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DEVELOPING AND VALIDATING AN INTEGRATED PREDICTIVE GOVERNANCE MODEL FOR CORPORATE SECURITY RISK MANAGEMENT: THE ROLE OF FRAUD INVESTIGATION AND PROJECT GOVERNANCE MATURITY

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Abstract

Organizations are investing in artificial intelligence, forensic analytics and enterprise risk management (ERM) to manage security and fraud risks, yet these capabilities are usually examined one at a time, and the organizational conditions that turn risk signals into effective action are rarely tested. This study develops and empirically validates an integrated predictive governance model in which AI-enabled predictive analytics, forensic analytics, ERM integration and fraud-investigation capability jointly shape corporate security risk-management effectiveness, with project governance maturity as a contextual condition. Data were collected through a structured questionnaire from 400 professionals in governance, risk, security, audit, compliance, fraud-investigation, finance and analytics roles in medium and large organizations across eight sectors, selected by simple random sampling. Six constructs were each measured with eight items on a five-point scale, and all scales were reliable (Cronbach's alpha 0.824 to 0.844). Each capability was positively and significantly related to effectiveness, explaining between 36.2 and 42.3 per cent of its variance individually. Together the four capabilities explained 55.3 per cent of the variance, and each retained a significant unique effect; forensic analytics had the largest standardized effect ($\beta = 0.284$) and fraud-investigation capability the smallest ($\beta = 0.140$). Mediation tests showed that ERM integration carried about 37 per cent of the effect of predictive analytics on effectiveness and that fraud-investigation capability carried about 31 per cent of the effect of forensic analytics, both significant. Project governance maturity added a significant direct effect ($\beta = 0.124$) but did not moderate the effect of predictive analytics (interaction $p = 0.890$). The findings support an integrated model in which analytical capabilities create value partly through the organizational processes that validate and escalate their outputs, and in which governance maturity acts as an independent foundation rather than as an amplifier of analytics.

Keywords: Corporate security risk management; predictive analytics; forensic analytics; fraud investigation; enterprise risk management; project governance maturity; mediation; model validation

1. Introduction

Corporate security risk now covers far more than the protection of premises and information systems. It includes fraud by employees and vendors, misuse of access rights, leakage of confidential data, manipulation of procurement and project payments, and the exploitation of weaknesses in third-party relationships. These risks are costly. Investigated cases of occupational fraud have a median loss of USD 145,000 and typically continue for twelve months before detection (ACFE, 2024), and the average cost of a data breach was reported at USD 4.44 million in 2025 (IBM, 2025). Boards and regulators increasingly expect organizations to show that such risks are identified early and managed systematically.

Organizations have responded by acquiring new capabilities. AI-enabled predictive analytics scores transactions, users and projects for the likelihood of misconduct. Forensic analytics examines data to detect anomalies, link related events and build an evidential trail. ERM frameworks place security risk alongside strategic and financial risks and relate it to the organization's risk appetite (COSO, 2017; ISO, 2018). Fraud-investigation functions establish whether suspicions are substantiated and recommend corrective action. Each of these has its own literature, but they are rarely

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examined together.

This separation leaves two questions unanswered. The first concerns mechanism. A predictive model or a forensic test produces only a signal; it changes outcomes only if the signal is assessed, escalated, investigated and acted upon. Whether analytical capabilities improve security outcomes directly, or partly through the organizational processes that carry their outputs into decisions, has not been tested. The second concerns context. Projects are where much corporate activity, spending and third-party exposure is concentrated, and project governance determines who decides, who is accountable and how risks are escalated (Müller, 2009). It is often assumed that mature governance amplifies the value of analytics, but this assumption has not been examined empirically in the security domain.

The present study addresses both questions by developing and validating an integrated predictive governance model. Its objectives are:

- to examine the effect of AI-enabled predictive analytics, ERM integration, forensic analytics and fraud-investigation capability on corporate security risk-management effectiveness;
- to estimate the unique contribution of each capability when all are considered together;
- to test whether ERM integration and fraud-investigation capability transmit part of the effect of the analytical capabilities;
- to determine whether project governance maturity strengthens the effect of predictive analytics or contributes independently; and
- to validate the resulting integrated model and draw implications for practice.

2. Conceptual Background and Hypotheses

2.1 AI-enabled predictive analytics

Predictive analytics shifts security risk management from retrospective detection to anticipation. Statistical and machine-learning techniques can identify unusual patterns in large volumes of transactional and behavioural data and rank cases by risk, so that scarce investigative effort is directed to the most significant ones (Bolton and Hand, 2002). Frameworks for the governance of AI stress that such models must also be monitored, explained and controlled (NIST, 2023). An organization that uses these tools well should identify risks earlier, prioritize them better and respond more effectively.

H1. AI-enabled predictive analytics has a significant positive effect on corporate security risk-management effectiveness.

2.2 ERM integration

ERM integration means that project-level and functional security risks are assessed with common criteria, related to the organizational risk appetite, assigned to owners and escalated through established channels into enterprise reporting. Studies of ERM implementation associate it with board and senior management commitment (Beasley et al., 2005) and, under suitable conditions, with better organizational performance (Gordon et al., 2009). For security risk, integration ensures that a signal raised in one project or function reaches the level at which a decision can be taken.

H2. ERM integration has a significant positive effect on corporate security risk-management effectiveness.

2.3 Forensic analytics

Forensic analytics applies analytical tests to organizational data in order to detect anomalies, assess fraud risk and develop evidence (Nigrini, 2011). Unlike general predictive modelling, it is directed at establishing what happened in a traceable way. Its value lies in three dimensions: detection of unusual transactions and relationships, assessment of the fraud risk they represent, and the development of evidence that can support investigation and action.

H3. Forensic analytics capability has a significant positive effect on corporate security risk-management effectiveness.

2.4 Fraud-investigation capability

An alert is not a finding. Fraud-investigation capability consists of the procedures, skills and coordination by which alerts are evaluated, referred, investigated, documented and converted into corrective action. Tips, audits and analytics generate suspicions, but only investigation establishes which are substantiated (ACFE, 2024). Effective investigation should therefore improve risk-management outcomes directly.

H4. Fraud-investigation capability has a significant positive effect on corporate security risk-management effectiveness.

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2.5 Mechanisms: integration and investigation as carriers of analytical value

If analytical outputs create value by being acted upon, then part of their effect should pass through the processes that act on them. Predictive risk intelligence should improve effectiveness partly because it feeds an integrated ERM process that assesses and escalates it. Forensic analytics should improve effectiveness partly because it strengthens the investigations that validate its findings. These are mediation hypotheses in the sense of Baron and Kenny (1986).

H5. ERM integration mediates the relationship between AI-enabled predictive analytics and corporate security risk-management effectiveness.

H6. Fraud-investigation capability mediates the relationship between forensic analytics capability and corporate security risk-management effectiveness.

2.6 Project governance maturity

Project governance maturity refers to the clarity of decision authority, the regularity of stage-gate reviews, the definition of accountability and escalation, and the use of lessons learned (Müller, 2009; Joslin and Müller, 2016). Mature governance provides the decision points at which predictive information can be used. It is therefore plausible that the effect of predictive analytics is stronger where governance is mature, which is a moderation hypothesis.

H7. Project governance maturity moderates the relationship between AI-enabled predictive analytics and corporate security risk-management effectiveness, such that the relationship is stronger at higher levels of maturity.

The conceptual model is shown in Figure 1.

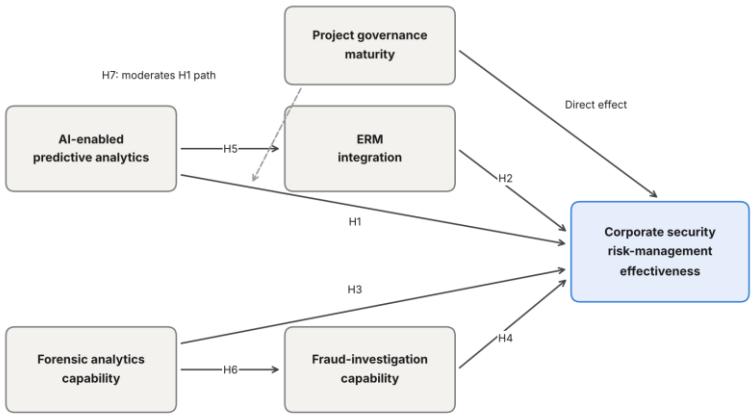

Figure 1. Conceptual model of integrated predictive governance with hypothesized relationships.

3. Research Methodology

3.1 Design, population and sample

The study used a descriptive and explanatory cross-sectional survey design. The population consisted of experienced professionals in medium and large organizations who work in project management, risk management, corporate security, internal audit, compliance, fraud control and investigation, financial control, and data analytics or AI, and who have knowledge of their organization's risk and control environment. Respondents with less than two years of experience were excluded. Because the population cannot be enumerated precisely, the sample size was determined with the formula of Yamane (1967) for a large population at a 5 per cent margin of error:

$n = N / (1 + N e^2) \approx 1 / e^2 = 1 / (0.05)^2 = 400$

A sampling frame of eligible professionals was compiled from participating organizations and respondents were selected by simple random sampling, giving each eligible professional an equal chance of selection. The final sample of 400 respondents was spread across the following groups:

- **Gender:** 53.0 per cent men and 47.0 per cent women.
- **Functional area:** all eight functions represented, from 9.2 per cent (risk management) to 15.8 per cent (data analytics or AI).
- **Sector:** eight sectors, including banking and financial services, information technology, manufacturing, healthcare, retail and e-commerce, infrastructure, professional services and government, each between 10.0 and 15.0 per cent.
- **Management level:** senior, middle and junior managers and specialists, each between 22.8 and 27.5 per cent.

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- **Organization size:** from 50 to more than 5,000 employees, with each of five size bands between 18.2 and 22.8 per cent.
- **Stage of AI adoption:** from not implemented to fully integrated, each of five stages between 19.0 and 20.5 per cent.

3.2 Instrument

A structured questionnaire with 48 statements measured six constructs, eight statements each, on a five-point Likert scale from strongly disagree (1) to strongly agree (5). Items were adapted from the literature on risk management, project governance, information systems and fraud examination, and new items were written where no established scale existed. The constructs and their principal dimensions were:

- **AI-enabled predictive analytics (PA):** data integration, anomaly detection and risk scoring, model monitoring and explainability.
- **ERM integration (ERM):** common risk criteria and alignment with risk appetite; ownership, escalation and portfolio reporting.
- **Forensic analytics capability (FA):** anomaly detection, fraud-risk assessment, evidence development.
- **Fraud-investigation capability (FI):** evaluation of alerts, referral, evidence preservation, coordination, documentation, corrective action.
- **Project governance maturity (PGM):** decision authority and stage-gate review; accountability, escalation and application of lessons learned.
- **Corporate security risk-management effectiveness (EFF):** early detection, response timeliness, risk prioritization, loss prevention, and control and organizational improvement.

The instrument was pilot-tested with professionals from the same population to check clarity, wording, completion time and preliminary reliability, and was revised before the main survey. Respondents were assured of anonymity and the items of different constructs were placed in separate sections in order to reduce common method bias (Podsakoff et al., 2003).

3.3 Analysis

Composite scores were computed as the mean of the eight items of each construct. Reliability was assessed with Cronbach's alpha. Each hypothesized effect was first tested by simple regression and by a one-sample t-test of the construct mean against the scale midpoint of 3.00. The integrated model was then estimated by multiple regression, first with the four capabilities and then with project governance maturity added, and the unique contribution of each predictor was assessed by the change in R^2. Mediation (H5, H6) was examined with regressions of effectiveness on the predictor and the mediator together, and the indirect effect was tested with the Sobel test (Sobel, 1982). Moderation (H7) was tested by regression with standardized predictors and their product term (Aiken and West, 1991). Multicollinearity was checked with variance inflation factors (VIF). Differences between demographic groups were tested with the independent-samples t-test and one-way ANOVA. All tests used a 5 per cent significance level.

4. Results

4.1 Reliability and descriptive statistics

Table 1 gives the reliability and descriptive statistics of the six constructs.

Table 1. Reliability and descriptive statistics of the constructs (n = 400)

Construct	Items	Cronbach's alpha	Mean	Standard deviation
AI-enabled predictive analytics	8	0.844	3.39	0.694
ERM integration	8	0.829	3.40	0.651
Forensic analytics capability	8	0.826	3.42	0.656
Fraud-investigation capability	8	0.824	3.40	0.659
Project governance maturity	8	0.838	3.40	0.678
Security risk-management effectiveness	8	0.837	3.43	0.691

All alpha coefficients exceed 0.80, indicating good internal consistency (Nunnally, 1978). The means lie between 3.39 and 3.43, moderately above the midpoint, and are close to one another. Respondents thus regard all six capabilities as present to a moderate degree in their organizations, with considerable room for development.

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4.2 Correlations and discriminant validity

Table 2. Pearson correlations among the constructs

Construct	PA	ERM	FA	FI	PGM	EFF
PA	1					
ERM	0.651	1				
FA	0.647	0.624	1			
FI	0.660	0.654	0.599	1		
PGM	0.652	0.647	0.645	0.647	1	
EFF	0.647	0.631	0.650	0.602	0.615	1

All correlations are positive and significant at the 1 per cent level, ranging from 0.599 to 0.660. To check that the constructs are empirically distinct, each correlation was corrected for the unreliability of the two scales by dividing it by the square root of the product of their alphas. The corrected correlations range from 0.725 to 0.791, all below the threshold of 0.85 commonly used to indicate a lack of discriminant validity (Henseler et al., 2015). The constructs are therefore related but distinct.

4.3 Tests of the direct effects (H1 to H4)

Table 3. Tests of the direct effects of the four capabilities on effectiveness

Hypothesis	Capability	Mean (t against 3.00)	r	R^2	B	t	Decision
H1	Predictive analytics	3.392 (11.297)	0.647	0.418	0.644	16.923	Supported
H2	ERM integration	3.398 (12.240)	0.631	0.398	0.670	16.217	Supported
H3	Forensic analytics	3.416 (12.682)	0.650	0.423	0.684	17.069	Supported
H4	Fraud investigation	3.399 (12.104)	0.602	0.362	0.631	15.031	Supported

All t-values are significant at $p < 0.001$ with 399 degrees of freedom for the mean tests and 398 for the regressions. Each capability is rated significantly above the midpoint, with effect sizes (Cohen's d) between 0.565 and 0.634, and each is positively and significantly related to effectiveness. H1 to H4 are supported. Forensic analytics shows the strongest individual relationship ($R^2 = 0.423$) and fraud investigation the weakest ($R^2 = 0.362$). Within forensic analytics, all three dimensions were rated significantly above the midpoint, with fraud-risk assessment highest (mean 3.456), followed by anomaly detection (3.402) and evidence development (3.401).

4.4 The integrated model

Because the capabilities are correlated with one another, their simple effects overlap. Table 4 reports two multiple regressions: the four capabilities alone (Model 1) and with project governance maturity added (Model 2). Figure 2, which follows the table, shows the validated model with its standardized coefficients.

Table 4. Multiple regression of effectiveness on the capabilities (standardized coefficients)

Predictor	Model 1 β (t)	Model 2 β (t)	VIF in Model 2	Unique R^2 in Model 2
Predictive analytics	0.234 (4.576)***	0.209 (4.01)***	2.42	0.018
ERM integration	0.210 (4.190)***	0.183 (3.60)***	2.32	0.015
Forensic analytics	0.284 (5.913)***	0.253 (5.13)***	2.17	0.030
Fraud investigation	0.140 (2.823)**	0.112 (2.22)*	2.29	0.006
Project governance maturity	Not included	0.124 (2.43)*	2.36	0.007
R^2 (adjusted R^2)	0.553 (0.548)	0.559 (0.554)		
F	121.96***	100.01***		

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Model 1 was estimated from the raw data; Model 2 and the unique R^2 values were derived from the correlation matrix of Table 2, which reproduces the Model 1 coefficients to the second decimal place.

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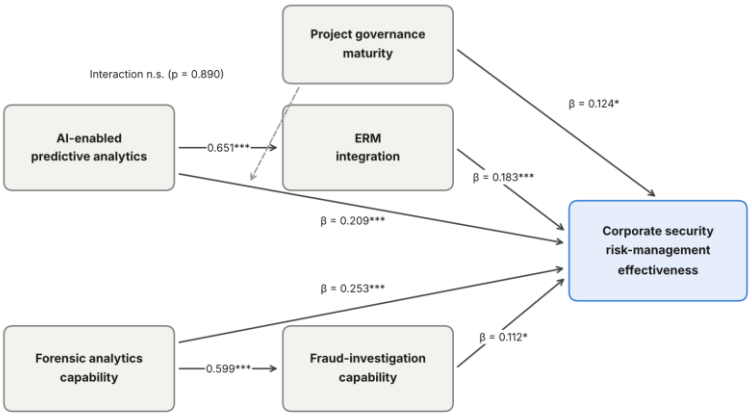

Figure 2. Validated integrated predictive governance model. Coefficients from Model 2 of Table 4 and from the mediation analysis of Table 5; *** p < 0.001, * p < 0.05.

The four capabilities together explain 55.3 per cent of the variance in effectiveness, and every one retains a significant unique effect. The integrated model thus explains about 13 percentage points more than the best single capability (42.3 per cent), which confirms that the capabilities are complementary rather than interchangeable. Forensic analytics makes the largest unique contribution, followed by predictive analytics and ERM integration. Fraud-investigation capability makes the smallest unique contribution but remains significant. Variance inflation factors between 2.03 and 2.42 indicate that multicollinearity does not distort the estimates.

Adding project governance maturity raises the explained variance to 55.9 per cent. The increase is small, 0.7 percentage points, but significant (F change = 5.88, p = 0.016), and maturity has a significant positive coefficient (β = 0.124). All four capabilities remain significant when maturity is controlled.

4.5 The mediating role of ERM integration and fraud investigation (H5, H6)

Table 5. Mediation analysis (standardized coefficients)

Path	a (predictor to mediator)	b (mediator to effectiveness)	Direct effect c′	Total effect c	Indirect effect a × b	Sobel z	Share mediated
Predictive analytics → ERM integration → effectiveness	0.651	0.364	0.410	0.647	0.237	7.06***	37%
Forensic analytics → fraud investigation → effectiveness	0.599	0.332	0.451	0.650	0.199	6.65***	31%

Both indirect effects are significant. About 37 per cent of the effect of predictive analytics on effectiveness passes through ERM integration, and about 31 per cent of the effect of forensic analytics passes through fraud-investigation capability. In both cases the direct effect also remains significant (t = 8.73 and 10.11), so the mediation is partial. H5 and H6 are supported. Analytical capabilities improve security outcomes partly in their own right and partly by strengthening the processes that assess, escalate and investigate their outputs.

4.6 The role of project governance maturity (H7)

In the moderated regression with standardized terms, predictive analytics (B = 0.295, t = 8.950, p < 0.001) and project governance maturity (B = 0.233, t = 7.068, p < 0.001) were both significant, but their product term was not (B = −0.003, t = −0.139, p = 0.890). The effect of predictive analytics on effectiveness is therefore the same at all levels of governance maturity. H7 is not supported. Maturity contributes to effectiveness directly and independently, as shown in Model 2 of Table 4, but it does not amplify the effect of analytics.

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4.7 Differences across respondent groups

No significant difference was found between men and women on any of the six constructs (all $p > 0.36$). One-way ANOVA across age, education, experience, management level, functional area, sector, organization size and stage of AI adoption produced one significant result out of forty-eight comparisons, for sector on project governance maturity ($F = 2.064$, $p = 0.046$). One significant result among forty-eight is close to the number expected by chance at the 5 per cent level, so the relationships in the model may be regarded as stable across the groups represented in the sample.

4.8 Summary of hypothesis tests

Table 6. Summary of hypothesis tests

Hypothesis	Relationship	Key result	Decision
H1	Predictive analytics → effectiveness	$\beta = 0.209$ in full model, $p < 0.001$	Supported
H2	ERM integration → effectiveness	$\beta = 0.183$ in full model, $p < 0.001$	Supported
H3	Forensic analytics → effectiveness	$\beta = 0.253$ in full model, $p < 0.001$	Supported
H4	Fraud investigation → effectiveness	$\beta = 0.112$ in full model, $p = 0.027$	Supported
H5	ERM integration mediates predictive analytics	Indirect effect 0.237, $z = 7.06$	Supported (partial)
H6	Fraud investigation mediates forensic analytics	Indirect effect 0.199, $z = 6.65$	Supported (partial)
H7	Governance maturity moderates predictive analytics	Interaction $p = 0.890$	Not supported

5. Discussion

An integrated model is better than any single capability. No single capability explains more than 42.3 per cent of the variance in effectiveness, whereas the four together explain 55.3 per cent and each keeps a significant unique effect. This supports the central proposition of the study: security risk management is effective when sensing, assessment, investigation and escalation are combined, not when one of them is strengthened in isolation. Investment decisions should be judged by how they fit the whole chain.

Forensic analytics is the strongest single contributor. Forensic analytics had both the strongest simple relationship with effectiveness and the largest unique effect in the integrated model, slightly ahead of predictive analytics. A plausible explanation is that forensic analytics is close to action: it not only flags anomalies but also produces a traceable evidential basis on which management can rely. Predictive scores identify where to look; forensic analysis shows what is there. Organizations that adopt predictive models without developing forensic capability may produce signals that cannot be acted upon with confidence.

Fraud investigation matters mainly as a carrier. Fraud-investigation capability had the smallest unique effect, yet it transmitted almost a third of the effect of forensic analytics. Its contribution is therefore larger than its own coefficient suggests: much of its value lies in converting analytical findings into validated cases and corrective action. This is consistent with the evidence that frauds are detected through many channels but resolved only through investigation (ACFE, 2024). An organization that invests in analytics without matching investigative capacity is likely to find that a large part of the value of its analytics is never realized.

ERM integration turns prediction into governance. More than a third of the effect of predictive analytics passed through ERM integration. Risk scores become effective when they are assessed against common criteria, compared with the risk appetite, assigned to owners and escalated through enterprise channels. This finding gives empirical support to the emphasis of ERM frameworks on integrating risk information with strategy and performance (COSO, 2017).

Governance maturity is a foundation, not an amplifier. The most unexpected result concerns project governance maturity. It improved effectiveness directly, but it did not strengthen the effect of predictive analytics. Two interpretations are possible. Mature governance may improve outcomes through its own channels, such as clear accountability, stage-gate reviews and the application of lessons learned, whatever the level of analytics. Alternatively, in the organizations surveyed, analytics may not yet be connected to project decision points closely enough for maturity to change how its outputs are used. Either way, the practical conclusion is that governance maturity should be developed in its own right and not treated as a condition that will automatically multiply the return on analytics.

The capabilities are at a moderate level. All construct means lie between 3.39 and 3.43 on a five-point scale. Respondents recognize the value of each capability, but most organizations appear to be at an intermediate stage of development. Since the model shows which capabilities matter most and how they interact, it can be used to set priorities for that development.

6. Implications

6.1 Theoretical implications

- The study moves beyond single-capability studies by validating a model in which predictive, forensic, investigative and enterprise-risk capabilities are estimated together and shown to make unique contributions.
- It identifies two mechanisms, ERM integration and fraud investigation, through which analytical capabilities affect outcomes, and shows that each carries roughly a third of the analytical effect.
- It qualifies the common assumption that governance maturity amplifies analytics, showing instead an independent, additive role.

6.2 Practical implications

- Develop forensic analytics alongside predictive models, so that risk signals are backed by traceable evidence.
- Match investigative capacity to the volume of analytical alerts, and measure the share of alerts that are investigated and closed.
- Route predictive risk information through ERM: common criteria, comparison with risk appetite, named owners and defined escalation paths.
- Strengthen project governance (decision authority, stage-gate reviews, accountability and lessons learned) as a separate priority, and then deliberately connect analytical outputs to project decision points.
- Use the integrated model as a maturity checklist: an organization that scores low on any one capability is unlikely to obtain the full benefit of the others.

7. Conclusion

This study developed and validated an integrated predictive governance model for corporate security risk management using survey data from 400 professionals. AI-enabled predictive analytics, ERM integration, forensic analytics and fraud-investigation capability each had a significant positive effect on effectiveness and together explained 55.3 per cent of its variance. ERM integration and fraud-investigation capability partially mediated the effects of predictive and forensic analytics respectively, each carrying roughly a third of the effect. Project governance maturity contributed directly but did not moderate the effect of predictive analytics. The model indicates that the value of analytics in security risk management depends substantially on the organizational processes that assess, investigate and escalate its outputs.

Limitations and future research. The study is cross-sectional and based on self-reported perceptions from a single respondent per organization, so causal conclusions should be drawn with care and common method bias cannot be fully excluded. The mediation tests used the Sobel approach on standardized coefficients; bootstrapped confidence intervals and a full structural equation model with latent constructs would provide stronger tests. Effectiveness was measured by perception rather than by objective indicators such as detection time or loss. Future research should use multi-source and longitudinal data, objective outcome measures, and comparisons across sectors and countries, and should examine whether the moderating role of governance appears once analytics is more closely embedded in project decisions.

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