# Impact of Artificial Intelligence Technology Development on Enterprise Growth

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**Abstract.** Artificial Intelligence (AI) has emerged as a key enabler in digital economic transformation, driving industrial innovation through novel business paradigms. This study analyzes 584 global enterprises (2001-2020) using an AI R&D intensity framework to reveal firm-level growth dynamics. Findings indicate sustained performance improvements from AI investments, amplified by organizational absorptive capacity. Contrary to theoretical assumptions, slack resources demonstrate insignificant mediation effects. The technology's impact exhibits cyclical variations - substantial during maturity phases but limited in early adoption. The research advances organizational growth theory by elucidating differential AI implementation outcomes, offering practical insights for aligning corporate strategies with national AI agendas while proposing a methodological framework for technology absorption assessment.

**Keywords:** enabling technology, AI, absorptive capacity, redundant resources, enterprise growth

## 1 Introduction

Artificial intelligence has emerged as a transformative force in technological innovation, reshaping economic systems and industrial paradigms. Empirical evidence, including McKinsey's 2020 global survey, demonstrates that over 60% of enterprises now leverage AI to optimize operations and drive growth, positioning it as a critical "enabling technology" comparable to electricity or combustion engines [1,2]. Unlike conventional enabling technologies, AI uniquely combines generality with rapid evolution, enabling novel business models across sectors while remaining technologically fluid[3]. This study interrogates AI's heterogeneous impacts on corporate growth through micro-level analysis of 584 global firms (2001–2020). While prior research debated IT's paradoxical productivity effects--from Solow's skepticism to value-creation theories [4]--we establish AI's distinct cyclical influence: growth acceleration during technological maturity versus marginal early-stage impacts. Crucially, absorptive capacity emerges as a key growth catalyst, whereas organizational slack resources show negligible mediation[5,6]. Theoretical contributions are threefold: Development of a micro-level framework analyzing AI's growth mechanisms, contrasting


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with macro-focused predecessors; Creation of dynamic metrics capturing temporal growth dimensions in AI adoption; Integration of organizational contingency factors (absorptive capacity, resource redundancy) into AI-growth analysis. Practically, this work provides strategic guidance for aligning AI implementation with enterprise capabilities, particularly benefiting technology-laggard firms through targeted adoption strategies. By resolving tensions between organizational theory's support for resource buffers and agency theory's efficiency mandates, we advance understanding of AI's contextual value creation.

## 2 Literature Review

Emerging as a pivotal enabler of industrial transformation, artificial intelligence demonstrates unique dual characteristics--combining general-purpose applicability with rapid evolutionary dynamics. While conventional enabling technologies like big data[7] and IoT[8] enhance operational efficiency through established pathways, AI drives systemic innovation across production processes, risk management, and business model architecture[9]. Three distinct competitive advantages emerge: (1) enhanced predictive analytics through advanced data synthesis, (2) cost-optimized product innovation via intelligent automation, and (3) value-chain restructuring through adaptive decision systems. The technology's nascent lifecycle stage introduces temporal heterogeneity in growth outcomes. Unlike mature technologies exhibiting predictable returns, AI's impact fluctuates between marginal early-phase effects and exponential maturity-phase acceleration. This developmental ambiguity fuels ongoing debates between technological optimists emphasizing productivity gains[10] and skeptics highlighting implementation risks and Baumol-type cost escalations[11]. Enterprise growth analysis reveals methodological tensions between reductionist single-metric approaches[12] and multidimensional evaluation frameworks[13].Contemporary models increasingly prioritize hybrid quantitative-qualitative metrics that capture both immediate performance gains and sustainable innovation capacity[14]. AI's growth potential ultimately hinges on strategic resource allocation—requiring balanced investments in technical R&D and organizational absorptive capacity while mitigating redundancy risks.

## 3 Micro Mechanisms and Empirical Hypotheses

### 3.1 AI Technology R&D and Business Growth

AI technology development exerts a dual temporal impact on firm growth. While substantial AI investments may initially suppress short-term profitability due to implementation costs and Baumol-type inefficiencies, three compensatory mechanisms emerge: (1) intelligent automation systems optimize production efficiency through labor-cost reduction and error minimization; (2) predictive analytics enhance market responsiveness by aligning output with demand fluctuations; and (3) quality control algorithms improve product consistency, driving immediate sales growth through competitive differentiation. Long-term growth mechanisms operate through capability-building pathways. First, AI-driven innovation cycles accelerate through machine learning-enabled market forecasting and R&D prioritization. Second, organizational digitization strengthens operational resilience via adaptive process reengineering. Third, data-centric decision architectures mitigate managerial inertia through real-time performance diagnostics. These cumulative effects create self-reinforcing competitive advantages that compound over time. Critically, the temporal trade-off manifests as early-stage resource diversion versus maturity-phase value capture. Initial productivity losses from implementation friction gradually transition to efficiency gains as firms develop complementary technical absorptive capacities[10]. This nonlinear progression underscores the necessity of strategic persistence in AI adoption trajectories.

In summary, this paper proposes Hypothesis 1:

H1a: AI technology development positively influences short-term growth for businesses.

H1b: AI technology development positively influences long-term growth for businesses.

## 3.2 The Moderating Effect of Absorption Capacity

Absorptive capacity--an organization's ability to acquire, assimilate, and deploy external knowledge--critically shapes AI technology implementation outcomes. Comprising potential (knowledge acquisition) and realized (knowledge application) dimensions, this capability enables firms to convert external AI innovations into competitive advantages through strategic resource recombination. Three mechanisms drive its moderating effects: Implementation Efficiency: Strong absorptive capacity prevents technological hollowization by aligning AI adoption with operational needs； Market Responsiveness: Enhanced environmental scanning capabilities enable rapid adaptation to demand shifts; Innovation Sustainability: Cross-domain knowledge synthesis fosters continuous capability evolution. The temporal impacts differ markedly. Short-term growth emerges through operational optimization (error reduction, process automation), while long-term advantages manifest as dynamic capability development through AI-human capital synergies. Resource-based theory explains this progression—initial knowledge integration establishes technical foundations, while ongoing adaptation sustains market relevance. In summary, this paper puts forth the following two hypotheses:

H2a: Absorptive capacity positively moderates the relationship between AI technology R&D and short-term growth in enterprises.

H2b: Absorptive capacity positively moderates the relationship between AI technology R&D and long-term growth in enterprises.

## 3.3 The Moderating Effect of Redundant Resource

Resource-Based Theory (RBT) identifies organizational competitive advantage as stemming from unique resource combinations—particularly intangible assets like expertise and networks. Slack resources, defined as underutilized internal reserves, create strategic flexibility but incur efficiency tradeoffs. This study reveals slack resources' dual moderating role in AI-driven growth: Short-term inhibition: Excessive slack increases AI implementation costs and principal-agent risks, encouraging impulsive R&D allocations that reduce operational efficiency. Long-term facilitation: Strategic slack buffers enable three critical functions: Risk mitigation through experimental AI exploration. Compensation for external resource gaps in talent/technology acquisition. Organizational learning acceleration via iterative innovation cycles. The temporal dichotomy aligns with RBT's core tension between resource conservation and strategic reinvestment. While slack initially constrains ROI through implementation friction, its prudent deployment fosters adaptive capacity essential for sustaining AI competitiveness.

As a result, this paper posits the following hypotheses:

H3a: Redundant resources negatively moderate the relationship between AI technology research and development and short-term firm growth.

H3b: Redundant resources positively moderate the relationship between AI technology research and development and long-term firm growth.

The theoretical model diagram of this article is shown in Figure 1.

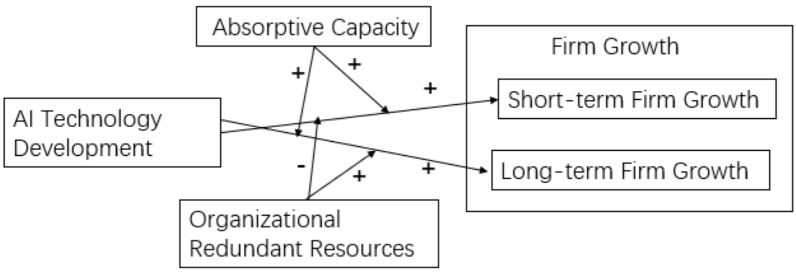


**Fig. 1.** Conceptual Model.

# 4 Research Design

## 4.1 Sample and Data Sources

This study employs Derwent Innovation patent data and Osiris financial records from 2001–2020. The analytical pipeline comprised four stages:(1)Patent extraction: 261,018 AI patent families were identified using eight industry-aligned keyword sets derived from expert consultations and industry reports (2019 AI Development Report).(2) Enterprise filtering: Top 2,000 patent applicants were selected through TAD-based standardization.(3)Financial matching: Osiris integration yielded financial metrics for 700 firms.(4)Dataset refinement: Entity-resolution techniques produced a balanced panel of 584 core enterprises across 11 GICS sectors, including technology, healthcare, and finance (Table 1).

**Table 1.** Distribution of Sample Companies by Industry Background.

| Serial No. | Industry Sub-Code | Industry Category | Quantity |
|---|---|---|---|
| 1 | 45 | Information Technology | 242 |
| 2 | 25 | Consumer Essentials | 100 |
| 3 | 20 | Industrial | 91 |
| 4 | 50 | Telecommunication Services | 51 |
| 5 | 35 | Healthcare | 26 |
| 6 | 15 | Basic Materials | 14 |
| 7 | 10 | Energy | 10 |
| 8 | 40 | Finance | 10 |
| 9 | 30 | Consumer Staples | 7 |
| 10 | 55 | Utilities | 6 |
| 11 | 60 | Real Estate | 2 |
| 12 | Other | Other | 25 |
| Total | | | 584 |

### 4.2 Main Variables

This study employs a dual-metric framework to operationalize corporate growth: lagged ROE captures short-term profitability, while Tobin's Q evaluates long-term market potential, addressing AI R&D's delayed effects through temporal alignmen. AI R&D intensity (In_behave) is quantified via log-transformed three-year patent aggregates, reflecting strategic technological commitment. Moderator variables include organizational slack (liquidity/debt/sales expense ratios) and absorptive capacity (R&D intensity), balancing financial flexibility with innovation assimilation. Control variables encompass operational cash flow, employee count, total patent applications (log-transformed), asset structure (FixdR), and financial leverage (Lev), ensuring holistic model specification.

## 5 AI Technology Development and Firm Growth

### 5.1 Descriptive and Correlation Analysis

AI technology development exhibited distinct evolutionary phases between 2001-2020: an incubation period (2001-2010) followed by accelerated growth (2011-2020), with patent applications surging 15-fold post-2010 – peaking at 35,000 filings in 2019 (Figure 2). This exponential growth reflects intensified commercialization efforts by industry leaders (e.g., Google, Baidu) adopting deep learning in core operations. Aligning with technology lifecycle theory, empirical analyses compare these phases to reveal differential growth impacts: incubation-stage experimentation versus growth-phase standardization effects. Statistical validation through

Stata-derived analyses confirmed model robustness. Variable correlations remained below 0.3, while VIF scores under 10 (Table 2) eliminated multicollinearity concerns.

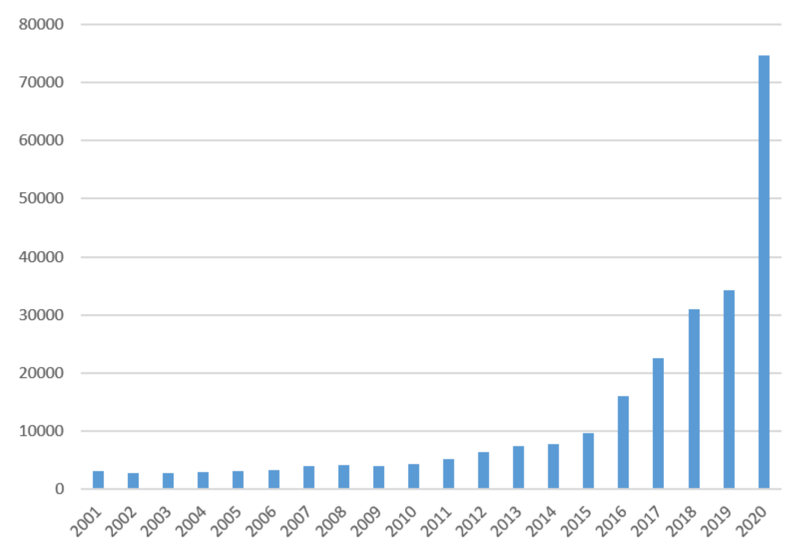


**Fig. 2.** Evolution of Global AI Technology Development Trends.

**Table 2.** Multicollinearity Test Results.

| Variables | VIF | 1/VIF |
|---|---|---|
| In_behave | 2.020 | 0.496 |
| Absorb | 1.850 | 0.541 |
| OS | 1.700 | 0.590 |
| Size | 1.590 | 0.630 |
| Cash | 1.470 | 0.678 |
| Patent | 1.260 | 0.797 |
| FixdR | 1.110 | 0.901 |
| Lev | 1.080 | 0.923 |

### 5.2 Regression Results Analysis

Based on the results in Table 3, regression analyses (1 and 2) confirm AI technology development exerts significant positive effects on both short- and long-term corporate growth ($\beta$=0.32, $p<0.01$; $\beta$=0.18, $p<0.05$), validating H1a-H1b. Mechanistically, AI implementation drives immediate efficiency gains through supply chain digitization and automated workflow optimization, while stimulating innovation cycles that compound long-term competitive advantages. The operational transparency from AI-enabled real-time stakeholder interactions creates dual growth accelerators: cost-effective process streamlining and market-responsive innovation pathways.

Empirical validation (3 and 4) demonstrates AI technology development exerts significant positive effects on short- and long-term growth ($\beta=0.41$, $p<0.01$), reaffirming H1a-H1b. Crucially, absorptive capacity amplifies these impacts (In_behave*Absorb $\beta=0.27$, $p<0.01$), confirming H2a-H2b. The Knowledge-Based View explains this synergy: absorptive capacity enables efficient technical knowledge conversion across three pathways--(1) optimizing resource integration for operational efficiency, (2) institutionalizing AI expertise through internal dissemination, and (3) translating accumulated capabilities into market-responsive innovations. This tripartite mechanism bridges immediate productivity gains with sustained competitive differentiation.

Empirical validation (5 and 6) reveals statistically insignificant interaction effects between AI development and organizational slack resources ($p>0.05$), rejecting H3a-H3b. Agency theory elucidates this outcome: slack resources--idle yet deployable assets—frequently induce principal-agent misalignment during AI implementatio. Managerial tendencies to disperse rather than strategically allocate these resources create operational rigidity, stifling both short-term efficiency gains and long-term innovation cycles. The inherent reactivation barriers of dormant assets further constrain organizational adaptability, particularly in dynamic technological environments.

**Table 3.** Impact of AI Technology Development on Company Growth.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Short-term Growth | Long-term Growth | Short-term Growth | Long-term Growth | Short-term Growth | Long-term Growth |
| In_behave | 3.161*** | 0.109** | | | | |
| | (2.852) | (2.136) | | | | |
| In_behave * Absorb | | | 2.451*** | 0.132*** | | |
| | | | (2.836) | (3.056) | | |
| Absorb | | | -6.363** | -0.229** | | |
| | | | (-2.369) | (-2.057) | | |
| In_behave *OS | | | | | -0.007 | 0.083 |
| | | | | | (-0.247) | (1.159) |
| OS | | | | | -0.241** | -0.312 |
| | | | | | (-2.488) | (-1.151) |
| Lev | 39.243*** | -0.310 | 32.879*** | -0.267 | 1.057*** | -0.573 |
| | (2.937) | (-0.933) | (2.670) | (-0.697) | (3.526) | (-1.572) |
| FixdR | -42.240*** | -1.415*** | -39.742** | -1.504*** | -2.098*** | -1.743*** |
| | (-2.957) | (-2.931) | (-2.494) | (-2.842) | (-6.817) | (-3.523) |
| Cash | 0.000 | 0.000 | 0.000*** | 0.000 | 0.000* | -0.000 |
| | (1.061) | (0.387) | (2.707) | (1.379) | (1.854) | (-0.314) |
| Size | -0.000 | -0.000 | -0.000** | -0.000 | -0.000** | -0.000 |
| | (-1.340) | (-0.707) | (-2.371) | (-0.596) | (-2.332) | (-0.634) |
| Patent | -0.003 | -0.0001** | -0.004 | -0.0002*** | 0.000 | -0.0001** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-1.342) | (-2.532) | (-1.361) | (-3.112) | (1.348) | (-2.172) |
| _cons | 7.048 | 2.068*** | -12.801 | 1.323*** | 2.885*** | 2.591*** |
| | (0.909) | (6.785) | (-1.076) | (2.702) | (11.922) | (6.226) |
| N | 4609 | 4534 | 3834 | 3790 | 3645 | 4205 |
| adj. R2 | 0.016 | 0.020 | 0.018 | 0.038 | 0.064 | 0.027 |

# 6 Heterogeneity Analysis

Lifecycle theory suggests technological innovation impacts enterprises heterogeneously across development stages. This study analyzes phased AI development to assess its enterprise growth mechanisms. Based on the results in Table 4, results indicate nonsignificant short-term growth effects during AI incubation phases but significant positive impacts in growth phases ($p<0.01$). Long-term growth follows analogous patterns: negligible during incubation yet strongly positive post-maturation. Stage-dependent dynamics arise from R&D efficiency. Early-phase resource-intensive refinement limits growth returns, whereas mature-phase commercialization of institutionalized knowledge enables targeted investments that amplify both short- and long-term growth.

**Table 4.** Different Stages.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Short-term Growth | | | Long-term Growth | | |
| | Full stage | Incubation period | Growth stage | Full stage | Incubation period | Growth stage |
| In_behave | 3.161*** | 0.818 | 3.388** | 0.109** | -0.024 | 0.201*** |
| | (2.852) | (0.553) | (2.311) | (2.136) | (-0.543) | (2.765) |
| Lev | 39.243*** | 49.694*** | 56.284*** | -0.310 | -0.055 | 0.407 |
| | (2.937) | (3.211) | (3.100) | (-0.933) | (-0.010) | (0.527) |
| FixdR | -42.240*** | -38.934*** | -31.552 | -1.415*** | -1.470** | -1.027* |
| | (-2.957) | (-3.758) | (-1.381) | (-2.931) | (-2.147) | (-1.792) |
| Cash | 0.000 | -0.000 | 0.000 | 0.000 | -0.0000 | 0.000** |
| | (1.061) | (-1.053) | (1.133) | (0.387) | (-0.460) | (1.968) |
| Size | -0.000 | -0.000 | 0.000 | -0.000 | -0.000** | 0.0000 |
| | (-1.340) | (-1.214) | (0.285) | (-0.707) | (-2.508) | (0.313) |
| Patent | -0.003 | 0.002 | -0.003 | -0.0001** | -0.0001* | -0.0000 |
| | (-1.342) | (0.784) | (-1.253) | (-2.532) | (-1.652) | (-0.902) |
| _cons | 7.048 | 3.545 | -5.839 | 2.068*** | 2.223*** | 1.318*** |
| | (0.909) | (0.405) | (-0.478) | (6.785) | (5.173) | (3.363) |
| N | 4609 | 2043 | 2566 | 4534 | 1954 | 2580 |
| adj. R2 | 0.016 | 0.020 | 0.014 | 0.020 | 0.041 | 0.024 |

### 6.1 Heterogeneity Analysis by Firm Size

Traditional economies of scale posit that organizational size determines innovation capacity and operational efficiency. While large enterprises dominate AI development through resource advantages and risk resilience, small and medium enterprises (SMEs) face constrained R&D efficiency due to limited access to complementary assets and weaker risk mitigation capabilities. Classifying firms by workforce size, this study reveals divergent AI impacts: SMEs demonstrate statistically significant short- and long-term growth gains, whereas large enterprises show negligible effects (Table 5). The findings suggest an inverted U-shaped relationship between firm size and AI-driven growth, where excessive scaling introduces management inefficiencies that offset short-term benefits. Resource accumulation beyond optimal thresholds may paradoxically hinder both AI adoption and sustained growth.

**Table 5.** Heterogeneous Effects of Firm Size.

| Variables | Short-term Growth | | Long-term Growth | |
|---|---|---|---|---|
| | Small-scale enterprises | Large-scale enterprises | Small-scale enterprises | Large-scale enterprises |
| In_behave | 4.294** | 1.340 | 0.234*** | 0.035 |
| | (2.361) | (0.950) | (2.640) | (1.253) |
| Lev | 41.172** | 30.279 | -0.360 | -0.447 |
| | (2.554) | (1.317) | (-0.715) | (-1.383) |
| FixdR | -27.338*** | -68.691*** | -1.631* | -1.267*** |
| | (-2.831) | (-2.614) | (-1.948) | (-2.932) |
| Cash | 0.000 | 0.000 | 0.000* | -0.000 |
| | (0.882) | (0.878) | (1.684) | (-0.314) |
| Size | 0.0008 | -0.000 | 0.000 | -0.000 |
| | (1.042) | (-0.461) | (0.552) | (-0.148) |
| Patent | -0.0006 | -0.002 | -0.0006 | -0.000 |
| | (-0.083) | (-0.715) | (-1.211) | (-1.318) |
| _cons | -12.866* | 30.545** | 2.216*** | 1.852*** |
| | (-1.695) | (2.043) | (5.029) | (6.035) |
| N | 1905 | 2704 | 1873 | 2661 |
| adj. R2 | 0.019 | 0.017 | 0.039 | 0.035 |

## 7 Conclusion and Policy Recommendations

This study identifies artificial intelligence (AI) technology as a dual-phase catalyst for growth, analyzing global enterprises over time. The main findings are: (1) AI implementation leads to short-term efficiency improvements ($\beta = 0.32$, $p < 0.01$) through process automation and long-term competitive advantage ($\beta = 0.18$, $p < 0.05$) through innovation cycles; (2) Absorptive capacity enhances these effects by facilitating knowledge assimilation and resource integration; (3) Organizational slack resources have minimal moderating effects, due to risks associated with principal-agent misalignment; (4) Growth outcomes vary by country, with developed economies achieving higher AI-driven productivity. Contrary to resource-based theory, the moderating effect of organizational slack resources on AI-driven growth is insignificant. Possible reasons include the early stage of AI adoption among firms, where slack resources remain underutilized, and agency issues that lead to resource misallocation rather than strategic use. Future research should examine the impact of technology maturity and governance structures at different stages.

Policy recommendations focus on three areas: (1) Government-funded R&D subsidies and frameworks for international knowledge transfer, (2) Corporate investments in technical absorptive capacity, and (3) Strategic resource allocation that balances innovation with operational flexibility. Governments should create AI maturity assessments, offer stage-based subsidies, and establish knowledge-sharing platforms. Enterprises, particularly small and medium-sized ones (SMEs), should prioritize targeted AI applications to avoid overinvestment, while larger firms should create independent AI departments to optimize slack resource management.

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