



International Journal of Research Publication and Reviews

Journal Homepage: www.ijrpr.com ISSN 2582-7421

Navigating the Algorithmic Boardroom: How AI-Driven Predictive Analytics Alter Executive Risk Appetite and Strategic Capital Allocation Decisions

Chenchu Swaraj Kumar¹, Dr. Md. Mazharunnisa²

¹Research Scholar, Department of Business Administration, KL Business School, KLEF, Vaddeswaram, Guntur, AP

²Research Guide, Associate Professor, KL Business School, KLEF

ABSTRACT

AI-driven predictive analytics now sit inside many of the routines senior executives use to weigh uncertainty, rank investment options, and commit capital. This study asks whether heavier use of these tools goes along with a higher executive risk appetite and a bigger share of capital in high-uncertainty strategic projects. Building on upper echelons theory, the behavioral theory of the firm, and prospect theory, it tests four hypotheses on a cross-sectional dataset of 300 senior executives, using a chi-square test of independence, one-way ANOVA with Tukey post-hoc comparisons, and two simple linear regressions. The dataset is simulated for illustration (Section 4.1), so the results show how the analytical pipeline works and should not be read as empirical findings about real executives. Within this dataset, AI adoption level and risk-appetite category are significantly associated, $\chi^2(4, N = 300) = 79.17, p < .001$, Cramér's $V = .36$. Mean risk appetite climbs from low to medium to high adopters (4.15, 4.75, 5.36), $F(2, 297) = 44.75, p < .001, \eta^2 = .23$. AI analytics usage predicts risk appetite ($b = 0.58, R^2 = .36$), and risk appetite in turn predicts the percentage of capital placed in high-risk projects ($b = 3.67, R^2 = .35$). Supplementary analyses suggest these relationships hold after controlling for firm size, sector and executive role, and that the link between usage and capital allocation runs through risk appetite. The pattern fits a view of predictive analytics as an input that reduces uncertainty and so widens, rather than narrows, the risks executives will accept. It also raises governance questions about over-reliance and model risk.

Keywords: predictive analytics; artificial intelligence; risk appetite; capital allocation; strategic decision-making; corporate governance; executive behavior

1. Introduction

For a long time, boardrooms committed capital under uncertainty by combining financial models, managerial experience, and negotiated judgment. That mix has been shifting over the past decade. Machine-learning forecasts of demand, credit exposure, supply-chain disruption, and project returns now land on executive dashboards next to human assessments, and sometimes ahead of them. Brynjolfsson and McAfee (2014) describe cognitive work once reserved for skilled professionals as increasingly shared with machines, and Agrawal, Gans and Goldfarb (2018) argue that the economic core of AI is a fall in the cost of prediction, which changes what judgment is worth.

If prediction gets cheaper and more accurate, an obvious question follows for strategy and governance: does it change how much risk executives are prepared to take? Two competing intuitions exist. The *emboldening* view holds that better forecasts reduce perceived uncertainty, so executives accept more ambitious bets and put more capital into high-variance projects. The *constraining* view holds that algorithmic transparency exposes downside scenarios that intuition would have missed, which pushes executives toward caution and toward simply following model outputs. Existing work on algorithm aversion and appreciation (Dietvorst, Simmons and Massey, 2015; Logg, Minson and Moore, 2019) tells us whether people take algorithmic advice. It says much less about how sustained analytical support shapes the *risk posture* and *capital allocation* choices of top decision-makers.

This paper takes up that gap through four questions. (RQ1) Is the level of AI analytics adoption associated with the executive's risk-appetite category? (RQ2) Does mean risk appetite differ across low, medium and high adopters? (RQ3) Does the intensity of AI analytics use predict risk appetite? (RQ4) Does risk appetite, in turn, predict the proportion of capital allocated to high-risk strategic projects? The study adds to the strategic decision-making literature in three ways. It ties technology-use intensity to a behavioral construct (risk appetite) instead of only to performance outcomes. It connects that construct to an observable resource-allocation outcome. And it offers a transparent, replicable workflow in spreadsheet software that practitioners and students can reuse.

The rest of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses, Section 3 sets out the conceptual framework, and Section 4 describes the research design. Section 5 reports the analysis. Sections 6 to 8 cover the findings, implications and limitations, and Section 9 concludes.

2. Literature Review and Hypothesis Development

2.1 Executive risk appetite and strategic choice

Risk appetite, meaning the amount and type of uncertainty a decision-maker will accept in pursuit of objectives, is a core construct in strategic management. March and Shapira (1987) showed that managers do not see risk as a plain trade-off between variance and return. They react to targets, aspirations, and how controllable an outcome feels. Prospect theory (Kahneman and Tversky, 1979) adds that people judge outcomes against reference points and weight losses more heavily than equivalent gains, so risk attitudes depend on context. Upper echelons theory (Hambrick and Mason, 1984) holds that organizational outcomes, strategic choices included, mirror the cognitions and values of top managers. Taken together, these ideas suggest that anything changing how executives perceive uncertainty, a new source of information for example, could shift how much risk they take.

2.2 AI-driven predictive analytics in decision-making

Predictive analytics applies statistical and machine-learning models to historical and real-time data to forecast outcomes. Early evidence tied data-driven decision-making to higher productivity and performance (Brynjolfsson, Hitt and Kim, 2011; McAfee and Brynjolfsson, 2012), and Davenport and Harris (2007) documented analytics as a source of competitive advantage. More recent work paints a more complicated picture. Shrestha, Ben-Menahem and von Krogh (2019) show that how well AI fits depends on how specific the decision space is and how much interpretability is needed, while Raisch and Krakowski (2021) describe an automation-augmentation paradox, in which using AI to replace human judgment and using it to support that judgment can pull organizations in opposite directions. Absorptive-capacity logic (Cohen and Levinthal, 1990) suggests firms gain most when they already have the knowledge to interpret and act on new analytical inputs, which fits the idea that effects differ across adoption levels.

2.3 Bounded rationality and the behavioral theory of the firm

Simon (1955) argued that decision-makers, limited by information and cognitive capacity, satisfice rather than optimize. Cyert and March (1963) extended the point to organizations, which rely on routines and uncertainty avoidance to keep decisions stable. Predictive analytics loosens some of these limits. It widens the information executives can process and supplies quantified probabilities that make uncertainty look more manageable. Under those conditions perceived uncertainty falls and, in line with the emboldening view, the acceptable risk threshold may rise. Overconfidence in model outputs can also push risk-taking beyond what the underlying uncertainty warrants, a point that returns in the governance discussion in Section 6.

2.4 Capital allocation under uncertainty

Capital allocation is the most consequential expression of executive risk appetite, since it decides which projects get scarce resources and which do not. Bromiley (1991) demonstrated that risk taking and performance are reciprocally related, and Bowman's (1980) risk-return paradox reminds researchers that low-risk firms do not always earn lower returns. Allocation choices can be observed and quantified, so the share of capital committed to high-uncertainty projects gives a behavioral counterpart to attitudinal risk appetite.

2.5 Hypotheses

Drawing these strands together, the study proposes the following hypotheses, stated in alternative form:

- H1: AI adoption level (low, medium, high) is associated with the executive's risk-appetite category (low, moderate, high).
- H2: Mean risk-appetite score differs significantly across low, medium and high AI-adoption groups, increasing with adoption.
- H3: AI analytics usage intensity has a significant positive linear effect on executive risk appetite.
- H4: Executive risk appetite has a significant positive linear effect on the percentage of capital allocated to high-risk strategic projects.

3. Conceptual Framework

The framework proposes a two-step behavioral pathway. AI-driven predictive analytics, measured by adoption level and usage intensity, shapes how executives perceive and tolerate uncertainty, captured here as risk appetite. Risk appetite then shapes a resource-allocation outcome: the percentage of the capital budget directed to high-uncertainty strategic projects. In short, AI analytics adoption and usage → executive risk appetite → high-risk capital allocation. Firm size, sector and executive role serve as descriptive context in the primary tests and as controls in the supplementary analysis in Section 5.7. The hypotheses map onto the pathway as follows: H1 and H2 look at group-level differences in risk appetite by adoption level, H3 tests the first link as a continuous relationship, and H4 tests the second link.

4. Research Methodology

4.1 Research design and sample

The study uses a cross-sectional, quantitative, survey-based design. The intended population is senior decision-makers (CEOs, CFOs, chief strategy officers and board members) in medium and large organizations across five sectors: manufacturing; banking, financial services and insurance (BFSI); information technology; healthcare; and energy and infrastructure.

Data disclosure. The dataset analyzed here is simulated. To demonstrate the full analytical workflow, 300 synthetic respondents were generated with a fixed random seed (2026), 100 in each AI-adoption group. The results in Section 5 therefore illustrate the method and the expected form of the findings. They are not evidence about real executives and should not be cited as such. The workbook that accompanies this paper recalculates every statistic once real responses are pasted into the Data sheet. The simulated sample is spread across sectors (Healthcare 22.3%, IT and Technology 20.3%, BFSI 19.3%, Manufacturing 19.0%, Energy and Infrastructure 19.0%), firm sizes (Small 31.3%, Medium 36.7%, Large 32.0%) and roles (CEO 23.0%, CFO 24.3%, CSO 27.7%, Board Member 25.0%).

Table 1. Sample profile ($N = 300$, simulated)

Sector	n	%	Firm size	n	%	Role	n	%
Manufacturing	57	19.0	Small	94	31.3	CEO	69	23.0
BFSI	58	19.3	Medium	110	36.7	CFO	73	24.3
IT & Technology	61	20.3	Large	96	32.0	CSO	83	27.7
Healthcare	67	22.3				Board Member	75	25.0
Energy & Infra.	57	19.0						

Source: Excel workbook, Descriptives sheet.

4.2 Measures

- AI adoption level (categorical): low, medium or high, based on the breadth of AI-enabled analytics embedded in strategic decision processes.
- AI Analytics Usage Index (continuous, 1 to 5): composite mean of Likert items capturing how frequently and how deeply executives use AI-generated forecasts, scenarios and risk scores.
- Risk Appetite Score (continuous, 1 to 7): composite mean of Likert items measuring willingness to accept uncertainty in strategic investments. For the chi-square analysis it is recoded as Low (below 4.0), Moderate (4.0 to below 5.0) and High (5.0 or above).
- High-Risk Capital Allocation (%): percentage of the annual capital budget committed to high-uncertainty strategic projects such as new markets, emerging technologies and acquisitions.

With real data, the internal consistency of each multi-item scale (Cronbach's alpha, for example) and construct validity should be reported here. These statistics cannot be computed for simulated data.

4.3 Analytical procedures

The primary analyses were built with Microsoft Excel worksheet formulas, so results update automatically when the data are replaced, and were independently recomputed in Python (NumPy and SciPy), with agreement to the reported precision. The significance level was $\alpha = .05$ throughout.

- Chi-square test of independence (H1): observed frequencies were cross-tabulated, expected frequencies were computed from the marginal totals, and the test statistic, degrees of freedom, p-value and effect size (Cramér's V) followed from those. The smallest expected cell count (24.0) clears the conventional threshold of 5.
- One-way ANOVA (H2): between- and within-group sums of squares, mean squares, the F statistic, p-value, critical value and eta squared were computed, followed by Tukey HSD pairwise comparisons (studentized range $q = 3.33$ for $k = 3$, $\alpha = .05$, large df). Homogeneity of variance was screened with the ratio of the largest to the smallest group standard deviation (1.33, below the rule-of-thumb value of 2). Levene's test was marginal, $p = .063$, but the balanced design ($n = 100$ per group) keeps the ANOVA robust to modest heterogeneity.
- Simple linear regression (H3, H4): for both models the intercepts, slopes, standard errors, t statistics, p-values, 95% confidence intervals, R^2 , adjusted R^2 , standard error of the estimate and overall F test were computed.

- Supplementary analyses (Section 5.7): the two regressions were re-estimated with controls for firm size, sector and role, and the indirect effect of usage on capital allocation through risk appetite was estimated using a percentile bootstrap (5,000 resamples).

Effect sizes are interpreted with the conventions of Cohen (1988).

4.4 Ethical considerations

In a real study, participation should be voluntary and anonymous, informed consent obtained, responses stored securely and reported only in aggregate, and institutional ethics approval secured before any data collection.

5. Data Analysis and Results

5.1 Descriptive statistics

Table 2 presents descriptive statistics and Pearson correlations. Executives reported moderately high AI usage ($M = 3.13$, $SD = 1.06$) and above-midpoint risk appetite ($M = 4.75$, $SD = 1.03$). On average, 21.6% ($SD = 6.35$) of capital went to high-risk projects. Skewness values ranged from -0.23 to 0.00, so the distributions are roughly symmetric and suit parametric analysis. All three variables were positively and significantly related.

Table 2. Descriptive statistics and correlations ($N = 300$)

Variable	Mean	SD	Min	Max	1	2	3
1. AI Analytics Usage Index	3.13	1.06	1.00	5.00	1		
2. Risk Appetite Score	4.75	1.03	1.99	7.00	.598	1	
3. High-Risk Capital Allocation (%)	21.60	6.35	0.60	39.90	.379	.592	1

Note: All correlations significant at $p < .001$. Source: Excel workbook, Descriptives sheet.

5.2 Chi-square test of independence (H1)

H0: AI adoption level and risk-appetite category are independent. The distribution of risk-appetite categories differed markedly across adoption groups (Table 3, Figure 1). Among low adopters, 47% fell into the low risk-appetite category and 21% into the high category. Among high adopters the pattern reversed, with only 6% in the low category and 74% in the high. The association was statistically significant, $\chi^2(4, N = 300) = 79.17$, $p < .001$, well above the critical value of 9.49. Cramér's $V = .36$ indicates a medium-to-large association. H1 is supported.

Table 3. AI adoption level by risk-appetite category, n (row %)

AI adoption	Low risk	Moderate risk	High risk	Total
Low	47 (47%)	32 (32%)	21 (21%)	100
Medium	19 (19%)	44 (44%)	37 (37%)	100
High	6 (6%)	20 (20%)	74 (74%)	100
Total	72 (24%)	96 (32%)	132 (44%)	300

Note: $\chi^2(4) = 79.17$, $p < .001$, Cramér's $V = .36$. Expected counts per cell: 24, 32 and 44 for the low, moderate and high columns respectively.

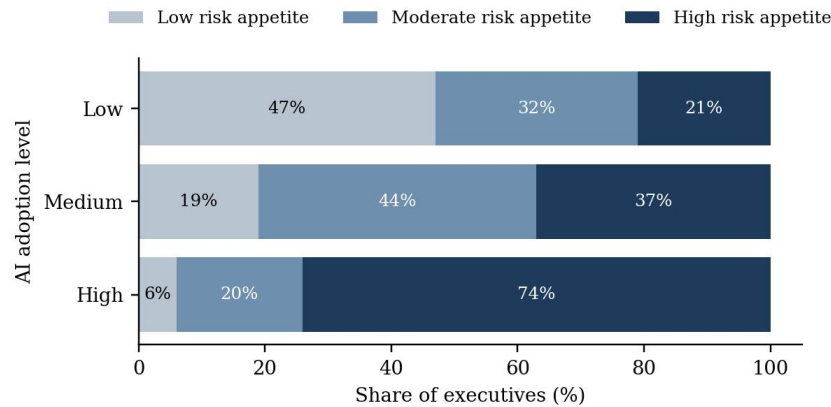


Figure 1. Risk-appetite category by AI adoption level (row percentages).

5.3 One-way ANOVA (H2)

H0: mean risk-appetite scores are equal across the three adoption groups. Mean scores rose steadily with adoption: low ($M = 4.15$, $SD = 1.01$), medium ($M = 4.75$, $SD = 0.92$) and high ($M = 5.36$, $SD = 0.76$). The omnibus test was significant, $F(2, 297) = 44.75$, $p < .001$, against a critical value of 3.03, and adoption level accounted for 23.2% of the variance in risk appetite ($\eta^2 = .23$, a large effect). Tukey HSD comparisons (critical difference = 0.30) showed that all three pairwise differences were significant: low versus medium (0.60), medium versus high (0.61), and low versus high (1.21). H2 is supported.

Table 4. One-way ANOVA: risk-appetite score by AI adoption level

Source	SS	df	MS	F	p
Between groups	72.83	2	36.42	44.75	< .001
Within groups	241.67	297	0.81		
Total	314.50	299			

Note: $\eta^2 = .23$. Group means: Low 4.15, Medium 4.75, High 5.36 ($n = 100$ each). Source: Excel workbook, ANOVA sheet.

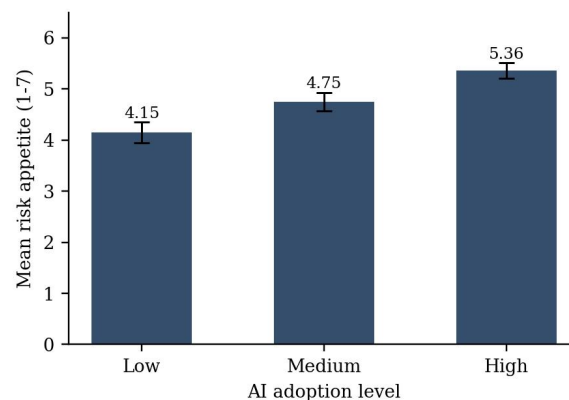


Figure 2. Mean risk-appetite score by AI adoption level (error bars: 95% CI).

5.4 Simple linear regression: AI usage and risk appetite (H3)

Model 1 regressed Risk Appetite Score on the AI Analytics Usage Index. The model was significant, $F(1, 298) = 165.93$, $p < .001$, and explained 35.8% of the variance (adjusted $R^2 = .356$; standard error of the estimate = 0.82). The slope was positive and significant ($b = 0.58$, $SE = 0.045$, $t = 12.88$, $p < .001$, 95% CI [0.49, 0.67]): each one-point rise in usage intensity goes with a 0.58-point rise in risk appetite. The fitted equation is Risk Appetite = $2.936 + 0.581 \times \text{AI Usage}$. H3 is supported.

5.5 Simple linear regression: risk appetite and capital allocation (H4)

Model 2 regressed the percentage of capital allocated to high-risk projects on Risk Appetite Score. The model was significant, $F(1, 298) = 161.08$, $p < .001$, with $R^2 = .351$ (adjusted $R^2 = .349$; standard error of the estimate = 5.12 percentage points). The slope ($b = 3.67$, $SE = 0.289$, $t = 12.69$, $p < .001$, 95% CI [3.10, 4.23]) means that a one-point increase in risk appetite goes with about 3.7 additional percentage points of the capital budget committed to high-risk projects. The fitted equation is Capital Allocation % = $4.169 + 3.666 \times \text{Risk Appetite}$. H4 is supported.

Table 5. Regression results

Statistic	Model 1: AI Usage → Risk Appetite	Model 2: Risk Appetite → High-Risk Capital %
Intercept (SE)	2.936 (0.149), $p < .001$	4.169 (1.405), $p = .003$
Slope b1 (SE)	0.581 (0.045)	3.666 (0.289)
t (slope), p	12.88, $< .001$	12.69, $< .001$
95% CI for slope	[0.492, 0.669]	[3.098, 4.235]
R^2 / Adjusted R^2	.358 / .356	.351 / .349
Std. error of estimate	0.823	5.123
$F(1, 298)$, p	165.93, $< .001$	161.08, $< .001$

Note: $N = 300$. Source: Excel workbook, Regression sheet.

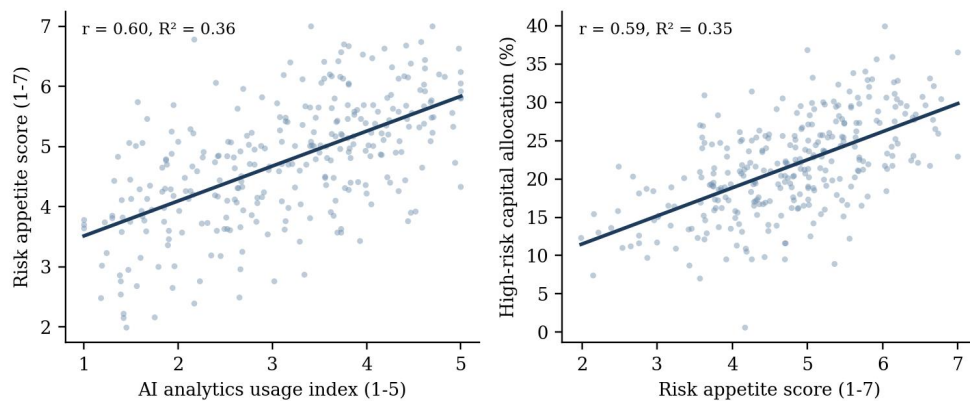


Figure 3. Scatter plots with fitted regression lines: (left) usage and risk appetite; (right) risk appetite and high-risk capital allocation.

5.6 Summary of hypothesis tests

Hypothesis	Test	Key statistic	Decision
H1: Adoption level associated with risk category	Chi-square	$\chi^2(4) = 79.17$, $p < .001$, $V = .36$	Supported
H2: Risk appetite differs by adoption level	One-way ANOVA + Tukey	$F(2, 297) = 44.75$, $p < .001$, $\eta^2 = .23$	Supported
H3: AI usage raises risk appetite	Linear regression	$b = 0.58$, $R^2 = .36$, $p < .001$	Supported
H4: Risk appetite raises high-risk capital share	Linear regression	$b = 3.67$, $R^2 = .35$, $p < .001$	Supported

5.7 Supplementary analyses: controls and indirect effect

Two checks address the limits of the simple regressions. First, both models were re-estimated with dummy-coded firm size, sector and executive role. The usage slope for risk appetite barely moved ($b = 0.58$, $SE = 0.046$, $p < .001$; $R^2 = .37$), and the risk-appetite slope for capital allocation stayed large and significant when usage and the controls were included ($b = 3.54$, $SE = 0.368$, $p < .001$; $R^2 = .36$).

Second, risk appetite and usage were entered together to predict capital allocation. Usage no longer had a significant direct effect ($b = 0.23$, $SE = 0.350$, $p = .51$), while risk appetite kept its effect ($b = 3.52$, $SE = 0.361$, $p < .001$; $R^2 = .35$). The indirect effect of usage on capital allocation through risk appetite was 2.04 percentage points per one-point increase in usage, with a 95% bootstrap confidence interval of [1.60, 2.51]. That is consistent with risk appetite carrying the association between usage and allocation, although with cross-sectional data it cannot establish causal mediation.

6. Discussion

The four tests point the same way: executives who rely more heavily on AI-driven predictive analytics report a higher risk appetite and commit a larger share of capital to high-uncertainty projects. That fits the emboldening view better than the constraining one. One plausible mechanism, grounded in bounded rationality (Simon, 1955), is that predictive models make uncertainty look more measurable, so the perceived cost of acting under uncertainty drops. The supplementary analysis in Section 5.7 sits comfortably with this account. The direct link between usage and allocation disappears once risk appetite is held constant, and the bootstrap indirect effect of about 2.0 percentage points is close to the product of the two simple slopes ($0.581 \times 3.666 \approx 2.1$).

The steady rise across adoption levels, together with the large effect sizes, suggests the relationship is not confined to the extreme groups. Still, three cautions apply. First, the data are simulated, so the size and direction of the effects reflect the parameters used to generate them and say nothing yet about real boardrooms. Second, a positive association between analytics and risk taking is not automatically a good thing. If executives treat model outputs as more certain than they are, higher risk appetite may reflect overconfidence rather than better-calibrated judgment, a worry that echoes the automation-augmentation tension identified by Raisch and Krakowski (2021). Third, cross-sectional data cannot establish the direction of causation; risk-tolerant executives may just as well be the ones more inclined to adopt advanced analytics.

7. Implications

7.1 Theoretical implications

The framework extends upper echelons and behavioral theories by treating AI analytics as an informational context that shifts the risk cognition of top managers, and by tying that cognition to an observable allocation outcome. It suggests that research on technology adoption should look beyond performance to the behavioral channels through which technology changes strategic choices.

7.2 Managerial and governance implications

- Boards should check whether a rise in risk appetite after analytics adoption comes with proportionate gains in forecast accuracy and downside controls.
- Model-risk governance, including validation, documentation of assumptions, and stress testing, belongs inside capital-allocation committees.
- Firms should train executives to read probabilistic outputs and confidence intervals, so that point forecasts are not mistaken for certainties.
- Capital-allocation policies could set explicit ceilings on high-risk exposure, keeping any increase in appetite within the organization's stated risk tolerance.

8. Limitations and Future Research

The most important limitation is that the empirical section rests on simulated data, so its substantive conclusions remain illustrative until real responses replace it. Even with real data, the design would be cross-sectional and self-reported, which invites common-method bias, social desirability, and reverse causality. Controls covered only firm size, sector and role; executive tenure, prior performance and firm risk profile were not modeled, and the three-band categorization of risk appetite depends on the chosen cut-offs. Future research could use structural equation modeling or multilevel models, test mediation with real data, adopt longitudinal or quasi-experimental designs around analytics implementation, draw on objective capital-expenditure records, and examine moderators such as algorithmic transparency, board composition and regulatory environment.

9. Conclusion

This paper examined how AI-driven predictive analytics relate to executive risk appetite and strategic capital allocation. Using chi-square, ANOVA and linear regression on an illustrative dataset, all four hypotheses were supported: higher AI adoption and usage went with greater risk appetite, and greater

risk appetite went with a larger share of capital placed in high-risk projects. The results cast predictive analytics as a force that can widen executive risk tolerance, which opens the door to bolder strategy while demanding stronger governance. As boardrooms grow more algorithmic, the real challenge is not just adopting AI but making sure the confidence it generates is matched by sound judgment and proper oversight.

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Appendix A. Excel Workbook Guide

The accompanying workbook (Algorithmic_Boardroom_Analysis.xlsx) contains the following sheets:

- README: purpose, hypotheses, variable definitions and assumptions.
- Data: 300 rows of respondent data (columns A to G and I are inputs; column H, the risk category, is a formula).
- Descriptives: means, medians, standard deviations, skewness, correlation matrix and sample profile.
- ChiSquare: observed and expected frequencies, χ^2 statistic, p-value, Cramér's V and row percentages.
- ANOVA: group statistics, ANOVA table, eta squared, Tukey HSD comparisons and a chart of group means.
- Regression: two simple regression models with full coefficient statistics, confidence intervals, F tests, fitted equations and scatter plots with trendlines.

To reproduce the analysis with real data, paste responses into the Data sheet in the same columns (rows 2 to 301, or extend the ranges if your sample size differs) and all statistics will update. The supplementary analyses in Section 5.7 were computed outside the workbook.