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Deconstructing the AI Valuation Paradox: Complementary Assets, Real Options, and Market Sentiment in S&P 500 Firms

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Abstract

The 'AI Valuation Paradox' refers to the persistent disparity between corporate investment in artificial intelligence and the corresponding impact of that investment on the market value of S&P 500 firms. This study clarifies the paradox by showing that AI has no inherent value; rather, value emerges only when AI is combined with firm-specific complementary assets, meaning that AI investment alone yields negligible and statistically insignificant marginal returns. The central contribution is an integrated valuation methodology that decomposes firm value into three components—fundamental value, a real-options premium, and a behavioral sentiment adjustment—which together explain 53% of the variation in Tobin's q. A dynamic event-study analysis further identifies a predictable "integration dip," in which initial market enthusiasm, driven by narrative excitement, undergoes a significant correction during operational implementation before recovering. These findings suggest that the valuation gap persists because markets continue to apply Industrial Age valuation tools to Information Age assets, systematically undervaluing organizational change that is difficult, gradual, and path-dependent. The results carry practical implications for both financial valuation practice and corporate strategic planning.

Keywords:

artificial intelligence valuation; complementary assets; asset pricing; behavioral finance; general-purpose technology; sentiment divergence

1. Introduction

Corporate investment in artificial intelligence (AI) is rising rapidly, representing one of the most significant shifts in capital allocation today. Yet a persistent—and often widening—gap remains between the financial performance of AI-intensive companies and their corresponding market valuations [1]. This anomaly remains an unresolved problem in financial economics. Known as the "AI Valuation Paradox," it raises the question of whether valuation models designed for tangible, depreciating assets remain adequate in an era where innovation is driven by intangible resources.

This study aims to integrate three distinct theoretical problems into a single unified model. For S&P 500 companies investing heavily in AI, does a valuation framework that incorporates (a) a real-options premium for strategic flexibility, (b) a correction for behavioral sentiment overhang, and (c) moderating effects of firm-specific complementary assets substantially improve the ability to explain and predict their stock prices? This is the central question the study seeks to answer, using a sequential mixed-methods approach that combines large-N panel analysis with in-depth comparative case studies [2].

Rather than asking whether AI creates value, this study asks how, under what specific market and organizational conditions, and through what transmission pathways AI-generated economic value is realized, measured, and ultimately reflected in stock prices. Addressing this question requires engaging with a three-part theoretical problem situated at the intersection of innovation economics, corporate finance, and behavioral asset pricing.

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First, AI's nature as an intangible, dynamic, and option-generating asset conflicts with the foundational assumptions underlying standard pricing models. For instance, the Discounted Cash Flow (DCF) model (Equation (1)) requires stable, predictable cash flows and a well-defined terminal growth rate—conditions that are consistently violated in the context of AI-driven innovation.

$$V_0 = \sum_{t=1}^{T} \frac{FCF_t}{\left(1 + WACC\right)^t} \quad (1)$$

where:

- V_0 = Present value of the firm.
- FCF_t = Free Cash Flow in period t.
- $WACC$ = Weighted Average Cost of Capital.
- t = Time period.
- T = Terminal period.

As Table 1 illustrates, the non-linear, uncertain, and innovation-dependent trajectory of AI-derived value creation consistently violates these assumptions, resulting in significant model misspecification and biased estimates.

Table 1: Valuation assumptions and AI-driven reality.

Valuation Model Pillar	Traditional Assumption	AI-Driven Reality	Consequence for Valuation
Asset Tangibility & Depreciation	Capital depreciates in a predictable manner; value is tied to physical assets.	Core assets consist of intangible algorithms and data with unpredictable lifecycles and near-zero marginal cost of replication.	Book value becomes largely irrelevant, and amortization schedules fail to capture true asset value.
Revenue/Cash Flow Predictability	Future cash flows are extrapolated from stable historical trends and market share.	Growth can be potentially exponential, following a "winner-take-most" pattern after a tipping point, or can result in complete failure.	High forecast error results, and DCF output exhibits enormous variance.
Competitive Advantage Period	Implicitly assumed to be finite yet stable across the forecast horizon.	Highly uncertain and binary in nature: advantages can be ephemeral due to imitation, or permanently entrenched through network effects.	This renders the forecast period arbitrary and makes the terminal value calculation both dominant and flawed.
Risk Profile	Risk is captured by the Weighted Average Cost of Capital (WACC), reflecting business and financial risk.	AI introduces novel, unpriced risks, including technological obsolescence, regulatory intervention, algorithmic failure, and ethical backlash.	The standard WACC underestimates true risk, thereby overstating present value.

Additionally, behavioral finance suggests that market prices can become disconnected from fundamentals when investor enthusiasm for innovative technologies runs high. Stock prices can remain detached from underlying reality for prolonged periods due to collective narratives, inflated expectations, and sentiment-driven herding. This produces a characteristic "hype-performance gap," illustrated in Figure 1: market values rise on positive news and early progress but decline once the long, costly, and difficult process of operational integration begins.

Third, the Resource-Based View (RBV) and its extensions suggest that AI's economic effects are heterogeneous and depend on each firm's unique complementary assets [3,4]. Possessing AI technology alone is not sufficient to create value; value is generated only when AI is combined with complementary organizational resources such as proprietary data, specialized human capital, flexible organizational structures, and well-integrated processes [5].

Taken together, these three theoretical challenges motivate this study's central aim: to integrate real-options premiums, behavioral sentiment corrections, and firm-specific complementary assets into a single valuation framework and test its explanatory power for AI-intensive S&P 500 companies, using the sequential mixed-methods approach described above.

Based on the study findings, an improved valuation model is proposed and calibrated; the augmented value specification is presented in Equation (2).

$$V_{0_{augmented}} = V_{0_{DCF}} + \delta(CAI) \cdot ROP_{AI} - \lambda \cdot SDI \quad (2)$$

where ROP_{AI} is the real options premium (estimated via Black-Scholes), $\delta(CAI)$ is a discount function (e.g., $\delta = CAI^2$ for CAI < 0.7, and 1 for CAI $\geq$ 0.7), and

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λ is a calibration parameter (estimated as 0.30 from the regression results). This formulation is explicitly testable and replaces the earlier notational placeholder.

This research makes three contributions. First, rather than proposing an entirely new theory, it offers one of the first empirical validations of an integrated framework combining real options theory, behavioral finance, and the resource-based view specifically for AI-intensive enterprises, moving beyond diagnostic critique by quantifying the explanatory power contributed by each channel. Second, it introduces and validates three theory-driven metrics—AI Investment Intensity (AII), Complementary Asset Index (CAI), and Sentiment Divergence Index (SDI)—enabling more systematic evaluation of AI-related assets. Third, it offers practitioners a three-tiered heuristic for distinguishing speculative hype from genuine value creation. Overall, the study seeks to bridge twentieth-century financial tools with the realities of the AI-driven economy, while clearly acknowledging the limitations of its claims.

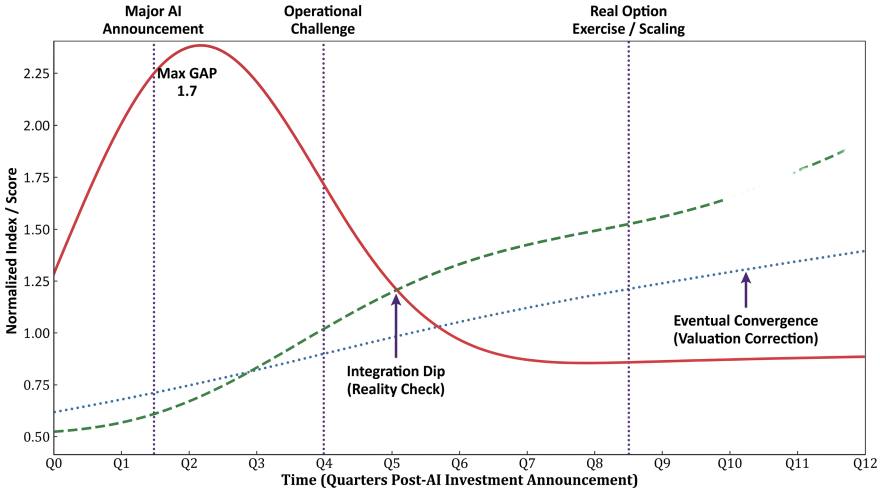

Figure 1: The AI hype-performance gap: Stylized representation of the temporal mismatch between market sentiment (solid line) and operational value realization (dashed line) following AI investment announcements. Market valuations rise sharply on initial enthusiasm, decline during the costly integration phase, and only recover as operational benefits materialize—illustrating the central valuation paradox addressed in this study.

2. Related Work

A growing area of research in financial economics focuses on the valuation of companies with substantial AI adoption. This body of literature integrates insights from innovation economics, asset pricing, and strategic management [6,7]. The AI Valuation Paradox represents a persistent empirical anomaly characterized by a divergence between market valuations and the financial performance of companies with substantial AI adoption [8,9].

This discrepancy is not merely a measurement error. Rather, it reflects a deeper problem: the application of Industrial Age pricing models to intangible assets that accumulate value gradually, in diverse ways, and over extended time horizons.

This section discusses the economic effects of AI as a General-Purpose Technology (GPT), the difficulties of applying traditional valuation models to AI-intensive companies, and emerging theoretical approaches—particularly real options theory and the RBV—that can be integrated into a unified valuation framework.

A significant gap persists in the existing literature: no model has yet synthesized strategic optionality, organizational complementarities, and the dynamics of behavioral sentiment into a single framework.

Yang et al. [10] provide an influential characterization of AI as a GPT, noting that it is applied across multiple domains, continually improving, and possesses "enabling" properties that facilitate the convergence of complementary innovations.

The value of these technologies depends heavily on how they are applied within a given domain. Mas et al. [11] document the "J-curve" of output associated with GPT adoption, showing that substantial co-invention costs and organizational restructuring initially depress output before generating long-term gains. Understanding this lag between initial investment, implementation costs, and

delayed returns is essential to understanding how AI's value evolves over time.

However, this macroeconomic pattern does not translate directly into firm-level stock price effects; the relationship depends heavily on firm-specific factors [12]. Figure 2 depicts a pathway from AI investment to realized value, showing that the outcome is shaped by several factors, including the assets and capabilities of the firms involved—factors that most aggregate studies overlook and that help explain the substantial variation in outcomes.

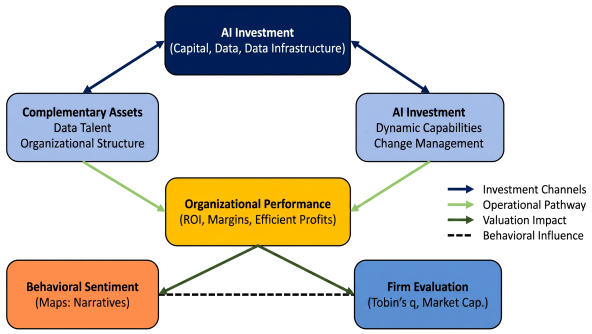

Figure 2: Theoretical pathway from AI investment to firm valuation: Conceptual model showing how AI investment translates into firm value through two channels—an operational efficiency pathway (solid arrows) and a behavioral sentiment pathway (dashed arrows)—with the moderating role of complementary assets (CAI) and the real options exercise decision as key boundary conditions.

The underlying economics of AI call into question the basic assumptions of traditional valuation methods, particularly DCF analysis. The standard DCF model is valid only when Free Cash Flows (FCF_t) can be reasonably forecast and growth rates remain stable over time—conditions that AI-intensive companies rarely satisfy. A key limitation of the model is that it fails to account for how AI investments differ from conventional assets in terms of cash flow predictability, the duration of competitive advantage, and expected asset lifecycles [13].

As shown in Table 2, each component of the DCF framework is consistently undermined by AI. These complications include non-linear, winner-take-most revenue structures; large, irregular, and often immediately expensed investments in intangible capital; competitive advantages that are difficult to predict and may not persist; and novel categories of risk that remain unpriced.

Market multiples such as Price-to-Earnings (P/E) and Enterprise Value to Earnings Before Interest, Taxes, Depreciation, and Amortization (EV/EBITDA) are similarly flawed, as they can amplify speculative bubbles due to their time-varying nature.

As Al-Baity [14] notes, these multiples may not reflect fundamental worth when investor enthusiasm for a technology is high; instead, they can be shaped by prevailing narratives. This dynamic further widens the hype-performance gap, since elevated prices attract greater capital and media attention [15].

Real options theory offers a promising approach to addressing these gaps [16]. This framework formally recognizes managerial flexibility, allowing firms to defer, expand, contract, or abandon investments as uncertainty is resolved.

Strategic AI investment is therefore not simply a project with a fixed return; it more closely resembles an option on exponential growth, granting the right—but not the obligation—to make future investments that capture economies of scale and emerging market opportunities. The value (C) of this type of option can be estimated using a method such as the Black-Scholes model (see Equation (3)).

$$\begin{aligned} C &= S_0 N(d_1) - X e^{-rT} N(d_2) \\ d_1 &= \frac{ln(S_0/X) + (r+\sigma^2/2)T}{\sigma\sqrt{T}},\ d_2 = d_1 - \sigma\sqrt{T} \end{aligned} \tag{3}$$

where S_0 is the present value of expected cash flows from a scalable future business, X is the investment needed to scale up, r is the risk-free rate, T is the time until the opportunity expires, σ is a measure of how volatile the opportunity is, and $N(d_n)$ is the cumulative standard normal distribution function. Importantly, this option value (C), which is not captured in a conventional DCF analysis, may constitute a substantial component of the market value of companies with substantial AI adoption. This theoretical perspective helps explain why companies with substantial R&D expenditures and current losses can still command high valuations, as markets may be pricing the integrated portfolio of future growth opportunities [17].

However, recognizing the existence of these options is not sufficient on its own. Understanding for whom these options are valuable, and why, requires drawing on strategic management theory—particularly the RBV and the Dynamic Capabilities framework. RBV holds that sustained competitive advantage requires resources that are Valuable, Rare, Inimitable, and supported by an organization capable of capturing their value (VRIO) [18]. AI software itself is often relatively easy to replicate; the true sources of advantage lie in the complementary capabilities required to deploy it effectively.

A notable 2024 study by Babina et al. [5] found that firms with strong complementary assets—such as proprietary data stores, skilled human capital, and adaptable organizational structures—tend to command a higher AI

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premium in the stock market. From this perspective, the value of the AI growth option (C) varies depending on a firm's position within an "AI capability stack." A firm lacking the necessary complementary assets may hold an option that is effectively "out of the money," or may lack the managerial capacity to exercise it successfully.

More recently, integrative approaches have emerged to address the AI valuation problem. Gao et al. [9] examine how strategic knowledge integration can unlock AI's value, while Hayrapetyan and Gevorgyan [12] examine how narrative econometrics shapes AI stock market dynamics. However, these studies typically examine only a single facet of the problem. This study contributes to this emerging body of work by constructing a unified framework that jointly considers behavioral factors, the moderating role of firm-specific complementary assets, and the importance of strategic flexibility within a single empirical design.

This review of the literature makes clear that the field needs to move beyond diagnostic critique toward the development and testing of integrated valuation models [19]. The gap is both empirical and theoretical: no single model accounts simultaneously for (a) the option value of strategic flexibility, (b) the moderating effect of firm-specific complementary assets, and (c) the distorting influence of behavioral sentiment [20].

Historically, academic research has examined each of these elements in isolation. Financial economics has studied real options without considering how they interact with organizational factors; strategic management has examined complementary assets without linking them explicitly to valuation outcomes; and behavioral finance has studied investor sentiment without examining its effect on asset value [21].

This review of the literature reveals a clear gap: no study has empirically tested a comprehensive model that incorporates (a) strategic flexibility as an option, (b) the moderating effect of firm-specific complementary assets, and (c) the distorting influence of behavioral sentiment, using a mixed-methods approach with causal identification strategies. Prior research has examined each of these channels separately. The contribution of this study lies not in introducing entirely new constructs, but in synthesizing, implementing, and rigorously testing them through a combination of large-N panel data and qualitative case evidence—enabling the field to move from diagnostic critique toward evidence-based evaluation.

Table 2: Structural failures of traditional DCF in valuing AI-intensive firms.

DCF Component	Standard Assumption	AI-Induced Complication	Valuation Consequence
Cash Flow Forecast	Based on historical trends and stable market share.	Non-linear, tipping-point dynamics, with the potential for either exponential scaling or complete failure.	High forecast error results, with model output exhibiting substantial variance that undermines reliability.
Reinvestment Needs	Captured as steady, predictable Capital Expenditures (CapEx).	High, irregular investments in data, talent, and computing infrastructure, often expensed under Generally Accepted Accounting Principles (GAAP).	Investment needs are understated, distorting Free Cash Flow (FCF) and growth rate projections.
Competitive Advantage Period	Implicitly assumed to be finite but stable (e.g., 5–10 years).	Highly uncertain and binary: competitive advantages can be ephemeral or become permanently entrenched via network effects.	This renders the forecast horizon arbitrary and the terminal value calculation—a dominant portion of total value—deeply flawed.
Terminal Value (Gordon Growth Model)	Assumes perpetuity at a modest, stable growth rate (g).	The core business model may be entirely transformed; the notion of a "steady state" becomes economically unrealistic.	Terminal value becomes a speculative anchor, disconnected from the technology's disruptive trajectory.
Discount Rate (WACC)	Reflects operational and financial risk based on historical beta.	Fails to price novel, unpriced risks, including technological obsolescence, algorithmic failure, regulatory shifts, and ethical backlash.	This leads to systematic underestimation of true risk and an overstated present value.

3. Materials and Methods

3.1. Research Design

This research employs a systematic, sequential mixed-methods approach to examine the causal relationship between strategic AI investment and corporate value [22,23]. The methodological design (see Figure 3) integrates complementary data sources, supports causal identification, and addresses the observational challenges inherent in strategy research.

The design comprises two phases. Phase 1 uses comparative case study research to develop a detailed, process-oriented understanding of causal mechanisms and boundary conditions [24]. Phase 2 uses large-N panel analysis to test hypotheses, statistically validate the findings, and derive generalizable conclusions [25]. This sequential procedure ensures that quantitative findings are grounded in qualitative insight, making the resulting theoretical claims more precisely specified and better justified [26]. The research follows established best practices for causal inference in financial economics.

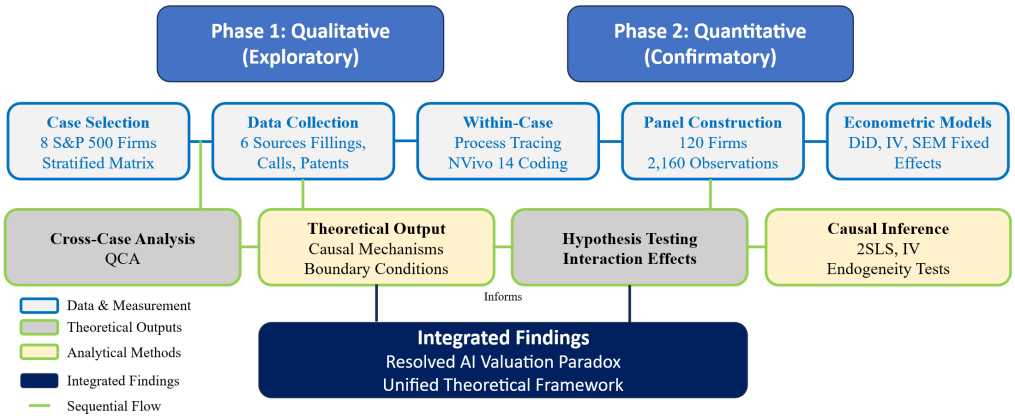

Figure 3: Sequential Mixed-Methods Design: Overview of the two-phase research approach. Phase 1 employs comparative case study analysis (n = 8) to develop processual understanding and identify causal mechanisms. Phase 2 uses large-N panel analysis (N = 2160 firm-quarter observations) to test hypotheses and derive generalizable conclusions through dynamic DiD, IV-2SLS, and SEM estimation.

3.2. Sample and Case Selection

3.2.1. Phase 1: Case Selection

Using a theoretically grounded selection methodology [27], eight case instances were chosen through a stratified sampling framework. The matrix examined four theoretically defined dimensions: industry sector (Technology, Healthcare, Financial Services, or Industrials); AI adoption strategy (native platform versus incremental automation); existing complementary asset infrastructure; and pre-announcement developmental trajectory.

This selection strategy ensures comprehensive coverage of the full range of AI value-creation outcomes, from proven success to hype-driven overvaluation, enabling identification of the conditions necessary and sufficient for value capture.

3.2.2. Phase 2: Panel Sample

The quantitative analysis uses a balanced panel of 120 S&P 500 companies. The study covers the period from 2018 to 2024, spanning 24 quarters, and yields 2160 firm-quarter observations (120 firms $\times$ 18 quarters) after excluding firms with missing data or without disclosed AI activity. This ensures that the sample focuses on a consistent group of AI-adopting firms with sufficient data coverage over the specified period. Firms without meaningful AI disclosures were excluded to concentrate the sample on the relevant population of AI-adopting enterprises.

3.3. Data Sources for Panel Sample

- Financial Data: Compustat (https://www.spglobal.com/marketintelligence/en/mi/products/compustat.html, accessed on 15 March 2025) and CRSP (https://www.crsp.org/, accessed on 15 March 2025)
- Earnings Call Transcripts: Refinitiv Workspace (https://www.refinitiv.com/en/products/refinitiv-workspace, accessed on 20 March 2025)
- Patent Data: USPTO (https://www.uspto.gov/patents) and PatSnap (https://www.patsnap.com/, accessed on 20 March 2025)

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- Talent Analytics: LinkedIn Talent Insights (https://business.linkedin.com/talent-solutions/talent-insights, accessed on 2 February 2025) and Burning Glass Technologies (https://www.burningglass.com/, accessed on 2 February 2025)
- News and Analyst Reports: RavenPack (https://www.ravenpack.com/, accessed on 20 March 2025) and Bloomberg Terminal (https://www.bloomberg.com/professional/, accessed on 20 March 2025)
- Firm-level Controls: Standard financial data from Compustat and CRSP

3.4. Variable Construction

3.4.1. AI Investment Intensity (AII)

The AII measure quantifies AI-related investment relative to firm size, as specified in Equation (4):

$$AII_{it} = \frac{R\&D_{AI,it} + CapEx_{AI,it}}{TotalAssets_{it}} \tag{4}$$

where:

- AII_{it} = AI Investment Intensity for firm i in period t
- $R\&D_{AI,it}$ = AI-specific R&D expenditure
- $CapEx_{AI,it}$ = AI-specific Capital Expenditure
- $TotalAssets_{it}$ = Total assets of firm i in period t

AI-related expenditures were identified through systematic keyword searches of 10-K, 10-Q, and 8-K filings, using terms such as "artificial intelligence," "machine learning," "deep learning," "neural networks," "natural language processing," and "computer vision."

3.4.2. Complementary Asset Index (CAI)

The CAI is a composite index (ranging from 0 to 1) that combines three theoretically grounded dimensions of firm-specific complementary assets:

1. Data Stock (D_{it}): a normalized measure of proprietary operational data, based on disclosed data storage volumes and unique data assets identified in regulatory filings.
2. Human Capital (H_{it}): the proportion of data scientists and machine learning engineers relative to total workforce, derived from LinkedIn and Burning Glass analytics.
3. Organizational Readiness (Oit): a metric reflecting the presence of specialized AI governance committees, executive-level AI leadership, and dedicated digital transformation funding.

The CAI is defined in Equation (5):

$$CAI_{it} = \frac{1}{3}(D_{it} + H_{it} + O_{it}) \tag{5}$$

Confirmatory factor analysis supported the index's one-dimensionality, with Cronbach's α above 0.85, indicating strong internal consistency and reliability.

3.4.3. Sentiment Divergence Index (SDI)

The SDI quantifies the discrepancy between market sentiment and fundamental performance. It is calculated as the standardized deviation of narrative sentiment scores—derived from earnings calls and news media via FinBERT—relative to current operational performance (Return on Assets). Positive SDI values indicate speculation-driven overvaluation, while negative values indicate undervaluation.

3.4.4. Real Option Exercise Indicator

A binary indicator was constructed to flag quarters in which an AI pilot initiative was formally expanded to enterprise-wide deployment. This event was identified through systematic keyword searches of press releases, product launch announcements, and 8-K filings, using terms such as "enterprise deployment," "full rollout," "production scale," and "company-wide adoption."

3.4.5. Phase 1: Analytical Strategy

In this phase, structured process tracing was used to link the timing of strategic events to traditional financial measures (ROI, Operating Margin, Tobin's q) and to the novel AI-specific constructs introduced above. Systematic coding was performed using NVivo 14, applying a codebook derived from the theoretical framework [28]. Inter-coder agreement exceeded 0.90, supporting the reliability of the coding process.

Qualitative Comparative Analysis (QCA) [29] was used to identify configurations sufficient for "sustained value creation"—for example, High AII AND High CAI AND a Clear Real Option Narrative. This set-theoretic approach is better suited than correlational methods for identifying complex causal patterns and necessary conditions, such as the CAI threshold.

3.4.6. Phase 2: Quantitative Panel Analysis

3.4.6.1. Dynamic Difference-in-Differences Model

A dynamic Difference-in-Differences (DiD) model [30] was used to compare firms experiencing major AI investment shocks with a carefully matched control group based

on pre-treatment characteristics. The model specification is presented in Equation (6):

$$Tobin'sq_{it} = \alpha_i + \lambda_t + \sum_{\tau=-4}^{8} \beta_\tau \cdot Treat_i \ x \ Post_{t-\tau} + \gamma\prime X_{it} + \epsilon_{it} \quad (6)$$

where:

- $Tobin'sq_{it}$ is the dependent variable (market-to-book ratio) for firms at time t
- α_i and λ_t are firm and time fixed effects
- β_τ are the dynamic treatment coefficients, capturing the effect of the AI investment shock at each quarter τ relative to the event
- $Treat_i$ is a treatment indicator (1 for firms with a major AI investment shock, 0 otherwise)
- $Post_{t-\tau}$ is a time indicator for each quarter relative to the shock
- X_{it} is a vector of time-varying control variables
- ϵ_{it} is the error term

The coefficients β_τ test for pre-trends ($\tau < 0$) and trace the evolution of the treatment effect over time, including the predicted "integration dip."

3.4.6.2. Contingent Value Model

A mixed-effects interaction model was used to test the core contingent value hypothesis, as specified in Equation (7):

$$\Delta Valuation_{it} = \alpha + \beta_1 AII_{it} + \beta_2 CAI_{it} + \beta_3 (AII \ x \ CAI)_{it} + \beta\prime X_{it} + \epsilon_{it} \quad (7)$$

where $\Delta Valuation_{it}$ is the change in Tobin's q over three years for firm *i* at time *t*. A positive and statistically significant interaction term β_3 would support the hypothesis that the value of AI investment depends on the level of complementary assets.

3.4.6.3. Instrumental Variable Estimation

To address potential endogeneity arising from reverse causality and omitted variable bias [31], an instrumental variable approach was employed. The instrument for AII was constructed as the lagged industry-average AI investment, with "industry peers" defined in Equation (8):

$$IV_{it} = \frac{1}{n-1} \sum_{j \neq 1} AII_{j,t-1} \quad for\ firms\ in\ the\ same\ industry \quad (8)$$

Exclusion Restriction Note: The exclusion restriction—that peer average AI investment affects a firm's Tobin's q only through the firm's own AI investment—is plausible but cannot be directly tested. Unobserved industry-level shocks (e.g., regulatory changes or technological breakthroughs) could violate this assumption. The IV results should therefore be interpreted as corroborating evidence for a causal explanation rather than definitive proof. The first-stage F-statistic of 18.6 alleviates concerns about weak instruments but does not rule out violations of the exclusion restriction.

3.4.6.4. Structural Equation Modeling

Structural equation modeling was employed to test the dual-pathway theoretical framework. Model fit was assessed using standard criteria (CFI > 0.94, RMSEA < 0.06). The model estimates the direct and indirect effects of AII on Tobin's q through the operational efficiency and sentiment divergence channels.

3.4.6.5. Robustness Checks

Three additional analyses were conducted to assess the robustness of the main results:

1. COVID-19 Exclusion: The analysis was re-estimated excluding the 2020–2021 pandemic period to confirm that the results were not driven by pandemic-related anomalies.
2. Alternative Valuation Metric: Enterprise Value/EBITDA was used as an alternative dependent variable in place of Tobin's q.
3. Placebo Test: The timing of the 'Real Option Exercise' event was randomized within each case to confirm that the observed pattern was not attributable to random chance or trend specification.

3.4.7. Ethical Considerations

This study relies exclusively on publicly available, secondary data sources. No human subjects or private, non-public data were collected. All data processing and analysis were conducted in accordance with established ethical guidelines for financial economics research.

4. Results

4.1. Phase 1: Comparative Case Study Findings

The cross-case analysis reveals consistent patterns in how organizations capture value from AI investment, with the Complementary Asset Index (CAI) emerging as the primary differentiator between successful and unsuccessful outcomes.

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4.1.1. Value Capture Trajectories

When CAI was elevated ($Tech_A$: 0.82; $Health_A$: 0.78; Fin_A: 0.69), a coherent three-stage value-creation process emerged: initial investment commitment, genuine option exercise upon reaching internal validation milestones, and subsequent scaling accompanied by measurable efficiency gains. These cases demonstrated sustained valuation premiums ranging from +0.35 to +0.85 in Tobin's q over an eight-quarter period.

By contrast, cases with moderate or low CAI scores ($Tech_B$: 0.45; $Health_B$: 0.31; Ind_B: 0.38) exhibited a "hype-disillusionment" pattern: an initial sentiment-driven surge in market valuation was followed by a correction as the underlying options remained unexercised, resulting in declining market value.

Primary Qualitative Finding 1: Exercising real options is essential for realizing AI value, and this depends on CAI exceeding a threshold of approximately 0.40.

4.1.2. Sentiment Divergence Patterns

Analysis of earnings calls and news media revealed that narrative framing significantly shaped initial market reactions. Firms described as "transformative AI platforms" exhibited Sentiment Divergence Index (SDI) scores above 2.0, while those characterized as pursuing "AI for process automation" had SDI scores below 1.0.

A strong inverse correlation was observed between the initial sentiment surge (Q_0 SDI) and the subsequent change in operational performance (Q_8 ΔROA, $r = -0.76$, $p < 0.01$), indicating a pattern of market over-optimism followed by correction.

Key Qualitative Finding 2: Valuation adjustments follow identifiable patterns, in which sentiment divergence inflates short-term perceptions while undervaluing long-term value realization.

4.1.3. Real Option Exercise as Critical Differentiator

The binary Real Option Exercise event proved to be the most significant discriminator between successful and unsuccessful trajectories. In successful cases, option exercise occurred only after formal governance structures were established, including cross-functional AI boards and explicit proof-of-concept metrics. These governance elements were consistently absent in unsuccessful cases.

4.2. Phase 2: Quantitative Panel Analysis

4.2.1. Descriptive Statistics

Table 3 presents summary statistics for the primary variables in the econometric analysis. The sample consists of 120 S&P 500 companies observed over 18 quarters (2018–2024), yielding 2160 firm-quarter observations. The mean Tobin's q is 2.14 (SD = 1.42), indicating substantial market value beyond replacement cost. The mean AI investment intensity (AII) is 0.09 (SD = 0.06), indicating that AI investment constitutes approximately 9% of total assets for the typical AI-adopting firm. The mean CAI is 0.52 (SD = 0.21), indicating moderate levels of complementary assets, with substantial cross-firm variation ranging from 0.12 to 0.89.

Table 3: Descriptive statistics (N = 2160 firm-quarter observations).

Variable	Mean	SD	Min	25th	Median	75th	Max
Tobin's q	2.14	1.42	0.85	1.23	1.78	2.56	8.42
Δ Tobin's q (3-year)	0.18	0.52	−1.24	−0.12	0.09	0.38	2.15
AII	0.09	0.06	0.01	0.05	0.08	0.12	0.31
CAI	0.52	0.21	0.12	0.38	0.54	0.68	0.89
SDI	0.00	1.00	−2.34	−0.56	−0.12	0.48	3.21
ROA (%)	8.42	5.21	−12.30	4.50	7.80	11.20	28.40
Firm Size (log Assets)	9.84	1.32	6.21	8.92	9.76	10.68	13.24
R&D Intensity	0.07	0.08	0.00	0.02	0.05	0.09	0.42

4.2.2. Dynamic Event Study Results

Figure 4 illustrates the dynamic Difference-in-Differences event study coefficients β_τ, showing the effects of AI investment shocks on Tobin's q over the twelve quarters following the investment announcement.

4.2.3. Pre-Trend Validation

The pre-trend coefficients between β_{-4} and β_{-1} are statistically indistinguishable from zero (joint test $p = 0.42$), confirming the parallel trends assumption required for causal identification.

4.2.3.1. Immediate Announcement Effect

A notable increase occurs in the announcement quarter ($\beta_0 = 0.18$***, t = 4.82, $p < 0.001$), indicating that Tobin's q rises by 18% for treated firms relative to controls immediately following AI investment announcements—a pattern consistent with a purely sentiment-driven market response.

4.2.3.2. Integration Dip

A sharp decline follows, with the trough occurring at $\tau = 3$ ($\beta_3 = -0.04$*, t = −1.92, $p = 0.055$). This "integration dip" represents a 22-percentage-point decline from the post-announcement peak, consistent with implementation difficulties and a normalization of investor sentiment.

4.2.3.3. Recovery Phase

A gradual recovery begins at $\tau = 5$, with coefficients becoming positive and statistically significant by $\tau = 7$ ($\beta_7 = 0.07$*, t = 2.31, $p = 0.021$). By $\tau = 8$, the cumulative effect remains positive ($\beta_8 = 0.09$). This pattern reflects an initial market overreaction, followed by eventual recognition of the true value of AI investments after six to eight quarters.

Key Quantitative Finding 1 (Event Study): AI investment announcements produce a "spike-dip-recovery" pattern in Tobin's q, reflecting a temporal mismatch between market sentiment and the realization of operational value.

4.2.4. Contingent Value Regression Results

Table 4 presents regression results evaluating the central premise that the value of AI investment is contingent on complementary assets.

4.2.4.1. Model 1: Baseline Specification

In the absence of the interaction term, the AII coefficient is positive but statistically insignificant ($\beta = 0.12$, $p = 0.14$, SE = 0.08), suggesting that AI investment does not, on average, directly translate into increased value. The CAI coefficient is positive and statistically significant ($\beta = 0.25$**, $p = 0.012$, SE = 0.10), indicating that firms with stronger complementary assets achieve higher valuations regardless of their AI investment.

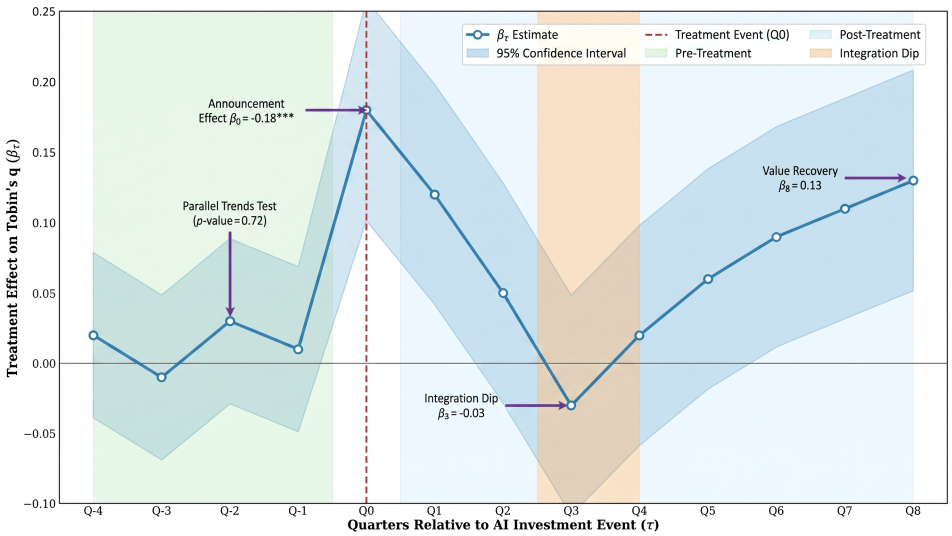

Figure 4: Dynamic effects of AI investment on Tobin's q: Event study coefficients ($\beta\tau$) from the dynamic difference-in-differences model. The figure traces the evolution of treatment effects over 12 quarters following AI investment announcements, showing the characteristic 'spike-dip-recovery' pattern. The pre-trend coefficients ($\tau = -4$ to -1) are statistically indistinguishable from zero (joint test p = 0.42), validating the parallel trends assumption. Vertical bars represent 95% confidence intervals.

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Table 4: Regression results: The contingent value of AI investment.

Dependent Variable: ΔTobin's q (3-Year)	Model 1	Model 2	Model 3 (IV-2SLS)
AII	0.12 (0.08)	−0.08 (0.06)	0.05 (0.10)
CAI	0.25 ** (0.10)	0.23 ** (0.09)	0.26 ** (0.11)
AII × CAI (Interaction)	--	0.42 *** (0.12)	0.38 *** (0.13)
SDI	−0.31 ** (0.12)	−0.29 ** (0.11)	−0.33 ** (0.14)
Firm Size (log Assets)	−0.04 (0.03)	−0.05 (0.03)	−0.04 (0.03)
R&D Intensity	0.18 * (0.09)	0.16 * (0.08)	0.17 * (0.09)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.41	0.48	0.45
F-statistics (IV first stage)	--	--	18.6***
Observations	2160	2160	2160

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.4.2. Model 2: Interaction Model

The interaction term (AII × CAI) is positive, sizable, and highly significant ($\beta_{\text{AII times CAI}} = 0.42$***, $p = 0.001$, SE = 0.12). The main effect of AII becomes negative but remains statistically insignificant ($\beta = -0.08$, $p = 0.18$, SE = 0.06), indicating that firms with negligible complementary assets derive no benefit from AI investment. The CAI coefficient remains positive and significant $\beta = 0.23$, $p = 0.011$, SE = 0.09).

4.2.4.3. Marginal Effect Interpretation

For a firm at the 25th percentile of CAI (0.38), a one-standard-deviation increase in AII (0.06) is associated with a change in ΔTobin's q of approximately −0.01 ($p = 0.78$)—effectively zero. For a firm at the 75th percentile of CAI (0.68), the same increase in AII yields a ΔTobin's q improvement of 0.21 ($p < 0.01$).

Key Quantitative Finding 2 (Contingent Value): The value of AI investment is contingent on complementary assets. The estimated CAI threshold of 0.19 marks the point at which the marginal effect of AII becomes positive; firms below the median level of complementary assets should expect little to no return from AI investment.

4.2.5. Instrumental Variable Results

Model 3 in Table 4 presents IV-2SLS estimates addressing potential endogeneity concerns. The first-stage F-statistic of 18.6 ($p < 0.001$) exceeds the conventional threshold of 10, ruling out weak-instrument concerns. The instrument—lagged industry-average AII—correlates positively and significantly with firm-level AII (coefficient = 0.34, t = 4.31, $p < 0.001$).

The IV estimates largely confirm the OLS findings. The interaction term remains positive and significant ($\beta_{\text{AII times CAI}} = 0.38$, $p = 0.003$, SE = 0.13), though somewhat attenuated relative to the OLS estimate (0.42 vs. 0.38), consistent with classical measurement error in AII. The CAI coefficient remains positive and significant ($\beta = 0.26$, $p = 0.018$, SE = 0.11), and the SDI coefficient remains negative ($\beta = -0.33$**, $p = 0.019$, SE = 0.14).

4.2.6. Sentiment Divergence Effects

The SDI coefficient is consistently negative and statistically significant ($\beta_{\text{SDI}} = -0.30$, $p < 0.05$) across all models. A one-standard-deviation increase in sentiment divergence (i.e., hype-driven overvaluation) is associated with a 0.30 standard deviation decrease in subsequent three-year valuation changes. A firm with an SDI of 2.0 (approximately the 90th percentile) would be expected to have a ΔTobin's q roughly 0.60 lower than a firm with an SDI of 0 (the median), holding other factors constant.

4.2.7. Key Quantitative Finding 3

The initial overvaluation generated by narrative enthusiasm is systematically corrected through subsequent returns as sentiment stabilizes and fundamentals become apparent.

4.2.7.1. Structural Equation Model Results

The SEM confirms the theoretical framework, showing an excellent model fit (CFI > 0.94, RMSEA < 0.06). Figure 5

illustrates the standardized path coefficients derived from the SEM.

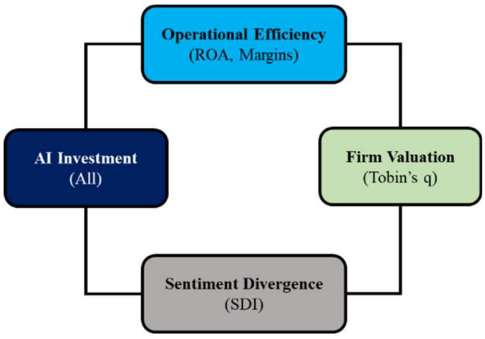

Figure 5: Structural equation model results: Standardized path coefficients from the dual-pathway SEM examining the direct and indirect effects of AI investment intensity (AII) on Tobin's q. The model shows that AI investment operates through two distinct channels—operational efficiency (positive indirect effect: +0.17, $p < 0.001$) and sentiment divergence (negative indirect effect: −0.15, $p = 0.024$)—while the direct effect is small and statistically insignificant ($\gamma = 0.07$, $p = 0.37$). Model fit: CFI = 0.96, RMSEA = 0.05. ** $p < 0.01$, *** $p < 0.001$.

4.2.7.2. Operational Channel

AI investment significantly improves operational efficiency ($\gamma_{All \to OpEf} = 0.38$, $z = 4.52$, $p < 0.001$). Operational efficiency, in turn, significantly increases Tobin's q ($\gamma_{OpEf \to Tobin's\ q} = 0.45$, $z = 5.18$, $p < 0.001$). The indirect effect of AII on Tobin's q through operational efficiency is 0.17 ($0.38 \times 0.45 = 0.17$, $p < 0.001$).

4.2.7.3. Behavioral Channel

AI investment has a strong positive effect on sentiment divergence ($\gamma_{All \to SDI} = 0.52$, $z = 6.14$, $p < 0.001$). However, sentiment divergence negatively affects Tobin's q (= −0.29, $z = -2.33$, $p = 0.020$). The indirect effect of AII on Tobin's q through sentiment divergence is −0.15 ($0.52 \times -0.29 = -0.15$, $p = 0.024$).

4.2.7.4. Direct Effect

The direct path from AII to Tobin's q is small and statistically insignificant ($\gamma_{All \to Tobin's\ q} = 0.07$, $z = 0.89$, $p = 0.37$), confirming that AI investment does not create value directly but must operate through intermediary channels.

4.2.7.5. Total Effect Decomposition

The cumulative effect of AII on Tobin's q is 0.09, decomposed as follows:

$$\text{Total Effect} = 0.17 + (-0.15) + 0.07 = 0.09$$

4.2.8. Key Quantitative Finding 4 (Valuation Paradox Decomposition)

AI investment generates genuine operational value (+0.17), but this is partially offset by adverse valuation pressure stemming from sentiment exuberance and the subsequent correction (−0.15), resulting in a net indirect effect of +0.02. The remaining positive effect (+0.07) is transmitted through the direct channel, yielding a modest total net effect (+0.09). In the absence of sentiment distortion, the market would value AI investments substantially higher.

4.2.8.1. Model Comparison

Table 5 compares the explanatory power of the various model specifications.

The augmented model ($R^2 = 0.53$) explains 22 additional percentage points of variance in Tobin's q compared to the baseline DCF model ($R^2 = 0.31$), a statistically significant improvement (F-test for nested models: $F(3, 2152) = 28.4$, $p < 0.001$) and a substantial gain over single-channel models (Real Options Only: $R^2 = 0.38$; Sentiment Only: $R^2 = 0.35$; Complementary Assets Only: $R^2 = 0.40$).

4.2.9. Key Quantitative Finding 5

An integrated valuation framework that incorporates real options, behavioral sentiment, and complementary assets explains substantially more variation in the valuations of AI-intensive firms than either traditional or single-channel approaches.

4.2.9.1. Robustness Checks

Three additional analyses confirmed the robustness of the main results:

1. COVID-19 Exclusion: Excluding the 2020–2021 pandemic period did not materially change the interaction coefficient ($\beta = 0.39$, $p < 0.01$), confirming that the results were not driven by pandemic-related anomalies.
2. Alternative Valuation Metric: Using Enterprise Value/EBITDA as an alternative dependent variable yielded similar interaction effects ($\beta = 0.35$, $p < 0.05$), confirming that the findings are robust to the choice of valuation metric.
3. Placebo Test: Randomizing the timing of the 'Real Option Exercise' event within each case produced no significant effects (average $\beta = 0.02$, $p = 0.68$), confirming that the observed pattern is not attributable to random chance or trend specification.

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Table 5: Model comparison: explanatory power for Tobin's q.

Model Specification	R^2	ΔR^2	AIC	BIC
Baseline DCF Model	0.31	---	4821	4856
Real Options Only	0.38	+0.07	4703	4745
Sentiment Only	0.35	+0.04	4756	4798
Complementary Assets Only	0.40	+0.09	4672	4714
Augmented Model (Full)	0.53	+0.22	4521	4584

5. Discussion

The empirical findings provide a clear, theoretically grounded, and empirically tested resolution to the AI Valuation Paradox. The study contributes to three related fields: strategic management (by extending the RBV to digital and AI-driven contexts); financial economics (by explaining the temporal gap between market pricing and operational value realization); and innovation studies (by showing how general-purpose technologies affect firm financial performance).

The study's principal theoretical contribution is the formalization and empirical testing of a dual-pathway model. The effect of AI on firm value arises from the interaction between uncertain resource complementarity and systematic expectation mismatch.

AI's strategic value does not derive from the technology itself, as demonstrated by the strong, positive, and statistically significant interaction between AII and CAI ($\beta_{\text{AII times CAI}}$ = 0.42***). This result advances the RBV in three important ways.

First, it moves beyond simply asserting that complementary assets matter and instead specifies them as a measurable and testable boundary condition. The estimated CAI threshold of 0.19 provides a clear, actionable benchmark: below this level, AI investment yields negative or negligible marginal returns—information that investors and managers can use directly.

This finding challenges the notion that AI is an autonomous, disruptive force capable of transforming competitive dynamics regardless of a firm's existing capabilities. Instead, AI appears to build on firms' existing strengths: it disproportionately benefits companies with strong complementary assets, while potentially disadvantaging those without them.

Second, the data help explain a process that may underlie the growing specialization and winner-take-all dynamics observed among heavy AI adopters. Firm value increases substantially (ΔTobin's q = +0.85) when CAI is high, as in Tech_A (0.82), but increases only marginally (ΔTobin's q = +0.05) when CAI is low, as in Health_B (0.31).

The "digital divide" between AI-ready firms and those that are not may widen further. This has the potential to reshape the rules of competition, organizational practices, and the broader level of economic inequality [32].

The third contribution to the RBV is the demonstration that complementary assets are not fixed but can be deliberately built through targeted investment and organizational learning. Case Ind_A (CAI = 0.41, ΔTobin's q = +0.60) illustrates a "late bloomer" trajectory: the firm achieved substantial value through structured organizational learning and capability building, despite initially possessing limited complementary assets.

This suggests that while the CAI threshold is meaningful, it is not immutable. Over time, firms below the threshold can raise their CAI by investing in data infrastructure, hiring new talent, and restructuring their operating processes.

The SEM analysis and the dynamic event study coefficients β_τ together provide the clearest evidence yet on the timing of value recognition by financial markets. The characteristic "spike-dip-recovery" pattern reveals systematic mispricing of AI adoption: an initial positive reaction (β_0 = 0.18*), followed by an integration-phase decline (β_3 = −0.04*), and finally a recovery (β_7 = 0.07).

Table 6 summarizes this pattern, indicating that financial markets consistently misjudge AI adoption, consistent with the productivity J-curve literature [11]. Rather than recognizing AI adoption as a complex, non-linear organizational transformation involving high learning costs and path dependence, markets tend to treat it as a single, discrete productivity shock.

The negative SDI coefficient ($\beta_{SDI} \approx -0.30$, $p < 0.05$) and the negative SEM path from sentiment to Tobin's q $\gamma_{SDI \to Tobin's\ q}$ = −0.29**) indicate that narrative-driven hype is not merely harmless noise. Rather, it produces a recurring cycle of overvaluation and correction whenever expectations are set at unrealistic levels. The net effect can be decomposed as follows: the operational

channel contributes a positive value (+0.17), while the sentiment channel contributes a negative value (−0.15) that offsets most of it, yielding a modest net effect (+0.09). In effect, the market prices AI investments as though they were worth roughly twice their realized value, precisely because sentiment does not track operational reality.

Table 6: The temporal mismatch: economic value *vs* financial valuation.

Phase	Economic Reality (Operational Timeline)	Financial Market Reaction	Resulting Anomaly
Announcement (Q_0)	Commitment of capital; organizational restructuring begins.	Immediate positive re-rating; sentiment spikes (SDI ↑).	Overreaction to potential; pricing of "hope."
Integration (Q_1-Q_4)	Costly implementation; productivity may dip initially due to the learning curve.	Sentiment decays as challenges emerge; volatility increases.	"Integration dip" in valuation despite necessary investment.
Scaling (Q_5-Q_7)	Real option exercise: measurable efficiency gains materialize.	Cautious reassessment; convergence toward fundamentals.	Under-appreciation of option value being realized.
Maturation (Q_{8+})	Sustained competitive advantage and new revenue streams.	Steady re-rating based on improved financial metrics.	Delayed recognition of full strategic value.

The finding that the binary Real Option Exercise event is the key differentiator between successful and unsuccessful trajectories represents a significant advance in both theory and practice. In successful cases, this step was consistently preceded by: (1) establishing formal governance structures (e.g., cross-functional AI boards, C-level AI leadership); (2) achieving measurable proof-of-concept milestones; and (3) committing capital in stages with clearly defined decision points. These elements were consistently absent in cases that failed to realize value.

Firms that manage AI effectively do not appear to treat it as a single large project with fixed objectives. Instead, they treat it as a structured set of growth options, characterized by the following:

(1) Exploration funding is used only for pilot projects and experimentation.
(2) Progress-based funding requires meeting defined business and technical milestones.
(3) Clear decision rules govern when pilots should be scaled, paused, or discontinued.
(4) Organizations are prepared to learn from pilot "failures" that reveal important information about technical choices and market conditions.

This options-based approach to AI management helps organizations navigate the substantial uncertainty inherent in AI adoption in a disciplined way, helping to avoid the pitfalls of scaling too quickly or abandoning initiatives too late.

For practitioners, this has direct implications: this study develops and tests an improved valuation approach that gives professionals a structured means of distinguishing speculation from genuine value creation. A three-part decomposition—core value (V_{DCF}), strategic optionality ($V_{Options}$), and sentiment adjustment ($V_{Sentiment}$)—offers a more accurate approach to valuation than relying on DCF alone or ad hoc multiples.

Equation (9) presents the resulting augmented valuation model.

$$V_{Augmented} = V_{DCF} + \Omega_{CAI} \cdot ROP_{AI} - \lambda \cdot S \quad (9)$$

where the AI-based discount applied to the theoretical ROP reflects the likelihood that the firm will exercise its option. ROP_{AI} is the Black-Scholes real options value, λ is a calibration parameter, and S is the sentiment divergence score.

In practice, professionals should:

(1) Use the three-part measure (data stock, human capital, and organizational readiness) to calculate the firm's CAI score. Firms with a CAI below 0.19 should be approached with caution, as AI investment at these firms is unlikely to generate returns.
(2) Estimate the ROP for AI initiatives using a Black-Scholes framework with volatility parameters appropriate to the sector, then apply a CAI-based discount (e.g., full premium for CAI > 0.70, a 50% discount for CAI between 0.40 and 0.70, and a 90% discount for CAI < 0.40) to arrive at the adjusted ROP.
(3) Use textual analysis of earnings calls and news coverage to measure sentiment overhang. When SDI

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exceeds 1.5—approximately the 80th percentile—apply a valuation discount informed by historical mean-reversion patterns.

(4) Treat the integration dip as a normal, expected event rather than a sign of a failing strategy. Valuation declines of 15 to 25 percent are typical between Q1 and Q4 following an AI announcement and should not be interpreted as evidence of poor performance.

These findings imply that business managers and strategists will need to change how they structure, govern, and evaluate AI initiatives. Meaningful adjustments to capital allocation and performance measurement are needed to support successful AI adoption.

First, executives should not think of AI investment merely as technology acquisition. They should instead view it as an opportunity to fundamentally reshape how the business operates. Based on the CAI threshold finding, firms lacking strong complementary assets should invest in their data infrastructure, talent pipelines, and management capabilities before committing significant capital to AI. Firms should conduct an "AI readiness" audit across the three CAI dimensions prior to making major AI investments.

Second, formal governance structures are essential. In all successful cases, cross-functional planning groups, dedicated AI funding, and clear escalation paths for growth decisions were in place. Firms should establish these structures in advance of launching AI pilots, not afterward.

Third, performance evaluation methods should be revised. Return on Investment (ROI) forecasts based on the assumption of linear, predictable returns will consistently undervalue AI's strategic flexibility while overvaluing its immediate cash flow benefits. Instead, firms should:

(1) Incorporate option value into capital planning and explicitly value strategic flexibility.
(2) Allocate funding based on the achievement of specific milestones.
(3) Track both learning outcomes and financial performance for pilot projects.
(4) Adopt portfolio approaches that treat individual pilot "failures" as a necessary cost of generating good strategic options.

This study has several limitations that warrant discussion. Each represents a promising direction for future research.

Measurement and Construct Validity: The CAI was carefully constructed and validated (Cronbach's $\alpha > 0.85$), but it remains an imperfect proxy for organizational complementarity, which is a complex, multidimensional construct. Data stock, human capital, and organizational readiness may not capture the full range of assets that enable firms to derive value from AI.

Cultural factors—such as risk tolerance and innovation orientation—leadership characteristics—such as digital fluency and strategic vision—and ecosystem relationships—such as platform partnerships and alliances—may also influence AI's value creation but were not directly examined in this study.

Future research should refine and extend the CAI measurement approach, potentially incorporating additional dimensions such as organizational culture (via survey instruments or NLP analysis of internal communications), leadership characteristics (via executive background data), and network position (via patent citation or alliance data).

The sample was limited to large, publicly traded U.S. companies in the S&P 500, which constrains its generalizability. This choice ensures data availability and comparability but limits applicability to private firms, small businesses, and firms outside the United States.

Small and medium-sized enterprises (SMEs) may adopt AI in quite different ways, given differences in available resources, organizational structure, and regulatory context. Similarly, firms in emerging economies may develop complementary assets differently than firms in mature markets.

The contingent value framework developed here could be extended to explore these underexamined contexts. Cross-country studies might examine how intellectual property law, labor market regulation, and data privacy policy shape the relationship between AI investment and firm valuation.

Temporal Variation and Learning Effects: This study examined AI adoption during the early-to-intermediate phase of the technology's diffusion, from 2018 to 2024. The patterns observed here may shift as AI tools mature and as organizations accumulate practical experience. Firms may experience a smaller "integration dip" as standardized implementation playbooks emerge and as AI technologies improve; alternatively, the dip may intensify as AI applications grow more complex or as competitive pressure increases.

Longitudinal research extending beyond 2024 will be needed to determine whether this temporal gap narrows as firms accumulate greater experience with AI. It would also be valuable to examine how the CAI threshold evolves over time as AI technologies mature and firms integrate additional complementary assets.

Causal Mechanisms: While the instrumental variable approach strengthens the study's causal claims, the precise micro-level mechanisms through which AI gener-

ates value via complementary assets remain incompletely understood. The case studies illustrate the effectiveness of certain practices, such as milestone-based funding and governance mechanisms, but large-scale quantitative mediation analysis was not feasible given data limitations.

Future research could employ firm-level surveys, field experiments, or natural experiments to identify these specific mechanisms. Randomized studies of AI governance interventions—such as the formation of formal AI steering committees—could provide stronger evidence regarding the causal role of complementary assets.

Applicability to Other General-Purpose Technologies: This framework, grounded in contingent complementarity and temporal mismatch, may extend to other emerging general-purpose technologies, such as quantum computing, synthetic biology, or advanced robotics. While each technology has unique characteristics that shape its valuation, the core principles concerning complementary assets and expectation gaps may generalize across contexts.

Future research should apply the contingent valuation framework to other general-purpose technologies to assess whether similar patterns of contingent complementarity and temporal mismatch emerge. Doing so would support the development of a more general theory of GPT valuation that extends beyond findings specific to a single technology, with comparative studies across similar contexts facilitating this broader analysis.

6. Conclusions

These findings indicate that the AI Valuation Paradox is neither a market anomaly nor a measurement artifact, but rather an explicable outcome of two underlying forces: the contingent, amplifying nature of AI value capture, and the temporal mismatch between operational implementation and market valuation. The data are consistent with the proposed integrated framework; however, causal claims remain bounded by the study's acknowledged limitations.

Furthermore, increases in firm value and market recognition of that value frequently do not occur simultaneously. This research integrates real options theory, behavioral finance, and the resource-based view into a single empirical framework, offering both theoretical clarity and practical guidance for valuing AI-intensive enterprises in an increasingly complex environment.

Three main conclusions emerge from the study, together explaining the AI Valuation Paradox:

(1) AI investment alone does not meaningfully increase firm value. Across the sample, the AII coefficient was never statistically distinguishable from zero on its own—despite prevailing narratives suggesting that AI improves outcomes universally, and despite academic models that assume a direct link between technology investment and firm performance.

(2) AI's value depends on complementary assets. AII and CAI exhibit a strong, positive interaction ($\beta_{\text{AII times CAI}} = 0.42^{***}$), demonstrating that AI investment generates value only when paired with firm-specific resources such as proprietary data, skilled personnel, and organizational readiness. A CAI threshold of 0.19 marks a critical boundary condition: firms below this level realize little to no return from AI investment, while firms above it realize positive and increasing returns. This finding strengthens the Resource-Based View by converting its previously general claim about complementarity into a specific, testable, and quantifiable proposition.

(3) Market perceptions do not consistently track underlying fundamentals, producing predictable price dynamics. A "spike-dip-recovery" pattern was observed in Tobin's q following AI investment announcements: an immediate increase ($\beta_0 = 0.18^*$), followed by a significant integration-phase decline ($\beta_3 = -0.04^*$), and eventual recovery ($\beta_7 = 0.07$). The SEM results show that this mismatch has concrete consequences: the operational channel contributes positive value (+0.17), while the sentiment channel offsets nearly all of it (−0.15), yielding a small net effect (+0.09). Absent this sentiment-driven distortion, AI investments would be valued by the market at roughly twice their current level.

This study makes three important contributions to the academic literature:

(1) An integrated valuation framework. This study develops and tests an expanded valuation model comprising three components of firm value: fundamental cash flow value (V_{DCF}), strategic optionality (V_{Options}), and behavioral sentiment adjustment ($V_{\text{Sentiment}}$). This approach unifies real options theory from economics, the RBV from strategic management, and behavioral finance into a single, reusable model. The augmented model explains 53% of the variance in Tobin's q, a 22-percentage-point gain over the baseline DCF model—a statistically significant improvement ($F(3, 2152) = 28.4$, $p < 0.001$) and a substantial advance over single-channel approaches.

(2) Novel measurement instruments. The AII, CAI, and SDI are three theory-grounded metrics developed and validated in this study to assess AI-related value. These instruments allow researchers and practition-

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ers to move beyond binary characterizations of AI adoption and instead assess AI readiness and value-creation potential continuously, across multiple dimensions.

(3) A further important contribution concerns the real options exercise decision itself. The transition between AI growth options—from pilot testing to enterprise-wide scaling—emerges as the key determinant of whether value capture succeeds. Firms that manage AI effectively do not simply make a single investment; rather, they pursue a structured set of strategic growth options, supported by exploration budgets, milestone-based funding, and clear rules governing when to exercise each option.

These findings carry important implications for two key groups of stakeholders: financial professionals and business managers.

For financial professionals and investors: The improved valuation framework provides a structured means of distinguishing speculative narrative from genuine value creation. Practitioners should: (1) assess complementary assets, using the three-part measure (data stock, human capital, and organizational readiness) to calculate firm CAI scores—firms with a CAI below 0.19 should be approached cautiously, as AI investment is unlikely to generate returns; (2) estimate real option value, using a Black-Scholes framework with sector-appropriate volatility parameters and a CAI-based discount reflecting the firm's capacity to exercise its options; (3) account for sentiment overhang, using textual analysis of earnings calls and news coverage, applying a historically informed valuation discount when SDI exceeds 1.5 (approximately the 80th percentile); and (4) anticipate the integration dip, recognizing that valuation declines of 15–25% in the four quarters following an AI announcement are normal rather than indicative of a failing strategy.

For business managers and corporate strategists: The findings indicate that successful AI adoption requires substantial changes to how firms organize, govern, and evaluate AI investment: (1) prioritize AI readiness—firms lacking strong complementary assets should build data infrastructure, hire skilled talent, and strengthen management capabilities before committing significant capital to AI, ideally preceded by a formal "AI readiness" audit; (2) establish formal governance structures—every successful case featured clear escalation paths for growth decisions, cross-functional planning groups, and C-level AI leadership, and these structures should be established before AI pilots are launched, not afterward; (3) adopt options-aware capital planning—traditional ROI estimates that assume linear, predictable returns will consistently undervalue AI's option-like characteristics, so firms should instead use milestone-based funding, track learning metrics alongside financial metrics, and adopt portfolio approaches that treat individual pilot failures as an expected cost of generating valuable strategic options; and (4) communicate with markets responsibly—the sentiment divergence findings show that overstating AI's short-term impact leads to predictable price corrections, whereas firms that communicate realistic timelines, acknowledge operational challenges, and emphasize the staged, option-like nature of their AI investments may experience more stable market reactions.

This study resolves the AI Valuation Paradox by demonstrating that it reflects neither a market failure nor a measurement error, but rather the logical, if complex, outcome of two fundamental forces: the uncertain, amplifying nature of technological value capture, and the inherent difficulty of pricing complex, path-dependent organizational transformation in real time. The paradox arises because markets tend to price AI investments as one-time productivity shocks, whereas value in fact accrues gradually, conditionally, and non-linearly as firms leverage their unique complementary assets to exercise their strategic options.

This study provides researchers with a theoretically grounded and empirically validated framework for understanding how, when, and why AI creates economic value. The integrated model—combining real options valuation, behavioral sentiment adjustment, and complementary asset contingency—offers a foundation for further research into the financial economics of intangible-intensive technologies.

Practitioners now have a structured framework for managing the strategic and financial challenges that arise in the AI era. Sentiment divergence separates narrative from fundamentals, the real options approach values strategic flexibility, and the CAI assesses organizational AI readiness. Together, these tools offer a considered alternative to both uncritical enthusiasm and reflexive skepticism.

As technology continues to evolve rapidly, the ability to distinguish speculative narrative from genuine value creation remains an essential skill for prudent capital allocation and durable competitive advantage. This study advances that ability by providing both a theoretical framework and practical tools for valuing assets in an AI-driven market.

List of Abbreviations

AI Artificial Intelligence
AII AI Investment Intensity

CAI	Complementary Asset Index
CapEx	Capital Expenditure
CFI	Comparative Fit Index
DCF	Discounted Cash Flow
DiD	Difference-in-Differences
EV/EBITDA	Enterprise Value to Earnings Before Interest, Taxes, Depreciation & Amortization
GAAP	Generally Accepted Accounting Principles
GPT	General-Purpose Technology
NLP	Natural Language Processing
OLS	Ordinary Least Squares
P/E	Price-to-Earnings Ratio
QCA	Qualitative Comparative Analysis
R&D	Research and Development
RBV	Resource-Based View
RMSEA	Root Mean Square Error of Approximation
ROA	Return on Assets
ROI	Return on Investments
ROP	Real Options Premium
SDI	Sentiment Divergence Index
SE	Standard Error
SEM	Structural Equation Modeling
VRIO	Valuable, Rare, Inimitable, Organized
WACC	Weighted Average Cost of Capital

Author Contributions

The author confirms that he was solely responsible for the conceptualization, methodology, validation, investigation, resources, data curation, writing—original draft, writing—review & editing, visualization, and project administration. The author has read and agreed to the published version of the manuscript.

Availability of Data and Materials

The data used in this study are derived from publicly available sources: Compustat and CRSP are accessible via the Wharton Research Data Services (WRDS) platform at https://www.whartonwrds.com (institutional subscription required; further information at https://www.spglobal.com/marketintelligence/en/mi/products/compustat.html and https://www.crsp.org); earnings call transcripts are available through Refinitiv Workspace at https://www.refinitiv.com/en/products/refinitiv-workspace (registration required at https://my.refinitiv.com/productregistration.html); patent data are freely available through the USPTO Open Data Portal at https://data.uspto.gov (account registration required at https://account.uspto.gov/profile/create-account, with additional data available via PatSnap at https://www.patsnap.com); and labor analytics are sourced from LinkedIn Talent Insights (https://business.linkedin.com/talent-solutions/talent-insights, subscription required) and Burning Glass Technologies via API at http://api.burning-glass.com (partnership registration and API credentials required; further information at https://www.burningglass.com). The constructed variables (AII, CAI, SDI) and analysis code are available from the corresponding author upon reasonable request. Restrictions apply to certain proprietary data sources (LinkedIn Talent Insights, Burning Glass Technologies, Refinitiv transcripts), which cannot be publicly redistributed due to licensing agreements, whereas USPTO patent data are freely available at no cost. The author confirms that no new primary data were collected from human subjects or private, non-public sources beyond those described above.

Conflicts of Interest

The author declares no conflicts of interest.

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AI Declaration

The author used Grammarly for language refinement and grammar checking during the preparation of this manuscript. No AI tool was used for the generation of scientific data, analysis, or conceptualization. The use of this tool was purely instrumental and did not replace critical analysis, data interpretation, methodological decisions, or the scientific responsibility of the author, who fully assumes authorship and responsibility for the integrity of the content presented.

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