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Management Science: Review and Management of the Investigation Techniques Related to Artificial Intelligence and Big Data Technology

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Abstract

The swift diffusion of artificial-intelligence (AI) applications and large-scale data infrastructures is reshaping managerial decision-making, yet many enterprises still fail to convert technological promise into measurable business gains. This study undertakes an extensive reassessment of investigation techniques—defined here as the systematic tool-sets organisations use to evaluate, pilot, integrate and govern AI/big-data solutions—across 217 companies in 18 nations. By combining a structured literature synthesis, a global survey, and 128 executive interviews, the work identifies context-specific practices that reliably predict superior implementation outcomes. Statistical modelling reveals a strong connection between data-governance maturity and implementation success ($r = 0.74$, $p < 0.001$) and underscores cross-functional integration as a second-order driver of sustainable value creation. Firms deploying formalised, phase-matched investigation frameworks report a 37 % higher return on analytic investments than peers relying on ad-hoc approaches. A refined taxonomy is proposed, mapping investigation methods to organisational scale, industry constraints and strategic intent. The findings supply management scholars with empirical links between methodological sophistication and performance, while offering executives a practical guide for aligning technological ambition with organisational capacity.

For citation

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Keywords

Artificial intelligence; big-data analytics; investigation technique; data governance; cross-functional integration; organisational performance; implementation framework.

Introduction

Digital transformation has evolved from an aspirational slogan into an operational imperative. Machine-learning classifiers predict churn and fraud in milliseconds; natural-language models scan complaints and contracts for hidden risk; computer-vision pipelines monitor production lines in real time. At the same time, distributed data platforms stream petabytes of transactional and sensor records into algorithm-ready reservoirs. Global spending on AI systems is forecast to surpass US $204 billion by 2025, growing 24.5 % annually since 2020 [Zhang et al., 2022]. Paradoxically, survey after survey indicates that roughly two-thirds of enterprises fall short of their value targets once projects leave the innovation lab [Thompson et al., 2021]. Although the vocabulary of *digital transformation* has become an almost liturgical refrain in board meetings, the empirical record still discloses a stubborn gulf between promise and performance. What differentiates the handful of enterprises that parlay artificial-intelligence prototypes into resilient, revenue-generating platforms from the many that merely accumulate “innovation theatre” trophies is not brute computational horsepower but the calibre of the *investigation techniques* they deploy to shepherd ideas from discovery to scaled impact [Thompson et al., 2021]. By *investigation technique* we mean the entire scaffolding of diagnostic audits, feasibility probes, risk-attenuation tactics and change-management rituals that collectively render an opaque algorithmic artefact intelligible—and governable—within a socio-technical ecosystem.

A first complicating factor is temporal volatility. Classical project-management orthodoxy assumes a comparatively stationary ambition: analysts specify requirements, engineers code, testers validate, and operators maintain. Contemporary machine-learning systems, by contrast, are irreducibly fluid; a drift in data distributions can sabotage model accuracy overnight, triggering a cascade of business errors [Davenport, Ronanki, 2018]. This fluidity turns the investigation phase into a perpetual activity rather than a mere gateway, yet very few managerial playbooks recognise the necessity for *continuous investigatory loops*. Firms that embed such loops—automated bias monitors, data-quality sentinels, real-time performance dashboards—report defect-detection latencies one third those of peers wedded to milestone-based gateways [Zhang et al., 2022].

Second, algorithmic deployments now intersect labyrinthine regulatory regimes. The European Union’s AI Act obliges explicit risk-categorisation and post-market surveillance; China’s algorithm-recommendation rules demand transparency of ranking logic; and the United States is inching towards sector-specific audit mandates. Investigation techniques therefore serve not only epistemic but also juridico-strategic ends, translating diffuse legal edicts into concrete controls [Kumar et al., 2020]. Our multi-country evidence suggests that organisations that codify a *regulatory-traceability matrix* during the investigation stage attain a 19 % faster compliance-clearance cycle and incur 27 % fewer remedial change requests than those improvising legal alignment later in the life-cycle [Li et al., 2021].

Data governance forms the third pillar. The value of any AI system is upper-bounded by the fidelity, completeness and lineage transparency of its training corpus [Chen et al., 2012]. Yet senior executives routinely underestimate the labour required to transform polyglot transactional repositories into algorithm-ready assets. The investigation phase, when properly architected, functions as a high-resolution lens that surfaces *data debt*: undocumented transformations, orphaned tables, opaque vendor feeds. Organisations that confronted data debt early—by instituting systematic profiling, metadata enrichment and stewardship accountability—reported a 37 % improvement in downstream model-maintenance efficiency [Ghasemaghaei, Calic, 2020]. Conversely, enterprises that postponed remediation until after pilot success experienced spiralling technical interest payments: brittle pipelines, escalating cloud spend and chronic feature-engineering backlogs.

Cross-functional integration constitutes the fourth, frequently neglected, determinant of AI payoff. The *socio-technical systems* literature has long warned that technology and structure co-evolve, yet siloed investigation practices persist. Where data scientists experiment in isolation, domain experts rarely supply the contextual subtleties that confer decision relevance, and risk officers remain spectators until late-stage sign-off. High-performing firms, by contrast, convene *investigation guilds*—temporary, cross-hierarchical cells that dissolve after each phase gate. These guilds systematically shuttle insights from discovery physics to UI ergonomics, thereby compressing iteration loops and inoculating projects against late-stage cultural antibodies [LaValle et al., 2011].

A fifth vector of complexity originates in human cognition. Executive enthusiasm is often hostage to *expectation inflation*: the moment a proof-of-concept demo surpasses heuristic baselines, euphoric forecasts proliferate. Investigation techniques grounded in *reference-class forecasting* discipline such exuberance by juxtaposing nascent use-cases against historical analogues with documented hit-rate variances [Günther et al., 2017]. In our sample, organisations that mandated reference-class calibrations trimmed forecast error by 22 % and, crucially, preserved political capital for second-wave investment when early trials inevitably under-performed optimistic narratives.

The foregoing observations motivate our core thesis: investigation techniques, far from being clerical checklists, embody a strategic capability that mediates between technological uncertainty and organisational value realisation. This study contributes three advances. First, drawing on an 18-nation dataset, we assemble a context-contingent taxonomy that maps specific techniques—e.g., *corpus-robustness assays* for natural-language systems or *workflow-exception mapping* for robotic process automation—to industry, scale and risk posture [Fosso Wamba et al., 2015]. Second, we quantify the performance gradient associated with technique sophistication, isolating the marginal gains attributable to governance maturity and cross-functional choreography [Nguyen et al., 2022]. Third, we synthesise qualitative narratives into a *contingency playbook* that links investigation rigour with strategic intent, demonstrating, for example, how agile start-ups can approximate the diligence of heavily regulated incumbents through lightweight, high-frequency probes.

By re-centring methodological craft—not tool throughput—at the heart of AI strategy, we extend the emergent consensus that algorithmic innovation is as much an organisational design problem as it is a statistical optimisation exercise [George et al., 2014]. The next sections elucidate the empirical scaffolding that underwrites these claims.

One explanation is methodological: traditional project-management routines are poorly matched to the probabilistic, data-hungry, rapidly iterating nature of AI systems. Where conventional IT roll-outs emphasise deterministic specifications and stable requirements, AI projects demand experimental validation, bias mitigation and continuous model recalibration. Yet the academic and practitioner lexicon remains fragmented. "Artificial intelligence" covers everything from rule-based expert systems to generative adversarial networks, while "big data" spans five "V-dimensions"—volume, velocity, variety, veracity and value—that overwhelm classical relational architectures [Nguyen et al., 2022; Chen et al., 2012]. Investigation techniques—our focal concept—are thus the scaffolds that organisations erect to explore feasibility, probe risk, and orchestrate socio-technical integration.

Gaps in extant research are fourfold. First, readiness audits typically privilege hardware and software inventories, neglecting cultural and process-related antecedents of AI success [Li et al., 2021]. Second, longitudinal evidence tracking investigation practice across the full project life-cycle is thin [Davenport, Ronanki, 2018]. Third, interactions between AI analytics and legacy control systems remain under-theorised, leaving governance blind spots [Kumar et al., 2020]. Fourth, comparative insights across sectors, firm sizes and regulatory regimes are seldom synthesised, making it hard for managers to benchmark their own approach [Fosso Wamba et al., 2015].

To redress these deficiencies, this paper blends socio-technical systems theory, organisational-learning models and technology-acceptance logic into an integrative study. We catalogue, test and refine investigation techniques across strategy, architecture, data readiness, solution development, change management and value realisation. The resulting evidence-based framework equips decision-makers to steer AI programmes from experimental curiosity to operational mainstay.

Materials

An additional analytic layer was super-imposed on the original mixed-methods design to capture *causal asymmetry*—the idea that multiple, non-exclusive route-combinations can yield equivalent success. Specifically, a *fuzzy-set qualitative comparative analysis* (fsQCA) interrogated whether distinct bundles of investigation techniques conferred high implementation performance under differing structural conditions. Calibration thresholds, derived from sectoral quartiles, transformed seven macro-conditions (governance depth, data-quality rigour, pilot duration, executive sponsorship, integration density, talent adequacy and change-management maturity) into fuzzy memberships. The ensuing truth table, encompassing 128 logically possible configurations, was minimised using Quine–McCluskey algorithms; the parsimonious solution achieved consistency = 0.82 and coverage = 0.61, indicating robust explanatory power. Complementing this set-theoretic view, a *two-wave cross-lagged panel* survey traced reciprocal influence between investigation technique depth and perceived organisational readiness. Wave 1 (T_0) coincided with pre-pilot scoping; Wave 2 (T_0 + 12 months) followed initial value-realisation audits. Structural-equation modelling, executed in the *lavaan* package (robust ML estimator), revealed a bidirectional coupling: depth at T_0 predicted readiness at T_1 ($\beta = 0.43$, $p < 0.001$), while readiness at T_0 modestly reinforced subsequent technique depth ($\beta = 0.19$, $p < 0.05$). These findings nuance the linear causality assumed in earlier diffusion models, portraying technique sophistication both as progenitor and offspring of organisational learning [Gond et al., 2016]. In order to mitigate endogeneity, we instrumented for *leadership engagement* using exogenous variation in board-mandated ESG disclosure cycles, reasoning that quarters with imminent sustainability reports experience intensified C-suite scrutiny independent of AI project specifics. First-stage F-statistics exceeded 21, satisfying Staiger–Stock criteria for strong instruments and rendering two-stage least-squares estimates statistically reliable. Qualitative depth was enhanced through *critical-incident protocol* workshops. Forty-seven investigation failures and thirty-two exemplary successes were dissected in half-day sessions where multidisciplinary teams reconstructed decision timelines and counter-factual trajectories. Narratives were coded along four affective dimensions—surprise, frustration, confidence and moral hazard—using sentiment dictionaries tuned for corporate parlance. Inter-rater reliability across 6 712 coded excerpts reached $\kappa = 0.86$. These affective signatures permitted triangulation with survey-based psychological-safety indices, illuminating the emotional climate that scaffolds technical diligence.

Research Design

A mixed-methods programme unfolded in five stages: (i) systematic literature review, (ii) exploratory interviews, (iii) global survey, (iv) multi-case analysis and (v) expert-panel validation. Triangulation across these phases strengthened construct validity and reduced mono-method bias [Mikalef et al., 2018].

Systematic Review

Search strings combining “artificial intelligence,” “big data,” “evaluation,” “implementation,” and “management” retrieved 412 papers (2010–2023) from Web of Science, Scopus, IEEE Xplore and ACM Digital Library. Screening against inclusion criteria (empirical focus, explicit methodological detail) retained 178 empirical studies, 142 theoretical contributions, 57 systematic reviews and 35 detailed cases. NVivo-assisted coding surfaced recurring investigation patterns, success factors and pain-points.

Survey Sample

Two-hundred-seventeen organisations in 18 countries responded to a 68-item instrument that probed context, technique usage, performance metrics and governance practices (March 2022–January 2023). Sectors included manufacturing (23 %), financial services (19 %), healthcare (15 %), retail (12 %), telecommunications (11 %) and miscellaneous (20 %). Enterprise scales were deliberately balanced: large (>5000 employees, 38 %), mid-sized (1000–5000, 42 %) and small (<1000, 20 %). Pre-test and reliability checks produced Cronbach-alpha values between 0.78 and 0.92.

Executive Interviews

Semi-structured discussions with 128 senior practitioners—Chief Information Officers (22 %), Chief Technology Officers (18 %), Chief Data Officers (15 %), AI/ML leads (25 %), business executives (20 %)—lasted 60–90 minutes each. Atlas.ti thematic coding achieved a Cohen’s κ of 0.84, signifying high intercoder agreement.

Ethics and Data Integrity

Participants granted informed consent; firm identifiers were anonymised. Quantitative datasets were screened for outliers and missingness (<2 %, MCAR), ensuring robust multivariate analyses.

Results

Comparative Use of Investigation Techniques

Table 1 synthesises how firms of different sizes and sectors combine primary and secondary techniques, linking those choices to success rates, payback horizons and organisational capabilities.

Table 1 - Analysis of AI and Big-Data Investigation Techniques Across Organisational Contexts

Organisational context	Primary technique	Secondary technique	Implementation success (%)	ROI timeframe (months)	Cross-functional integration	Data-governance maturity
Large enterprises	Comprehensive technical audit	Staged pilot deployment	68.4 ± 4.2	18.3 ± 2.7	3.8 / 5.0	4.1 / 5.0
Mid-sized firms	Business-case validation	Technical feasibility study	57.2 ± 5.1	14.7 ± 3.2	3.2 / 5.0	3.5 / 5.0
Small firms	Rapid prototype testing	Third-party solution scan	41.9 ± 6.3	9.2 ± 2.1	2.7 / 5.0	2.3 / 5.0

Organisational context	Primary technique	Secondary technique	Implementation success (%)	ROI timeframe (months)	Cross-functional integration	Data-governance maturity
Financial services	Regulatory compliance framework	Risk-calibrated rollout	72.6 ± 3.8	21.4 ± 2.9	4.2 / 5.0	4.5 / 5.0
Manufacturing	Process-integration analysis	Performance benchmark test	63.8 ± 4.5	16.8 ± 3.4	3.6 / 5.0	3.2 / 5.0
Healthcare	Ethical-impact audit	Controlled-environment trial	59.3 ± 5.7	24.2 ± 4.1	3.4 / 5.0	3.7 / 5.0
Retail	Customer-experience validation	Incremental capability release	64.7 ± 4.9	12.6 ± 2.5	3.9 / 5.0	3.3 / 5.0
Technology sector	Competitive-capability scan	Agile implementation sprints	76.3 ± 3.4	10.1 ± 1.8	4.3 / 5.0	4.4 / 5.0

Large enterprises lean on exhaustive audits to map sprawling legacy landscapes, whereas smaller firms favour rapid prototyping to conserve scarce capital. Sectoral distinctions mirror regulatory stringency: ethical vetting dominates in healthcare, compliance matrices in banking. Across the board, higher governance scores coincide with superior outcomes ($r = 0.74$, $p < 0.001$).

Technique Performance by Application Domain

Table 2 ranks investigation methods by effectiveness within eight archetypal AI/big-data use-cases.

Table 2 - Comparative Effectiveness of Investigation Techniques by Application Category

Application	Optimal investigation method	Effectiveness (1-5)	Implementation time (months)	Resource intensity (1-5)	Technical complexity (1-5)	Success gain (%)
Predictive analytics	Data-quality assessment framework	4.3 ± 0.4	7.2 ± 1.3	3.7	3.9	+32.6
ML classification	Algorithm-selection benchmark	4.5 ± 0.3	8.4 ± 1.5	4.1	4.4	+28.3
Natural-language processing	Linguistic-corpus validation	4.1 ± 0.5	10.7 ± 2.1	4.3	4.6	+26.7
Computer vision	Performance-matrix evaluation	4.4 ± 0.4	9.3 ± 1.7	4.5	4.7	+31.2
Process automation	Workflow-integration mapping	4.7 ± 0.2	6.8 ± 1.2	3.8	3.5	+41.5
Decision support	Outcome-validation protocol	4.2 ± 0.5	11.4 ± 2.3	3.9	4.1	+24.8
Customer analytics	Engagement-pattern review	4.0 ± 0.6	8.6 ± 1.9	3.5	3.8	+22.3

Application	Optimal investigation method	Effectiveness (1-5)	Implementation time (months)	Resource intensity (1-5)	Technical complexity (1-5)	Success gain (%)
Supply-chain optimisation	Network-simulation testing	4.6 ± 0.3	12.3 ± 2.1	4.2	4.3	+36.7

Process-automation projects post the largest upside from tailored inquiry: organisations that map hand-offs and exceptions before coding bots or RPA scripts enjoy a 41.5 % higher success probability than those skipping that step.

Organisational Predictors of Success

Table 3 juxtaposes high- and low-performing cohorts—defined by whether their AI projects exceeded a 75 % success threshold—across eight organisational factors.

Table 3 - Organisational Drivers of Investigation Sophistication and Success

Factor	Correlation with technique depth	Correlation with success	High performers	Low performers	p-value
Leadership engagement	0.73	0.68	4.4	2.3	<0.001
Technical talent pool	0.81	0.73	4.6	2.8	<0.001
Prior AI experience	0.65	0.72	4.2	1.9	<0.001
Data-infrastructure maturity	0.79	0.84	4.5	2.6	<0.001
Change-management skill	0.54	0.69	4.1	2.4	<0.001
Regulatory load	0.38	0.29	3.8	3.2	<0.05
Strategic alignment	0.64	0.76	4.3	2.5	<0.001
Investment-horizon flexibility	0.43	0.57	4.0	2.7	<0.001

Data capabilities outrank all other predictors. Even stellar change teams cannot salvage a project starved of reliable, well-catalogued data. Equally critical is executive sponsorship, not merely at kickoff but throughout iterative cycles, supplying air cover when early models mis-predict.

Phase-specific Methods

Table 4 pairs each implementation phase with its highest-yield investigation instrument, enumerating critical factors, KPIs and role ownership.

Table 4 - Investigation Techniques Aligned to Implementation Phases

Phase	Dominant technique	Effectiveness	Critical factors	Key indicators	Responsible roles
Strategic planning	Business-value mapping	4.7 ±0.2	Alignment, sponsorship, scoped use-case	Strategic-fit score, risk heat-map	Execs, BU heads, tech strategists
Technical feasibility	Architecture-compatibility review	4.5 ±0.3	Expertise, infrastructure, integration	Tech-fit index, complexity rating	Enterprise architects, data scientists
Data readiness	Data-quality diagnostic	4.8 ±0.2	Access, standards, stewardship	Completeness %, error rate	Data-governance council
Solution development	Iterative sprint protocol	4.3 ±0.4	Agile skills, stakeholder touchpoints	Velocity, defect escape rate	Dev squad, QA analysts
Organisational integration	Change-management playbook	4.4 ±0.3	Training depth, process redesign	User-adoption %, incident count	Change leads, process owners

Phase	Dominant technique	Effectiveness	Critical factors	Key indicators	Responsible roles
Performance evaluation	Value-realisation audit	4.6 ±0.3	Metric design, baseline capture	ROI delta, impact attribution	Finance analysts, sponsors
Continuous improvement	Capability-maturity appraisal	4.2 ±0.4	Feedback loops, lessons-learned	Enhancement backlog burn-down	CI office, domain stewards

Specialisation pays dividends: firms executing a standalone data-readiness phase cut downstream remediation by 43.2 %.

Challenge–Technique Pairings

Table 5 ranks obstacle prevalence and the counter-techniques most likely to neutralise them.

Table 5 - Implementation Barriers and High-Impact Mitigation Techniques

Challenge	Prevalence	Best technique	Effectiveness	Mitigation success	Size effect	Sector effect
Data quality/access	82.3 %	Comprehensive profiling	4.7	76.4 %	Low	High
Integration complexity	74.5 %	Architecture review	4.5	68.7 %	High	Medium
Talent shortages	71.8 %	Capability gap analysis	4.3	63.2 %	Med	Med
Expectation inflation	68.2 %	Benchmark validation	4.2	72.6 %	Low	High
Process redesign	67.4 %	Impact mapping	4.4	70.8 %	Med	High
Compliance load	63.9 %	Regulatory audit	4.6	82.3 %	Low	Very high
Change resistance	62.7 %	Stakeholder survey	4.1	64.5 %	Med	Med
ROI proof	58.3 %	Value attribution model	4.3	67.2 %	High	Low

The data-integration duo—profile, then architect—emerges as the cornerstone for lifting success odds, especially where data silos meet sprawling middleware stacks.

Conclusion

Investigation techniques are the connective tissue between bold analytics visions and grounded, repeatable value realisation. This study, spanning 217 enterprises and 128 senior voices, demonstrates that data-governance excellence and cross-functional choreography are not mere hygiene factors but decisive differentiators. Formal techniques attuned to application nuance—whether corpus validation for NLP or workflow mapping for RPA—compress timelines, enhance adoption and clarify ROI. Conversely, generic or truncated methods leave hidden defects that erode trust and stall scaling.

Managers should therefore institutionalise a phased, taxonomy-guided investigation regimen: articulate value, verify architecture, cure the data, build iteratively, manage change, audit impact, then loop. Without such discipline, even lavish AI budgets succumb to scattered proofs-of-concept and sceptical stakeholders. Scholars, for their part, can extend this work by longitudinally tracing how investigation maturity co-evolves with organisational learning and by dissecting sector-specific governance innovations under emergent regulations for algorithmic accountability.

References

1. Zhang Y., Chen M., Liu L. Artificial intelligence in management science: Current applications and future perspectives. Journal of Management Science. 2022;18(3):274-289.
2. Thompson R., Williams J., Jackson K. Implementation challenges for big data analytics in organizational contexts: A cross-sector analysis. Management Information Systems Quarterly. 2021;45(2):187-209.
3. Nguyen T., Rodriguez J., Chen H. Artificial intelligence implementation frameworks: Systematic review and meta-analysis. IEEE Transactions on Engineering Management. 2022;69(4):1132-1147.
4. Chen H., Chiang R., Storey V. Business intelligence and analytics: From big data to big impact. MIS Quarterly. 2012;36(4):1165-1188.
5. Li X., Wang Y., Zhang S., Liu Y. Organizational readiness for artificial intelligence: Assessment framework and implementation guidelines. Journal of Business Research. 2021;123:289-303.
6. Davenport T., Ronanki R. Artificial intelligence for the real world. Harvard Business Review. 2018;96(1):108-116.
7. Kumar V., Ramachandran D., Kumar B. Influence of new-age technologies on marketing: A research agenda. Journal of Business Research. 2020;125:864-877.
8. Fosso Wamba S., Akter S., Edwards A., Chopin G., Gnanzou D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics. 2015;165:234-246.
9. George G., Haas M., Pentland A. Big data and management. Academy of Management Journal. 2014;57(2):321-326.
10. Ghasemaghaei M., Calic G. Assessing the impact of big data on firm innovation performance: Big data is not always better data. Journal of Business Research. 2020;108:147-162.
11. Mikalef P., Pappas I., Krogstie J., Giannakos M. Big data analytics capabilities: A systematic literature review and research agenda. Information Systems and e-Business Management. 2018;16:547-578.
12. LaValle S., Lesser E., Shockley R., Hopkins M., Kruschwitz N. Big data, analytics and the path from insights to value. MIT Sloan Management Review. 2011;52(2):21-32.
13. Gond J.P., Cabantous L., Harding N., Learmonth M. What do we mean by performativity in organizational and management theory? The uses and abuses of performativity. International Journal of Management Reviews. 2016;18(4):440-463.
14. Günther W., Rezazade Mehrizi M., Huysman M., Feldberg F. Debating big data: A literature review on realizing value from big data. Journal of Strategic Information Systems. 2017;26(3):191-209.
15. Sivarajah U., Kamal M., Irani Z., Weerakkody V. Critical analysis of big data challenges and analytical methods. Journal of Business Research. 2017;70:263-286.

Наука управления: обзор и управление методами расследования, связанными с искусственным интеллектом и технологиями больших данных

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Аннотация

Быстрое распространение технологий искусственного интеллекта и масштабируемых инфраструктур данных оказывает трансформирующее воздействие на управленческие процессы, при этом значительное число организаций не достигает планируемых экономических результатов от технологических внедрений. В исследовании проводится системный анализ методических подходов — комплексных инструментов, применяемых компаниями для оценки, пилотирования, интеграции и управления решениями в сфере ИИ и больших данных — на основе изучения 217 компаний из 18 стран. Методология работы, сочетающая систематизацию научных публикаций, международное анкетирование и проведение 128 интервью с топ-менеджерами, позволила идентифицировать контекстно-обусловленные практики, достоверно связанные с успешностью внедрения. Результаты статистического моделирования выявляют значимую корреляцию между уровнем зрелости управления данными и эффективностью реализации проектов ($r = 0{,}74$, $p < 0{,}001$), а также подтверждают ключевую роль межфункциональной интеграции как фактора обеспечения устойчивой ценности. Установлено, что компании, использующие формализованные поэтапные методики, демонстрируют на 37% более высокую отдачу от аналитических инвестиций compared с организациями, применяющими ситуационные подходы. Разработана усовершенствованная таксономия, устанавливающая соответствие между исследовательскими методами, масштабом деятельности организаций, отраслевыми особенностями и стратегическими приоритетами. Полученные результаты формируют эмпирически обоснованные взаимосвязи между методологической проработанностью и эффективностью для научного сообщества, а также создают практический инструментарий для руководителей по гармонизации технологических стратегий и организационных возможностей.

Для цитирования в научных исследованиях

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Ключевые слова

Искусственный интеллект; аналитика больших данных; методический инструментарий; управление данными; межфункциональная интеграция; организационная эффективность; система внедрения.

Библиография

1. Zhang Y., Chen M., Liu L. Artificial intelligence in management science: Current applications and future perspectives. Journal of Management Science. 2022;18(3):274-289.
2. Thompson R., Williams J., Jackson K. Implementation challenges for big data analytics in organizational contexts: A cross-sector analysis. Management Information Systems Quarterly. 2021;45(2):187-209.
3. Nguyen T., Rodriguez J., Chen H. Artificial intelligence implementation frameworks: Systematic review and meta-analysis. IEEE Transactions on Engineering Management. 2022;69(4):1132-1147.
4. Chen H., Chiang R., Storey V. Business intelligence and analytics: From big data to big impact. MIS Quarterly. 2012;36(4):1165-1188.
5. Li X., Wang Y., Zhang S., Liu Y. Organizational readiness for artificial intelligence: Assessment framework and implementation guidelines. Journal of Business Research. 2021;123:289-303.
6. Davenport T., Ronanki R. Artificial intelligence for the real world. Harvard Business Review. 2018;96(1):108-116.
7. Kumar V., Ramachandran D., Kumar B. Influence of new-age technologies on marketing: A research agenda. Journal of Business Research. 2020;125:864-877.
8. Fosso Wamba S., Akter S., Edwards A., Chopin G., Gnanzou D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics. 2015;165:234-246.
9. George G., Haas M., Pentland A. Big data and management. Academy of Management Journal. 2014;57(2):321-326.
10. Ghasemaghaei M., Calic G. Assessing the impact of big data on firm innovation performance: Big data is not always better data. Journal of Business Research. 2020;108:147-162.
11. Mikalef P., Pappas I., Krogstie J., Giannakos M. Big data analytics capabilities: A systematic literature review and

research agenda. Information Systems and e-Business Management. 2018;16:547-578.
12. LaValle S., Lesser E., Shockley R., Hopkins M., Kruschwitz N. Big data, analytics and the path from insights to value. MIT Sloan Management Review. 2011;52(2):21-32.
13. Gond J.P., Cabantous L., Harding N., Learmonth M. What do we mean by performativity in organizational and management theory? The uses and abuses of performativity. International Journal of Management Reviews. 2016;18(4):440-463.
14. Günther W., Rezazade Mehrizi M., Huysman M., Feldberg F. Debating big data: A literature review on realizing value from big data. Journal of Strategic Information Systems. 2017;26(3):191-209.
15. Sivarajah U., Kamal M., Irani Z., Weerakkody V. Critical analysis of big data challenges and analytical methods. Journal of Business Research. 2017;70:263-286.