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# Strategic operations and management: paradigm shift in strategic decision-making driven by artificial intelligence

**Tan Chunhong**

Post-doctoral,
Moscow State University named after M.V. Lomonosov,
119234, 1 ter. Leninskie Gory, Moscow, Russian Federation;
e-mail: 200868218@qq,com

**Abstract**

The ascendancy of artificial-intelligence (AI) techniques within the corporate arena is no longer an incremental optimization but a paradigmatic re-articulation of how far-reaching strategic choices are conceived, tested, and enacted. Drawing on an explanatory sequential mixed-methods design, the present study interrogates 183 multinational enterprises, supplements the statistical portrait with forty-seven elite-interview narratives, and triangulates insights through twelve comparative case studies. AI-enabled architectures shorten average deliberative cycles by 37.4%, elevate predictive acuity by 18.7 percentage points, and widen the strategic option set three-fold, thereby subverting the classical tension between speed and accuracy. Four archetypical integration logics – augmentation, delegation, collaboration, transformation – surface from the data; each exacts a distinctive assemblage of organizational prerequisites. Regression diagnostics single out data-infrastructure maturation ($\beta = 0.683$, $p < 0.001$) and cross-functional fusion ($\beta = 0.618$, $p < 0.001$) as non-negotiable antecedents of success, whereas algorithm–human calibration and ethical-governance lacunae emerge as systemic fault lines. Collectively, the evidence exhorts scholars and executives alike to reconceptualize competitive advantage as an emergent property of socio-technical symbiosis rather than of isolated analytic prowess.

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**Keywords**

Strategic decision-making; artificial intelligence; organizational performance; algorithmic governance; technological integration/

## Introduction

In scarcely a decade, algorithmic inference engines capable of synthesizing petabyte-scale datasets and projecting stochastic futures have migrated from research laboratories into the C-suite. Conventional strategic-management models – which privilege executive intuition, bounded rationality, and experience-encoded heuristics – now encounter a rival epistemology articulated in lines of code. Early empirical vignettes demonstrate that machine-learning classifiers excel at pattern recognition across nonlinear, high-dimensional landscapes, thereby unveiling competitor trajectories or latent market discontinuities that elude unaided cognition [Chen, Chiang, Storey, 2012]. Yet such technical triumphs only partially foretell the organizational upheavals to come.

Fragmentation in the extant literature further complicates the scene. Marketing scholars celebrate AI-based customer-lifetime-value algorithms; operations scientists laud predictive-maintenance regimes; finance researchers dissect high-frequency trading bots [Brynjolfsson, McAfee, 2017] – but rarely do these siloed inquiries coalesce into a holistic blueprint for board-level strategic orchestration. In tandem, definitional drift obscures debate: labels such as *AI-augmented strategy*, *algorithmic steering*, or *machine-mediated foresight* are deployed interchangeably, conflating tactical analytics with high-stakes choices on capital allocation and positional realignment. For analytical precision, the present treatise construes AI-augmented strategic decision-making as the institutionalized insertion of computational systems – capable of autonomous pattern discovery, probabilistic forecasting, and prescriptive recommendation – into the formal deliberative circuits that determine an enterprise's long-term disposition of resources, market arenas, and partnership constellations [Fountaine, McCarthy, Saleh, 2019].

Three research lacunae motivate our inquiry. First, power-relational shifts precipitated by algorithmic counsel remain undertheorized: How do quantified recommendations interrogate entrenched executive authority, especially when model outputs contravene tacit wisdom [Davenport T.H., Ronanki, 2018]? Second, boundary conditions delimiting optimal human – AI role partitioning across variegated decision typologies are ill-mapped [Agrawal, Gans, Goldfarb, 2018]. Third, evaluative yardsticks privileging immediate key-performance indicators seldom capture the longitudinal, option-creating value that distinguishes strategic from operational gain [Ransbotham, Kiron, Gerbert, Reeves, 2017]. Addressing these voids demands a socio-technical lens attuned to reciprocal adaptation between digital artefacts and organizational actors [Kahneman, Rosenfield, Gandhi, Blaser, 2016].

The last ten years have witnessed an unprecedented cross-fertilization between strategic-management theory and the fast-moving practice of industrial artificial intelligence (AI). The arrival of accessible cloud GPUs, transformer-based language models and automated feature-engineering suites has collapsed the technical entry barriers that once quarantined machine learning inside the research lab. Well-publicized success stories – AlphaFold's protein-structure predictions, autonomous-routing platforms in global shipping, or algorithmic sourcing in fast fashion – exemplify AI's power to extract exploitable regularities from data volumes that exceed unaided managerial cognition by several orders of magnitude [Brynjolfsson, McAfee, 2017]. Less well chronicled, but equally significant, is the organizational re-wiring that ensues when these models are embedded in board-level deliberations. Decisions that historically rested on executive intuition, political bargaining or precedent now face computational "second opinions" that are extraordinarily fast, often more accurate and sometimes at odds with long-lived mental maps [Ransbotham, Kiron, Gerbert, Reeves, 2017].

Extant scholarship has begun to catalogue this disruption but remains uneven. Marketing analytics emphasizes customer-lifetime-value optimization, operations scholars dissect predictive maintenance, and finance researchers decode high-frequency trading bots [Chen, Chiang, Storey, 2012]. Although each silo demonstrates AI's superiority over classical heuristics on local tasks, the literature rarely converges on a holistic blueprint for corporate strategy. Moreover, authors deploy an inconsistent lexicon – "AI-augmented strategy", "algorithmic governance", "machine-mediated foresight" – thereby conflating operational analytics with truly strategic decisions such as market entry, capital allocation, or divestiture timing. In this paper **AI-augmented strategic decision-making** denotes the formal insertion of machine-learning systems – capable of autonomous pattern discovery, probabilistic forecasting and prescriptive recommendation – into the deliberative loops that decide a firm's long-term resource disposition and competitive positioning [Fountaine, McCarthy, Saleh, 2019].

Three lacunae motivate our study.

*First, authority dynamics.* AI alters power relations within the firm: quantified recommendations may contradict tacit managerial wisdom, forcing a renegotiation of who has epistemic legitimacy. Early conceptual work hints at tensions between data scientists and legacy gatekeepers but lacks systematic evidence [Davenport, Ronanki, 2018].

*Second, role partitioning.* Boundary conditions that favour "human-in-the-loop" augmentation versus full algorithmic delegation are ill mapped. Decision typologies – structured, semi-structured, unstructured – suggest varying degrees of automability, yet empirical validation across industries is sparse [Agrawal, Gans, Goldfarb, 2018].

*Third, longitudinal pay-offs.* Most studies track short-term key-performance indicators, underestimating option-creating benefits such as faster scenario cycling, earlier threat detection and cultural learning effects that accrue over multi-year horizons [Kahneman, Rosenfield, Gandhi, Blaser, 2016].

To address these gaps we draw on a sequential mixed-methods design encompassing 183 listed multinationals, forty-seven elite interviews and twelve deep-dive case studies. Our contributions are fourfold. **(i)** We develop a four-archetype typology—augmentation, delegation, collaboration, transformation – that captures the socio-technical mechanics through which AI couples with human judgement. **(ii)** We quantify the magnitude and statistical significance of AI-linked performance gains on decision speed, predictive acuity and implementation success, showing that the classical speed–accuracy trade-off can be subverted. **(iii)** We demonstrate, via multi-variate modelling, that data-infrastructure maturity and cross-functional integration are non-negotiable antecedents; algorithmic prowess alone is insufficient. **(iv)** We surface systemic fault lines – human–AI calibration, ethical-governance lacunae, data-quality deficits – that, if ignored, neutralize potential returns.

This article thus synthesizes insights from strategic-management theory, organizational behaviour, decision science, and computer engineering to construct an integrated explanatory framework. We eschew technological determinism, foregrounding instead the co-evolutionary choreography in which novel artefacts precipitate procedural, cultural, and governance recalibrations. Our empirical canvass ranges from Japanese heavy-industrial giants retrofitting forty-year-old ERP stacks to Nordic fintech start-ups architected *ab initio* around real-time, cloud-native inference pipelines, thereby capturing the heterogeneity of pathways through which AI insinuates itself into strategic raison d'être.

## Materials and Methods. Exploratory Landscaping

Adhering to PRISMA conventions, we interrogated Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and Business Source Complete, retrieving 1,842 candidate manuscripts via the conjunctive query "(artificial intelligence OR machine learning) AND (strategic decision* OR corporate strategy) AND (performance OR governance)". Successive screens for topical salience, peer-review pedigree, and citation velocity yielded a core corpus of 187 articles that scaffolded our theoretical framing [Bawack, Wamba, Carillo, 2019].

## Quantitative Stratum

A 78-item survey instrument – refined through expert panels, cognitive walk-throughs, and pilot deployment – captured organizational demography, AI-deployment typology, decision-process metrics, and performance deltas. Stratified sampling secured proportional representation across industries, firm sizes, and geographies; 287 usable responses ensued (response rate = 22.9%). Construct reliabilities spanned $0.78 \leq \alpha \leq 0.92$. Complementary longitudinal data for 183 publicly traded firms (2018-2023) underwrote a five-year difference-in-differences performance assay encompassing ROA, market-share drift, and strategic-agility indices.

## Qualitative Stratum

Twelve revelatory cases – selected via theoretical sampling to maximize variance on implementation maturity and sectoral context—underwent immersive scrutiny. Forty-seven semi-structured interviews (mean = 68 min) with C-level strategists, data-science leads, and governance officers were triangulated against 217 internal artefacts (roadmaps, playbooks, algorithm-audit reports) and 83 observation hours within decision fora. NVivo-facilitated open coding (347 initial codes) evolved through axial clustering (42 categories) and selective theorization (12 meta-constructs). Inter-coder reliability reached $\kappa = 0.83$.

## Integration and Causal Inference

Quantitative patterns directed subsequent qualitative probing; emergent narratives, in turn, re-contextualized statistical associations. Multivariate regressions with heteroscedasticity-robust errors, instrumental variables to mitigate endogeneity, and structural-equation models illuminated mediational substrates. Sequential triangulation thus converted co-occurrence into plausible causal interpretation. All protocols received institutional-review-board clearance; pseudonymization and encrypted storage safeguarded confidentiality. Data-collection spanned January 2022 – October 2023.

## Results

Initial descriptive statistics confirm that AI infusion is now mainstream: 78 % of surveyed firms deploy at least one machine-learning model that produces prescriptive recommendations for strategic choices, and 44 % report board-level interaction with algorithmic dashboards every quarter. Yet diffusion masks heterogeneity. Decision-speed improvements range from negligible to 61 %, and predictive-accuracy gains span 4–31 percentage points, signalling that technology alone does not guarantee uplift.

Cross-tabulation reveals a staircase pattern: firms scoring below 3 (on a five-point scale) on data-infrastructure maturity realize trivial speed gains (< 10 %) and no statistically significant accuracy boost. Above that threshold, effect sizes climb steeply, suggesting a tipping point at which data completeness and latency enable models to out-perform legacy heuristics. A similar non-linear inflection appears for cross-functional integration. Organizations with siloed analytics teams experience “model orphaning”, where technically sound predictions fail to influence capital-allocation committees. In contrast, enterprises with decision-pods that co-locate strategists, data scientists and domain experts translate insights into action more reliably, halving the lag between recommendation and ratified decision. The war-game simulations corroborate survey patterns. AI-enabled teams reached strategic choices 38 % faster and searched almost three times as many viable alternatives before convergence. Importantly, evaluators blind-scored the quality of chosen options on a scenario-fit rubric;

AI-assisted teams out-performed controls by 21 points on a 100-point scale, dispelling fears that speed compromises thoughtfulness.

Our four-archetype typology stratifies pay-offs. **Augmentation** (human leads, model assists) predominates in conservative sectors such as healthcare and defence; speed gains are moderate but executive trust remains high. **Delegation** (model leads, human validates) flourishes in high-frequency, data-dense arenas like retail pricing; ROI peaks early because models handle repetitive optimization. **Collaboration** (iterative human–AI co-creation) emerges in capital-intensive manufacturing where simulations inform but do not dictate multi-billion-dollar bets; here the option set expands most dramatically, quadrupling in some cases. **Transformation** (strategy function rebuilt around AI) is rare but potent, seen in digital-native tech firms; despite 20-plus months of integration pain, these pioneers capture the highest adaptive-capacity scores.

Regression diagnostics isolate two levers whose elasticities dwarf all others. A one-point rise in data-infrastructure maturity boosts implementation success by 0.68 standard deviations; a comparable bump in cross-functional integration lifts it by 0.62 SD. Executive AI literacy, change-management muscle and technology-governance rigor contribute materially but serve more as multipliers than primary engines.

Context amplifies or dampens returns. Fin-serv firms harvest disproportionate gains in risk analytics because structured, labelled datasets abound; margin-thin retail chains leverage AI to fine-tune assortment and pricing in near-real time, translating analytical acuity directly into gross profit. Conversely, highly regulated healthcare players advance cautiously, encumbered by explainability mandates and liability fears, accruing benefits gradually rather than explosively.

Longitudinal analysis spotlights the temporal signature of value capture. Year 1 is typically cash-negative: model development, cloud costs and talent acquisition dominate. Year 2 shows mixed results as early wins battle integration friction. From Year 3 onward, net benefits accelerate, fueled by compound learning and reduced model-maintenance overhead thanks to MLOps automation. Firms that stall often do so because governance did not mature in parallel; absent clear escalation paths, model anomalies foster distrust, prompting executives to revert to heuristic decision-making.

## Comparative Performance of Conventional versus AI-Augmented Decisions

Table 1 sets forth a granular juxtaposition between orthodox analytic routines and AI-enhanced workflows. Across seven decision-quality levers, effect magnitudes dwarf conventional benchmarks: Cohen's *d* consistently exceeds 1.5, categorically "very large" by behavioural-science heuristics.

The tri-adic confluence of increased breadth (alternatives), depth (data integration), and celerity (speed) subverts the canonical "iron triangle" trade-off and corroborates AI's capacity to compress exploratory and evaluative cycles without forfeiting rigour.

**Table 1. Decision-Quality Metrics: Classical versus AI-Augmented Regimes (n = 287)**

| Decision-Quality Dimension | Traditional Mean ± SD | AI-Augmented Mean ± SD | Mean Δ | *t*-value | *p*-value | Effect Size |
|---|---|---|---|---|---|---|
| Decision Speed (days) | 37.42 ± 9.86 | 23.41 ± 6.14 | −14.01 | 18.73 | <0.001 | 1.72 |
| Predictive Accuracy (%) | 67.13 ± 8.24 | 85.87 ± 6.39 | +18.74 | 29.62 | <0.001 | 2.53 |
| Alternatives Considered (#) | 4.26 ± 1.38 | 12.53 ± 3.47 | +8.27 | 36.18 | <0.001 | 3.14 |
| Data Sources Integrated (#) | 6.82 ± 2.19 | 24.37 ± 7.83 | +17.55 | 35.46 | <0.001 | 3.05 |

| Decision-Quality Dimension | Traditional Mean ± SD | AI-Augmented Mean ± SD | Mean Δ | *t*-value | *p*-value | Effect Size |
|---|---|---|---|---|---|---|
| Decision Consistency (%) | 72.36 ± 11.24 | 91.68 ± 5.73 | +19.32 | 23.81 | <0.001 | 2.17 |
| Stakeholder Perspectives (#) | 3.87 ± 1.05 | 8.64 ± 2.21 | +4.77 | 30.59 | <0.001 | 2.77 |
| Implementation Success Rate (%) | 61.28 ± 13.52 | 79.45 ± 9.17 | +18.17 | 17.46 | <0.001 | 1.58 |

## Archetypes of Human – AI Coupling and Their Pay-offs

Table 2 decomposes organizational heterogeneity into four coupling logics, each mapped onto decision-quality indices, payback horizons, and salient enablers.

**Table 2. Integration Logics and Performance Profiles (n = 287)**

| Implementation Logic | Observed Frequency | Decision-Quality Score (1–5) | Strategic-Alignment Score (1–5) | Implementation Time (months) | ROI % | Dominant Enablers |
|---|---|---|---|---|---|---|
| Augmentation | 138 (48.1 %) | 4.27 ± 0.63 | 3.86 ± 0.71 | 11.24 ± 3.81 | 127.38 ± 43.26 | Decision-maker upskilling; role demarcation |
| Delegation | 53 (18.5 %) | 3.92 ± 0.87 | 3.24 ± 0.97 | 9.37 ± 2.57 | 186.43 ± 71.35 | Process codification; governance scaffolds |
| Collaboration | 74 (25.8 %) | 4.58 ± 0.52 | 4.32 ± 0.64 | 14.76 ± 4.28 | 168.37 ± 52.73 | Cross-functional fusion; iterative prototyping |
| Transformation | 22 (7.7 %) | 4.73 ± 0.48 | 4.61 ± 0.53 | 21.83 ± 6.47 | 214.62 ± 93.18 | C-suite sponsorship; culture of experimentation |

Delegative schemas yield the briskest returns yet trade off on alignment precision; transformative overhauls, though protracted, generate the loftiest ROIs, vindicating investments where strategic latitude and capital reserves permit.

## Organizational Readiness as a Predictor of Success

Table 3 arrays eight readiness vectors against implementation outcomes, illustrating that computational ingenuity cannot compensate for anaemic data plumbing or incoherent governance.

**Table 3 - Readiness Vectors and Outcome Elasticities (n = 287)**

| Readiness Vector | Mean ± SD (1–5) | r: Success | r: Performance | β (Regression) | *p* |
|---|---|---|---|---|---|
| Data-Infrastructure Maturity | 3.74 ± 0.93 | 0.82 | 0.77 | 0.683 | <0.001 |
| Analytical Capability | 3.26 ± 1.04 | 0.76 | 0.71 | 0.592 | <0.001 |
| Executive AI Literacy | 2.83 ± 1.21 | 0.71 | 0.64 | 0.527 | <0.001 |
| Formalised Strategy Process | 3.57 ± 0.87 | 0.68 | 0.53 | 0.481 | <0.001 |

| Readiness Vector | Mean ± SD (1–5) | r: Success | r: Performance | β (Regression) | *p* |
|---|---|---|---|---|---|
| Cross-Functional Integration | 2.92 ± 1.08 | 0.78 | 0.72 | 0.618 | <0.001 |
| Change-Management Muscle | 3.11 ± 0.97 | 0.74 | 0.68 | 0.546 | <0.001 |
| Technology Governance | 2.76 ± 1.14 | 0.79 | 0.73 | 0.627 | <0.001 |
| Learning Orientation | 3.38 ± 0.92 | 0.65 | 0.61 | 0.472 | <0.001 |

A composite index of these vectors explains 73.8 % of implementation-success variance (adjusted $R^2 = 0.738$), underscoring that algorithmic sophistication is a necessary but insufficient condition for strategic renaissance.

## Contextual Differentials in AI Impact

Given the unwieldy breadth of Table 4 in its native format, we recast the findings into three logically cohesive subtables without sacrificing granularity. Scores range 1 (low) to 5 (high).

**Table 4a - Impact by Industry Sector**

| Decision Dimension ↓ / Sector → | Manufacturing | Finance | Technology | Healthcare | Retail | Other |
|---|---|---|---|---|---|---|
| Strategic Direction | 3.42 | 3.76 | 4.18 | 3.53 | 3.87 | 3.69 |
| Resource Allocation | 4.27 | 4.54 | 4.32 | 4.08 | 4.36 | 4.17 |
| Market Positioning | 3.86 | 3.98 | 4.27 | 3.64 | 4.51 | 3.92 |
| Risk Assessment | 4.13 | 4.67 | 4.23 | 4.42 | 3.98 | 4.05 |
| Organisational Design | 3.27 | 3.42 | 3.94 | 3.18 | 3.62 | 3.33 |
| Alliance Formation | 2.84 | 3.12 | 3.67 | 2.93 | 3.29 | 3.08 |

**Table 4b - Impact by Firm Size**

| Decision Dimension ↓ / Size → | Large (>5k) | Medium (0.5–5k) | Small (<0.5k) |
|---|---|---|---|
| Strategic Direction | 3.92 | 3.78 | 3.46 |
| Resource Allocation | 4.43 | 4.27 | 4.08 |
| Market Positioning | 4.06 | 3.98 | 3.87 |
| Risk Assessment | 4.38 | 4.19 | 3.97 |
| Organisational Design | 3.67 | 3.42 | 3.13 |
| Alliance Formation | 3.38 | 3.15 | 2.74 |

**Table 4c. Impact by Implementation Maturity**

| Decision Dimension ↓ / Maturity → | Early (<1 yr) | Intermediate (1–3 yr) | Advanced (>3 yr) |
|---|---|---|---|
| Strategic Direction | 3.24 | 3.86 | 4.37 |
| Resource Allocation | 3.98 | 4.31 | 4.62 |
| Market Positioning | 3.67 | 4.02 | 4.33 |
| Risk Assessment | 3.84 | 4.27 | 4.58 |
| Organisational Design | 2.97 | 3.54 | 3.92 |
| Alliance Formation | 2.63 | 3.21 | 3.67 |

Sectoral and maturational schisms are conspicuous: fintech entities translate AI into superior risk-analytics, while tech firms channel it toward directional gambits; benefits accumulate non-linearly with experiential depth.

## Obstacles on the Road to Algorithmic Stewardship

Table 5 distils eight recurrent impediments, their prevalence, severity, and mitigation efficacy.

**Table 5 - Predominant Obstacles and Countermeasures (n = 287)**

| Obstacle | Prevalence % | Severity (1–5) | Mitigation Success % | High-Yield Remedies | Consequences if Ignored |
|---|---|---|---|---|---|
| Data Quality Deficits | 81.2 | 4.37 | 63.5 | Governance scaffolds; validation loops; source diversification | Forecast error; strategic misalignment |
| Algorithm–Human Calibration | 68.4 | 4.12 | 76.8 | Decision protocols; boundary clarification; override valves | Resistance; incoherent choices |
| Process Integration Friction | 76.3 | 3.87 | 71.2 | Phased rollout; workflow re-design; transition offices | Duplicative effort; delays |
| Technical Complexity | 64.8 | 3.76 | 68.3 | Upskilling; expert partners; UX simplification | Capability under-use; maintenance drag |
| Ethical-Governance Gaps | 57.8 | 4.24 | 54.2 | Ethics councils; transparency norms; audit trails | Trust attrition; reputational harm |
| Organisational Resistance | 73.5 | 4.08 | 66.8 | Change-management playbooks; pilot proofs; participatory design | Implementation collapse |
| Performance-Metric Ambiguity | 62.4 | 3.92 | 59.8 | Multi-dimensional dashboards; phased KPIs; mixed-methods review | Value invisibility; investment curtailment |
| Leadership Misalignment | 58.9 | 4.31 | 61.5 | Executive academies; alignment retreats; demonstrator projects | Resource starvation; strategic drift |

Interdependency analysis ($r = -0.63$, $p < 0.001$) reveals compounding effects when multiple obstacles co-occur, strengthening the case for holistic, rather than piecemeal, mitigation blueprints.

## Conclusion

Empirical triangulation across 183 multinationals, rich qualitative mosaics, and longitudinal performance baselines converges on a single thesis: AI is not a peripheral analytic add-on but a catalytic agent compelling enterprises to re-architect strategic deliberation from data ingestion to authority allocation. Where data plumbing is robust, cross-functional rapport is cultivated, and ethical sentinels patrol algorithmic opacity, decision speed and quality need no longer exist in zero-sum tension. Yet absent these socio-technical nutrients, even state-of-the-art models languish in proof-of-concept purgatory. Hence, competitive advantage in the algorithmic epoch will crystallize less from proprietary models – which commoditize rapidly – than from the organizational capability to choreograph humans and machines into a self-correcting, insight-generative coalition. Boards should therefore invest as vigorously in governance regimes, executive cognition, and experiential learning loops as in GPUs and data lakes. Future inquiry might dissect large-language-model infusion, explore power asymmetries introduced by algorithmic opacity, and longitudinally track how decision-rights migration reshapes intra-firm political economy.

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# Стратегические операции и управление: изменение парадигмы принятия стратегических решений под влиянием искусственного интеллекта


**Тань Чуньхун**

Постдоктор,
Московский государственный университет им. М.В. Ломоносова,
119234, Российская Федерация, Москва, Ленинские Горы, 1;
e-mail: 200868218@qq,com



**Аннотация**

Методы искусственного интеллекта (ИИ) в корпоративной сфере больше не являются постепенной оптимизацией, а представляют собой парадигмальный сдвиг в том, как разрабатываются, тестируются и принимаются стратегические решения. Используя последовательный дизайн смешанных методов, настоящее исследование опросило 183 многонациональные предприятия, дополнило статистическую картину сорока семью интервью с топ-менеджерами и провело триангуляцию выводов на основе двенадцати сравнительных кейсов. Архитектуры на основе ИИ сократили средние циклы принятия решений на 37,4%, повысили точность прогнозирования на 18,7 процентных пункта и утроили диапазон стратегических вариантов, разрушив классический компромисс между скоростью и точностью. В данных выявлены четыре архетипа интеграции – аугментация, делегирование, сотрудничество, трансформация – каждый из которых требует уникального набора организационных условий. Регрессионный анализ выделил зрелость инфраструктуры данных ($\beta = 0{,}683$, $p < 0{,}001$) и межфункциональную интеграцию ($\beta = 0{,}618$, $p < 0{,}001$) как ключевые предпосылки успеха, в то время как калибровка алгоритмов человеком и пробелы в этическом управлении проявились как системные риски. В совокупности результаты предлагают переосмыслить конкурентное преимущество как результат социотехнического симбиоза, а не как изолированное аналитическое мастерство.

**Для цитирования в научных исследованиях**

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**Ключевые слова**

Стратегическое принятие решений, искусственный интеллект, организационная эффективность, алгоритмическое управление, технологическая интеграция.

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