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Capturing Return on Investment From Artificial Intelligence: Evidence, Mechanisms, and Organizational Conditions

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Abstract: Interest in artificial intelligence (AI) as a source of business value has outpaced the evidence on what AI investments return. This structured review examined peer-reviewed research on the return on investment (ROI) of AI in organizational settings, how that value was generated, and which organizational conditions accompanied it. A semantic search in the Elicit search engine identified nine studies that met initial screening criteria, and four remained after appraisal for peer review, relevance to AI, empirical grounding, and duplication. None reported an independently audited ROI from a completed deployment, and the largest figures came from models and simulations. A hospital ROI calculator estimated a five-year return of 451 percent for an AI radiology platform, and the best neural network models lowered simulated risk-weighted asset density by 2 to 27 percentage points relative to logistic regression at all but one of six large banks in France. Across the studies, reported value was associated with regulatory fit, business-led use-case selection, data readiness, workforce skills, and disciplined measurement. The evidence base was too small and heterogeneous to estimate typical returns or to establish which capabilities caused them.

Keywords: Artificial Intelligence, Return On Investment, Organizational Capabilities, Dynamic Capabilities, AI Value Realization, Digital Transformation

Introduction

Artificial intelligence (AI) is widely promoted as a source of business value, supported by growth in available data and computing capacity. Adoption has proved harder than that promise suggests, and many organizations still struggle to adopt AI and put it to work in their operations (Enholm et al., 2022). A large body of work describes what AI can do or is expected to deliver, whereas considerably less examines the returns organizations realize or the conditions under which those returns appear.

The empirical record is mixed. U.S. public firms that invested more in AI between 2010 and 2018 grew faster in sales, employment, and market valuation, chiefly through product innovation (Babina et al., 2024). When a generative AI assistant was rolled out in stages to 5,172 customer-support agents, issues resolved per hour rose by 15% on average (Brynjolfsson et al., 2025). Investors have been less certain: across 119 AI investment announcements by 62 listed firms, share prices fell by 1.77% on the day of the announcement (Lui et al., 2022).

Part of the difficulty is one of measurement. AI requires substantial complementary investment in processes, skills, and data, much of it intangible, and such investment can cause measured productivity to understate benefits early in adoption and overstate them later (Brynjolfsson et al., 2021). Adoption, maturity, operational improvement, and realized return are also different outcomes.

The review makes two contributions. It assembles quantitative evidence on AI returns from peer-reviewed sources and classifies each figure as realized, modeled, simulated, or self-reported, so that readers can judge how much weight to assign to it. It also relates the value mechanisms, enablers, and barriers reported in these studies to resource-based, dynamic capability, and complementarity arguments.

Problem Statement

Organizations commit large sums to AI with little credible evidence of what a given investment returns. In an earlier survey of 1,817 companies in the United States, Europe, and Asia, conducted in the first quarter of 2019 and cited by Grebe et al. (2023), only 8% said they could fully exploit AI's potential, and 58% had not progressed beyond strategizing, rollout planning, or pilots. These figures describe progress in scaling AI, not the returns it produced. In the 2018 Annual Business Survey, whose sample of 447,000 firms represents more than four million U.S. firms, only 5.8% used AI (McElheran et al., 2024). The peer-reviewed literature offers no reliable estimate of how often AI investments fail to recover their costs. The gap matters for investment appraisal, capital allocation, and accountability. Because measured gains lag behind intangible investment (Brynjolfsson et al., 2021), early appraisals may lead firms to abandon projects that would have paid off. In regulated sectors, the risk takes a different form, because a model that fails supervisory validation yields no return, however accurate it is (Fraisse & Laporte, 2022).

Existing studies also measure different things. Firm-level studies estimate associations from résumé-based or survey measures of AI (Babina et al., 2024; Czarnitzki et al., 2023). Field and experimental studies identify gains at the task level but not net returns to the organization (Brynjolfsson et al., 2025; Noy & Zhang, 2023), and capability studies rely on performance as managers report it (Mikalef & Gupta, 2021).

The practical problem, then, is that managers must appraise AI investments with little verified evidence of what comparable investments returned. The knowledge gap is that the literature has not separated realized, modeled, simulated, and self-reported returns or linked each to the mechanisms and conditions it is said to reflect.

Purpose Statement

The purpose of this structured review is to examine what peer-reviewed research reports about the returns organizations obtain from AI investments. It evaluates the reported quantitative outcomes, distinguishes realized, modeled, simulated, and self-reported evidence, examines how value is created, and synthesizes the organizational conditions associated with capturing it. The review addresses three questions:

(1) What quantitative returns have peer-reviewed studies reported for business applications of AI?

(2) Through what mechanisms does AI create measurable value?

(3) Which organizational capabilities and conditions are associated with capturing, or failing to capture, that value?

Literature Review

Theoretical Framework

Four perspectives frame the review. The resource-based view and dynamic capabilities theory form its primary foundation. The resource-based view explains why two organizations that buy the same AI tool need not obtain comparable returns (Barney, 1991), and dynamic capabilities theory adds an account of change, in which firms sense opportunities, seize them through resource commitments, and transform their operations (Teece, 2007). Two further perspectives play supporting roles. The technology-organization-environment (TOE) framework organizes the conditions of adoption (Chatterjee et al., 2021), although it does not

by itself establish effects on ROI. Complementarity arguments and the productivity J-curve explain why value depends on intangible complements and why it tends to appear only after a lag (Brynjolfsson & Hitt, 2000; Brynjolfsson et al., 2021).

AI Investment and Performance

A growing empirical literature links AI to performance, although the outcomes differ from one study to the next. AI investment, measured from employee résumés, was associated with faster firm growth (Babina et al., 2024), and AI use was associated with higher productivity among German firms (Czarnitzki et al., 2023). In an experiment involving 453 professionals, access to ChatGPT reduced writing time by 40% and improved quality by 18% (Noy & Zhang, 2023). Three features of this literature limit what it can say about ROI. Much of it reports projected or potential benefits rather than outcomes measured after implementation. It often treats AI as a single technology, although different methods may create value through different mechanisms. It also tends to examine individual functions in isolation, leaving open the question of how integration across functions affects returns.

Organizational Resources and Capabilities

The resource-based view holds that sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and not readily substitutable (Barney, 1991). Technology that any firm can purchase rarely meets these conditions on its own. Brynjolfsson and Hitt (2000) reach a compatible conclusion, showing that complementary organizational investments strongly influence the value of information technology. Mikalef and Gupta (2021) carry the argument to AI itself. They define and measure an AI capability and find that it is associated with greater organizational creativity and firm performance.

Implementation and Scaling

A working pilot, an enterprise deployment, and a demonstrated return are distinct achievements. Among six leading manufacturers, scaling AI required data pipeline, algorithmic, and democratization capabilities, as well as changes to the business model (Sjödin et al., 2021). AI use was far more common among the largest U.S. firms than among smaller ones (McElheran et al., 2024). Because the evidence on scaling comes largely from successful firms, it says less about why scaling fails.

The Measurement Problem

Conventional ROI calculations presuppose well-defined costs and benefits. AI investments rarely satisfy that condition, because much of their value depends on intangible complements such as redesigned processes, new skills, and data assets. Brynjolfsson et al. (2021) formalize the consequence as the productivity J-curve: measured productivity understates the benefits of a general-purpose technology in the early years of adoption and overstates them later, once earlier intangible investment begins to pay off.

Two further problems compound this one. Baselines are difficult to establish when AI is introduced alongside other organizational changes, which complicates attribution. The relevant time horizon is also uncertain, because AI systems may improve or degrade after deployment.

Contextual Conditions

In regulated industries, external requirements decide which models can be used at all. Bank credit-risk models, for instance, must pass supervisory validation before they affect capital (Fraisse & Laporte, 2022). AI use was concentrated in very large firms (McElheran et al., 2024). Few studies compare regulated and unregulated settings directly.

Synthesis of the Literature

Table 1 compares the principal recent studies. Taken together, most associate AI use with better firm or task performance, but they differ on the size, timing, and distribution of the

effects, largely because they define outcomes, time horizons, and designs differently. None links the full cost of a specific investment to its observed benefits, and that gap is the starting point of this review.

Table 1. Evidence Matrix of Recent Empirical Studies

Study	Design and Sample	Outcome and Key Finding	Limit for ROI Inference	RQ
Babina et al. (2024)	Firm regressions; U.S. public firms, 2010 to 2018	Faster growth in sales, employment, and market value	Association; AI measured from résumés	1, 3
McElheran et al. (2024)	National survey; about 447,000 U.S. firms	Fewer than 6% used AI; concentrated in large firms	Adoption only	3
Brynjolfsson et al. (2025)	Staggered rollout; 5,172 agents in one firm	Issues resolved per hour rose 15%	No cost or ROI data	1, 2
Noy and Zhang (2023)	Preregistered experiment; 453 professionals	Writing time fell 40%; quality rose 18%	Experimental tasks	1, 2
Lui et al. (2022)	Event study; 119 announcements by 62 firms	Share prices fell 1.77%	Investor expectations	1, 3
Mikalef and Gupta (2021)	Survey and structural model; 143 senior technology managers	AI capability linked to creativity and performance	Perceived performance	3

Method

Search and Screening

The review is a structured, semi-systematic review (Snyder, 2019). It searched a single engine without a registered protocol and so does not qualify as a systematic review, although the flow of records is reported using the PRISMA 2020 stages (Page et al., 2021). The search used Elicit, which indexes more than 138 million papers from Semantic Scholar, PubMed, and OpenAlex. The semantic query "How Businesses Actually Capture ROI from AI" was run on June 23, 2026, and the 50 papers the engine ranked as most relevant were exported for screening. No publication-date, language, or document-type restrictions were applied. Because no other databases were searched, the conclusions apply only to this search. The aim was to identify empirical studies of returns from AI in organizational settings, including hospitals that evaluated AI as an investment. Each record was screened against six criteria, and 41 were excluded:

- Business Context: Focus on commercial enterprises or other organizations that have deployed or evaluated AI solutions
- Quantitative ROI Measurement: Measurement, calculation, or modeling of returns from AI initiatives
- Empirical Evidence: Real-world data, case studies, or empirically parameterized models rather than purely conceptual arguments
- ROI Methodology Description: Description of the methods, metrics, or frameworks used to estimate returns

- Beyond Theoretical Framework: Empirical validation or real-world application rather than only theoretical proposals
- Nature of ROI Data: Realized returns, or modeled returns clearly identified as such, rather than illustrative or hypothetical figures

Quality Appraisal

Nine studies met the screening criteria. Each was then appraised against four further requirements: (a) publication in a peer-reviewed journal with a verifiable bibliographic record; (b) AI as the technology under study; (c) original data or empirically parameterized modeling rather than illustrative or hypothetical figures; and (d) no duplication of another included study. Five studies were excluded at this stage: a working-paper version of a later journal article (Fraisse & Laporte, 2021); a paper whose only ROI figures came from a hypothetical example (Katragadda, 2024); two papers that reported figures without disclosing the underlying data, both published in outlets with limited or discontinued indexing (Aziz et al., 2025; Dheerajkumar et al., 2025); and a case study of real-time BI that predates contemporary AI (Anderson-Lehman et al., 2004). Four studies were retained. None of the retained studies calculates a realized return. As criteria 2 and 4 allow, the hospital and banking studies were admitted as clearly labeled modeled returns, and the maturity and cognitive automation studies as evidence on the correlates, scaling, and cost of AI value.

Data Extraction and Synthesis

Data extracted from each study covered AI implementation characteristics, the approach to measuring return, quantitative results, value mechanisms, business context, success factors, implementation challenges, and study design. Every value reported here was checked against the source article. Only the abstract of Helm et al. (2022) was accessible, so no quantitative results are reported for that study, and no conclusion depends on it.

Because the studies differed widely in context, design, and outcome measures, statistical pooling was not appropriate. A narrative synthesis was used instead. Findings were organized by value mechanism, enabler, and barrier, and each quantitative result is reported together with the type of evidence that produced it.

Results

Study Characteristics

The four studies cover corporate credit risk in banking (Fraisse & Laporte, 2022), hospital radiology (Bharadwaj et al., 2024), AI maturity across nine industries (Grebe et al., 2023), and cognitive automation in insurance auditing, healthcare, and banking (Helm et al., 2022), as summarized in Table 2.

Table 2. Characteristics of Included Studies

Study	Industry	AI Technology	Business Function	Design	Setting and Data
Fraisse and Laporte (2022)	Banking	Random forest, gradient boosting, ridge regression, neural networks	Corporate credit risk; regulatory capital	Simulation of pseudo-internal credit-risk models	Six largest banking groups in France; credit register and firm-level accounting data, 2009 to 2015

Study	Industry	AI Technology	Business Function	Design	Setting and Data
Bharadwaj et al. (2024)	Healthcare	AI-powered diagnostic imaging platform	Hospital radiology workflow	ROI calculator with scenario and sensitivity analyses	U.S. hospital; parameters from expert interviews and literature; 5-year horizon
Grebe et al. (2023)	Nine industries	AI (general)	Enterprise-wide	Cross-sectional survey plus three case studies	2,296 managers in 28 countries, October 2019 to January 2020
Helm et al. (2022)	Insurance auditing, healthcare, banking	Cognitive automation of textual and visual data	Data extraction from unstructured documents	Case studies	Not reported in abstract

How Returns Were Measured

No two studies measured return in the same way, and none calculated ROI from financial data observed after deployment. The design of Fraisse and Laporte (2022) is the most rigorous. Its pseudo-internal credit-risk models for six banking groups were evaluated against supervisory compliance tests and their effect on capital requirements.

Reported Returns

Because the quantitative results differ in unit and evidentiary basis, they are not directly comparable. The largest figure comes from the hospital radiology model. Bharadwaj et al. (2024) estimated that introducing an AI platform into a U.S. hospital's radiology workflow would reduce labor time and yield a five-year ROI of 451%, rising to 791% when radiologist time savings were included. The estimates were sensitive to time horizon, center type, and scan volume.

Fraisse and Laporte (2022) found noticeable differences among AI models, both in their ability to pass regulatory tests and in their effect on capital. Neural networks passed the compliance tests about as well as the traditional model and, in some cases, reduced capital requirements by a wide margin. For all but one bank, the best-performing neural network lowered risk-weighted asset density by 2 to 27 percentage points relative to logistic regression under the most conservative calibration of default probabilities. These are simulated effects of hypothetical internal models, not savings realized by any bank.

The survey evidence bears on scale, not on return. In the main survey reported by Grebe et al. (2023), digital champions' market capitalization grew by 23% between February 2020 and January 2021, against 7% for laggards. These comparisons concern overall digital maturity, of which AI is only one component, and they are associations, not estimates of AI returns.

Value Creation Mechanisms

The studies point to five routes through which AI created, or was expected to create, value. In banking, the simulated gain took the form of lower regulatory capital requirements rather than lower operating costs, and it was conditional on the model passing supervisory compliance tests. In the hospital model, value came from reduced labor time and from revenue associated with clinically beneficial follow-up care (Bharadwaj et al., 2024).

Two further mechanisms concern the scope of automation. Digital champions reported having automated 25% of their core processes with AI, 2.3 times more than digital laggards (Grebe et al., 2023). Helm et al. (2022) examine cognitive automation as a means of extracting information from unstructured text and images for further analysis, although the study reports no figures on returns. The fifth route is the combination of AI with human capability. As AI absorbs standardized tasks, people are expected to contribute domain expertise, judgment, and creativity (Grebe et al., 2023).

Enablers

Most of the evidence on enablers comes from a single cross-sectional survey, so the factors reported here should be read as correlates of AI maturity, not as demonstrated causes of ROI. According to Grebe et al. (2023), firms that scaled AI defined use cases from a business perspective, relied on domain expertise, and prioritized by value and ease of implementation. They also invested in digital and data platforms and in a data-centric organization with solid governance, and between 77% and 79% of AI leaders were in the top two maturity stages for data strategy, data governance, and digital and data platforms.

Digital champions were nearly twice as likely as laggards to devote more than 15% of full-time equivalents to digital roles (44% vs. 23%) and more likely to plan re- or upskilling for over 15% of the workforce (51% vs. 28%; Grebe et al., 2023). Leading firms also tracked the financial and business impact of AI initiatives and reprioritized or stopped projects that fell short of expectations.

Barriers

The banking study most directly shows that predictive strength did not, by itself, determine value. Random forest models were prone to overfitting and failed the compliance tests, while gradient boosting produced capital charges above those of the standardized approach, eliminating the capital benefit that motivated its use (Fraisse & Laporte, 2022). Organizational constraints were also reported. Most surveyed firms had not moved beyond pilots, and the studies did not identify the causes of scaling failures (Grebe et al., 2023).

Discussion

Answers to the Research Questions

On the first question, the retained studies reported modeled and simulated returns, some of them large, but no independently audited ROI from a completed deployment. Within the limits of this search, the figures most likely to be quoted in practice rest on models, simulations, and self-reports rather than on observed outcomes.

On the second, the five mechanisms are plausible routes to value, but none is demonstrated, since each rests on simulation, modeling, self-report, or an abstract.

On the third, regulatory fit, business-led use cases, data governance, digital talent, and measurement were associated with maturity or modeled value, while skills shortages, failed validation, and stalled pilots appeared as barriers. Table 3 maps each mechanism and condition to the evidence behind it.

Table 3. Mechanisms and Conditions by Strength of Evidence

Mechanism or Condition	Studies	Outcome Type	Strength of Evidence
Lower regulatory capital, conditional on validation	Fraisse and Laporte (2022)	Simulated	Moderate within banking; no realized savings
Reduced labor time and added clinical revenue	Bharadwaj et al. (2024)	Modeled	Limited; sensitive to assumptions

Mechanism or Condition	Studies	Outcome Type	Strength of Evidence
Broader automation; AI with domain expertise; data extraction	Grebe et al. (2023); Helm et al. (2022)	Self-reported; case studies	Limited; Helm et al. abstract only
Business-led use cases, data governance, talent, measurement	Grebe et al. (2023)	Self-reported maturity	Limited; association only
Skills shortage; gap between pilots and scale	Grebe et al. (2023)	Self-reported	Moderate as description; silent on causes

Fit Before Sophistication

The banking results are the clearest sign that technical performance was not enough. The models that created value were those that fit the regulatory environment, not the most complex ones (Fraisse & Laporte, 2022). In TOE terms, the environment limited which technological options could pay off.

Complementary Capabilities and the Scaling Problem

The survey evidence associates AI maturity with business-led use-case selection, data platforms and governance, dedicated talent, upskilling, agile cross-functional teams, and active measurement of impact (Grebe et al., 2023). This pattern accords with resource-based and complementarity arguments (Barney, 1991; Mikalef & Gupta, 2021), but the cross-sectional, self-reported survey cannot show that these capabilities cause higher returns.

The gap between experimentation and scaled use deserves particular attention. In dynamic capability terms, turning a pilot into an operating solution is a transforming activity (Sjödin et al., 2021; Teece, 2007). The productivity J-curve suggests one explanation for the gap: complementary intangible investment must precede visible benefits, so early measurement may understate eventual returns (Brynjolfsson et al., 2021). An alternative that the evidence does not exclude is that many pilots fail to generate value worth scaling.

Implications for Theory

For the resource-based view, the findings are consistent with the proposition that widely available AI tools confer little advantage on their own and that complementary data, governance, and human capital resources shape outcomes (Mikalef & Gupta, 2021), although they do not demonstrate it. The banking simulation supports using the TOE framework to organize implementation conditions, whereas the dynamic capability and J-curve accounts of stalled pilots have yet to be tested.

Practical Recommendations for Organizations

With these limits in mind, several actions follow for managers. They draw on the evidence and theory reviewed here, but the retained studies do not show that any of them increases ROI.

1. Select use cases from defined business problems with measurable objectives. AI proposals should be evaluated on business fit and organizational readiness, not on model performance alone (Grebe et al., 2023).
2. Agree on baselines, measures, and a multiyear horizon before deployment. Attribution requires comparing performance with and without AI (Brynjolfsson et al., 2025), and early measures may understate eventual returns (Brynjolfsson et al., 2021).
3. Count the full cost. Estimates should include the data management and model lifecycle work that AI implementation requires (Weber et al., 2023).

4. Assess data quality, governance, and infrastructure before scaling. AI leaders were concentrated in the top maturity stages for data (Grebe et al., 2023).
5. Invest in expertise and cross-functional teams. A lack of skilled staff was the most often cited implementation challenge in survey data reported by Grebe et al. (2023), and human capital is a complementary resource (Mikalef & Gupta, 2021).
6. Build validation and regulatory risk into project selection. In regulated settings, validation belongs in model selection from the outset, because a model that cannot be validated delivers no benefit (Fraisse & Laporte, 2022).
7. Define pilot-to-scale criteria and stop rules, and monitor realized outcomes. Scaling beyond pilots should be treated as a distinct management problem, with agreed conditions for stopping a project (Grebe et al., 2023).
8. Separate vendor forecasts and modeled benefits from verified outcomes. Much cited evidence comes from case studies published by AI vendors (Wamba-Taguimdje et al., 2020), so each figure should be labeled as realized, modeled, simulated, or self-reported.

Limitations

Several limitations qualify these conclusions. The evidence base is small: four studies were retained, and one was available only as an abstract. The search relied on a single engine and query and was limited to the 50 top-ranked results, so relevant studies may have been missed, and the scarcity of realized ROI evidence describes this search rather than the whole literature. Screening and extraction were also not performed independently by two reviewers. The included studies rely on heterogeneous modeled, simulated, or self-reported outcomes, and several author teams had industry affiliations. A single survey also supplies most of the evidence on enablers.

Recommendations for Future Research

Future reviews should search multiple bibliographic databases with structured search strings and document screening in a PRISMA flow diagram (Page et al., 2021). The most pressing need is for audited, post-implementation ROI studies, and longitudinal designs are needed to test whether AI returns follow the delayed pattern predicted by the productivity J-curve (Brynjolfsson et al., 2021) and whether capability thresholds exist. Firm panels with difference-in-differences or instrumental-variable designs could test whether data governance, skills, and cross-functional teams cause higher returns. Delphi studies could help standardize what an AI ROI calculation includes. Prospective studies that compare forecasts with outcomes, together with multi-industry panels linking maturity to financial statements, would show how regulation and maturity relate to returns.

Conclusion

Within the search performed, peer-reviewed evidence on the realized returns from AI was scarce. The four studies retained here report substantial modeled or simulated benefits, but none reports an independently audited return from a completed deployment. Where value did appear, it was associated with regulatory fit, with use cases grounded in business problems, and with the data platforms, skills, and measurement practices required to scale. The evidence therefore supports a qualified proposition rather than a finding: organizational readiness may matter as much as technical capability in capturing value from AI. Firmer conclusions about the size and sources of AI returns will require longitudinal studies that report audited outcomes.

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