusion further limits evidence of a stable moderation effect.

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Meanwhile, the positive association between EPS and DPS (β = 0.1190; p = 0.0305) is consistent with the relevance of earnings emphasized in traditional payout models.

Overall, the findings do not challenge the established dividend-smoothing literature but provide insufficient evidence that AI exposure introduces an additional systematic moderation effect within the observed sample.

4.6.3 H2: cash-dividend intensity versus AI and payout studies

(Fan, Chen, & Chen, 2026) report a significant negative association between corporate AI adoption and cash dividend distributions among Chinese firms, identifying investment crowding-out and operational risk as potential mechanisms. The present study also yields a negative H2 coefficient, but the association is statistically insignificant (β = −0.0520; p = 0.7037). These findings are not directly contradictory, given differences in institutional context, AI measurement, and dividend outcomes. (Fan, Chen, & Chen, 2026). examine AI application intensity and cash dividend distributions, whereas this study measures institutional AI exposure and the cash-dividend-to-positive-net-income ratio.

In the Egyptian context, (Abdel-Gawad, Sakr, & Abdou, 2021) identify profitability, free cash flow, and managerial ownership as relevant determinants of payout ratios. Similarly, (El Khayati & Saidi, 2026) highlight profitability, firm size, and historical payout behavior in predicting Moroccan payout ratios using explainable machine learning. However, the latter study employs AI as an analytical method rather than examining corporate AI exposure as a financial-policy determinant.

The H2 findings therefore extend the emerging AI–dividend literature to a distinct measurement framework and institutional setting, without establishing a systematic relationship between AI exposure and payout intensity. Although investment–distribution trade-offs remain economically plausible, the present estimates do not identify the mechanisms underlying such a relationship.

4.6.4 H3: propensity to pay and the corporate life-cycle literature

The dividend literature distinguishes the decision to distribute cash dividends from the amount distributed. (Fama & French, 2001) document changes in corporate payout propensity, while (DeAngelo, DeAngelo, & Stulz, 2006) link dividend payment to the balance between earned and contributed capital. (Denis & Osobov, 2008) further identify firm size, profitability, and retained earnings as important correlates of dividend payment across international markets. (Abdel-Gawad, Sakr, & Abdou, 2021) similarly examine the payout decision separately from the payout ratio in the Egyptian context.

Extending this distinction, H3 investigates whether corporate AI exposure is associated with the subsequent decision to pay cash dividends. The benchmark coefficient is statistically insignificant (β = −0.0505; p = 0.7315), a finding consistent with the restricted wild-cluster inference and firm-exclusion checks. Moreover, the pooled Logit and Probit sensitivities produce positive but insignificant AI estimates, providing no stable directional evidence across specifications.

These findings do not establish an additional systematic association between AI exposure and payout propensity within the study sample. They neither contradict the established life-cycle literature nor constitute a direct test of its proposed mechanisms, as the present analysis does not estimate the earned-to-contributed capital relationship central to that framework.

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4.6.5 Why economically relevant AI findings need not translate into payouts

Evidence of AI-related economic benefits does not necessarily imply corresponding changes in dividend policy. (Babina, Fedyk, He, & Hodson, 2024) associate firm-level AI investment, measured using employee resumes, with product innovation and corporate growth. Similarly, (Laviola, Renzi, Taragoni, & Vagnani, 2026) find that AI investment announcements alone do not generate significant positive abnormal returns, while their strategic-alliance context influences market responses. These studies examine different dimensions of AI engagement and economic outcomes rather than its relationship with dividend distributions.

The present study measures documented stages of institutional AI exposure rather than investment intensity, realized productivity gains, or distributable cash flows. Accordingly, the insignificant payout findings may reflect differences between observable AI engagement and its eventual financial implications. Potential explanations include delayed realization of benefits, competing investment priorities, and variation in deployment intensity. These mechanisms remain avenues for future investigation rather than established explanations of the present results.

4.6.6 Contribution and limits of the cross-study comparison

Building on the traditional dividend-policy literature and emerging evidence on corporate AI adoption, this study examines three distinct payout outcomes within a unified Egyptian firm-level panel. Its contribution lies in applying a documented, stage-based AI-exposure measure to dividend persistence, payout intensity, and payout incidence, thereby extending existing evidence beyond individual payout dimensions and alternative AI measurement frameworks.

The findings provide no statistically significant evidence of an AI-related association across the three benchmark outcomes. However, the confidence intervals accommodate effects of either sign, and the estimates remain subject to sample-size constraints, specification sensitivity, and potential dynamic-panel bias. Accordingly, the results contribute outcome-specific associational evidence rather than establishing economic equivalence to zero or identifying a causal effect of corporate AI exposure on dividend policy.

4. Conclusion and Implications

5.1. Conclusion

This study examines the association between corporate AI exposure and three distinct dimensions of cash-dividend policy—dividend persistence, payout intensity, and payout incidence—using a panel of 12 Egyptian listed firms over 2017–2025. AI exposure is measured through a documented, stage-based index, and the empirical analysis employs two-way fixed-effects models with firm-clustered inference, complemented by restricted wild-cluster bootstrap procedures.

The findings do not provide statistically significant support for any of the three hypotheses. Neither the benchmark estimates nor the complementary inference and sensitivity analyses establish a systematic association between AI exposure and the examined payout outcomes. The estimated H1 interaction is also sensitive to the exclusion of HRHO, warranting caution in interpreting its magnitude. Nevertheless, the confidence intervals remain compatible with potentially meaningful associations in either direction; statistical non-significance should not be interpreted as economic equivalence to zero.

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5.2. Contributions to the Corporate-Finance and AI Literature

This study contributes to the emerging AI–dividend literature by examining documented corporate AI exposure across three distinct dimensions of cash-dividend policy within a unified empirical framework. Building on established research on dividend smoothing and payout propensity (Lintner, 1956); (Fama & French, 2001); (Leary & Michaely, 2011), it investigates the potential moderating role of AI exposure in conditional dividend persistence, alongside its associations with payout intensity and payment incidence.

Related research has already examined payout stability in technology-intensive firms (Barros, Verga Matos, Miranda Sarmento, & Rino Vieira, 2023) and distinguished dividend-payment likelihood from payout levels in the context of digital-finance development (Song, Lee, & Wang, 2025). The present contribution therefore does not lie in introducing these payout dimensions individually, but in examining their potentially differentiated associations with firm-level AI exposure within a common empirical setting.

The study also extends the measurement perspective of existing AI research. Whereas (Barrios, Campbell, Johnson, & Liu, 2025) investigate the informativeness of corporate AI disclosures, the present study employs an evidence-graded, stage-based index to distinguish documented corporate engagement from generic AI references. This measure captures identifiable stages of technological engagement rather than investment intensity or realized financial returns.

In terms of empirical evidence, (Fan, Chen, & Chen, 2026) report a negative association between AI application intensity and cash-dividend distributions among Chinese firms, while (Damle & Sinha, 2025) associate corporate AI investment with increased cash holdings and reduced payouts among US firms. The present study complements these findings by examining distinct dividend-policy outcomes in Egypt. Its statistically non-significant estimates do not establish an equivalent negative relationship, although differences in measurement, institutional context, and outcome definitions preclude interpreting this as a direct contradiction. Relative to earlier Egyptian evidence distinguishing payout decisions from payout ratios ((Abdel-Gawad, Sakr, & Abdou, 2021), the analysis additionally incorporates documented AI exposure and conditional dividend persistence.
Overall, the contribution lies in integrating a stage-specific AI-exposure measure with outcome-specific dividend analysis, while providing context-dependent evidence that leaves the direction and economic magnitude of these relationships open to further investigation.

5.3. Implications for Corporate Managers, Investors, and Disclosure Users

For corporate managers, the findings indicate that documented AI engagement, considered in isolation, does not provide a statistically established basis for revising dividend policy. Capital-allocation decisions should continue to account for earnings sustainability, cash generation, technological investment requirements, and financial flexibility. The liquidity considerations identified in prior AI-investment research (Damle & Sinha, 2025) further reinforce the importance of assessing technology-related commitments alongside other financing needs, rather than presuming a uniform dividend response.

For investors and financial analysts, the results support evaluating AI-related information alongside conventional financial indicators. The documented exposure score should not be treated as an independently established predictor of future dividend behavior, and its incremental forecasting value requires separate examination. Equally, the absence of statistically significant associations in

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the present sample should not be interpreted as evidence that AI-related investment or implementation has no potential financial implications.

For firms, disclosure preparers, and standard-setters, clearer distinctions between AI awareness, planned investment, operational implementation, strategic integration, and realized economic benefits could improve the interpretability and comparability of corporate reporting. Consistent with the importance of disclosure informativeness highlighted by (Barrios, Campbell, Johnson, & Liu, 2025), more specific documentation of technological engagement may also facilitate more precise measurement and subsequent financial research.

5.4. Directions for Future Research

Future research could extend the examination of corporate AI exposure and dividend policy to larger samples and longer time horizons, while developing measures that distinguish documented AI engagement, deployment intensity, associated investment expenditure, and realized financial returns. Further investigation into the timing of AI-related economic benefits and the roles of cash-flow volatility, financing constraints, and growth opportunities may help clarify whether the relationship between AI exposure and dividend decisions varies across implementation stages and firms' financial conditions.

Appendix: Supplementary Estimation Tables

Appendix Table A1. H1 leave-one-firm-out influence analysis

Omitted firm	N	Interaction β	Clustered SE	t-based p	95% confidence interval
ADIB	90	0.5946	0.4119	0.1795	[-0.3232, 1.5123]
ALCN	91	0.4458	0.4069	0.2990	[-0.4609, 1.3524]
CIB	90	0.6369	0.3860	0.1300	[-0.2232, 1.4969]
CIEB	90	0.3686	0.5379	0.5088	[-0.8300, 1.5672]
EFIG	92	0.5909	0.4093	0.1794	[-0.3211, 1.5029]
ETEL	90	0.6686	0.3734	0.1036	[-0.1634, 1.5007]
FWRY	91	0.6206	0.4024	0.1540	[-0.2760, 1.5172]
GBCO	90	0.6891	0.4156	0.1283	[-0.2370, 1.6151]
HRHO	90	-0.0147	0.3497	0.9673	[-0.7939, 0.7644]
QNBA	90	0.7620	0.3675	0.0649	[-0.0568, 1.5807]
RAYA	90	0.6292	0.4422	0.1852	[-0.3560, 1.6144]
TALM	95	0.6027	0.3900	0.1533	[-0.2663, 1.4718]

The outcome is DPS; the focal coefficient is DPS(t−1) × AI(t−1). Each regression omits exactly one of the original 12 firms and retains the remaining regressors and firm and year fixed effects. All

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rows use G = 11 firm clusters, CR1 standard errors, and two-sided t(10) inference. The full-sample H1 estimate (N = 99) remains the benchmark; excluding HRHO materially changes the point estimate without yielding statistical significance.

Appendix Table A2. H2 and H3 leave-one-firm-out influence analyses

Omitted firm	H2 N	H2 AI β	H2 p	H3 N	H3 AI β	H3 p
ADIB	90	0.0004	0.9980	90	−0.0726	0.6632
ALCN	91	−0.0668	0.6451	91	−0.0007	0.9969
CIB	90	−0.0530	0.7246	90	−0.0619	0.7178
CIEB	90	−0.1319	0.2155	90	−0.0896	0.4921
EFIG	91	−0.0664	0.6430	92	−0.0310	0.8507
ETEL	90	−0.0461	0.8101	90	−0.0572	0.7797
FWRY	90	−0.0750	0.6267	91	−0.0905	0.5779
GBCO	91	−0.0754	0.6015	90	−0.0807	0.6238
HRHO	90	0.0489	0.6360	90	0.0454	0.7403
QNBA	90	−0.0395	0.7897	90	0.0073	0.9610
RAYA	92	−0.0549	0.6944	90	−0.1252	0.2748
TALM	94	−0.0467	0.7523	95	−0.0624	0.6900

H2 is the primary DPR two-way fixed-effects model with five financial controls; H3 is the two-way fixed-effects linear probability model including lagged payout status, lagged AI exposure, EPS, and the same five controls. The two models retain their own complete-case membership. Each row excludes one firm (G = 11); p-values are two-sided, based on firm-clustered CR1 standard errors and t(10). The original N = 99 full-sample specifications remain the benchmarks. No firm-exclusion estimate is significant at the 5% level.

Appendix Table A3. Listing-year eligibility sensitivities for all three hypotheses

Hypothesis	Eligibility rule	N	Focal β (CR1 SE)	p, t(11)
H1	Baseline	99	0.588390 (0.401090)	0.170381
H1	Outcome year at/after listing	96	0.589901 (0.408754)	0.176840
H1	Outcome and AI lag year at/after listing	94	0.577198 (0.396073)	0.172982
H2	Baseline	99	−0.051982 (0.133164)	0.703721
H2	Outcome year at/after listing	94	−0.075469 (0.135673)	0.589169
H2	Outcome and AI lag year at/after listing	91	−0.070541 (0.149072)	0.645323

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Hypothesis	Eligibility rule	N	Focal β (CR1 SE)	p, t(11)
H3	Baseline	99	−0.050459 (0.143343)	0.731480
H3	Outcome year at/after listing	96	−0.078453 (0.146667)	0.603358
H3	Outcome and AI lag year at/after listing	94	−0.048893 (0.164517)	0.771859

The retrospective full-sample benchmark retains the approved historical company-year records. Filter 1 requires the outcome year to be at or after the recorded annual listing year; Filter 2 additionally requires the preceding AI-exposure source year to be at or after listing. All models retain their respective benchmark regressors, firm and year fixed effects, and company-clustered CR1 standard errors. Conventional two-sided p-values use t(11), with G = 12 firms. No wild-bootstrap results are claimed for the filtered samples. The annual listing-year indicator does not establish the precise within-year admission date. Neither restriction changes the 5% decisions for H1–H3.

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