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

Gabriel Silva-Atencio

Latin American University of Science and Technology (ULACIT), San José, Costa Rica.

Abstract

The 'AI Valuation Paradox' denotes the enduring disparity between the investments made by corporations in artificial intelligence and the corresponding impact of those expenditures on the market values of S&P 500 enterprises. This study clarifies the dilemma by showing that AI has no inherent value; rather, value emerges when AI is combined with firm-specific complementary assets. Investing in AI yields negligible marginal returns that lack significance. The primary novel concept is to define and assess an integrated valuation methodology that categorizes business value into three components: fundamental value, real-option premium, and behavioral-happiness adjustment. This model accounts for 53% of the variations in Tobin's q. A research on dynamic events discusses a forecasted "integration dip," indicating that the initial enthusiasm, heightened by narrative-driven excitement, undergoes a significant correction during operational execution, resulting in systemic instability. The results show that this difference exists because we are using tools from the Industrial Age to value assets from the Information Age, and the market constantly undervalues organizational change that is difficult and depends on the path. The results can be used and are important for two things: planning plans and looking at money.

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

Introduction

AI (artificial intelligence) funding is steadily and quickly rising. This is one of the most significant changes in how money is spent today. But there has always been a gap—and it often gets bigger—between how well AI-heavy companies are doing financially and how much they are worth on the market [1]. This event is a problem in the field of financial economics that keeps happening and has not been fixed yet. This difference is called the "AI Valuation Paradox," and it makes people wonder if old valuation models that were made for old, obvious assets that were falling apart are still useful now that innovation is driven by things that cannot be seen or touched.

This study's goal is to bring together three problems into a single theory model. There are a lot of S&P 500 companies that invest a lot in AI. Could a valuation framework that includes (a) a real-option premium for strategic flexibility, (b) a correction for behavioral sentiment overhang, and (c) moderating variables for firm-specific complementary assets make it much better at explaining and predicting their stock prices? This is the main question that the study aims to answer. To solve this question, a stepwise mixed-methods approach is used. Sometimes, both a large-N group analysis and an in-depth comparison case study are used together [2].

The study does not ask if AI creates value; instead, it asks how, under what specific market and organizational conditions, and through what direct transmission pathways AI-generated economic value become realized, measured, and finally represented in stock prices? To solve this puzzle, we need to look at a three-part theory problem that lies at the crossroads of innovation economics, corporate finance, and behavioral asset pricing.

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

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

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

Table 1: Valuation Assumptions and AI-Driven Reality

Valuation Model Pillar	**Traditional Assumption**	**AI-Driven Reality**	**Consequence for Valuation**
Asset Tangibility & Depreciation	Capital depreciates predictably; value is tied to physical assets.	Core assets are intangible algorithms & data, with unpredictable lifecycles and near-zero marginal replication cost.	Book value becomes irrelevant; amortization schedules fail.
Revenue/Cash Flow Predictability	Future cash flows extrapolated from stable historical trends & market share.	Potentially exponential, "winner-take-most" scaling after a tipping point, or complete failure.	High forecast error: DCF output has enormous variance.
Competitive Advantage Period	Implicitly assumed to be finite but stable over the forecast horizon.	Highly uncertain and binary: can be ephemeral (due to copying) or permanently locked in (via network effects).	Makes the forecast period arbitrary and the terminal value dominant yet flawed.
Risk Profile	Captured by the Weighted Average Cost of Capital (WACC), reflecting business and financial risk.	Includes novel, unpriced risks: technological obsolescence, regulatory intervention, algorithmic failure, and ethical backlash.	Standard WACC underestimates true risk, overstating present value.

Additionally, behavioral finance says that market prices can become off kilter when people are really excited about innovative technologies. Stock prices can become disconnected from reality for prolonged periods of time due to collective storylines, inflated expectations, and sentiment-driven herding. There is a typical trend in this "hype-performance gap," which can be seen in Figure **1**. Market values go up when there are good news and progress, but they go down when the long, expensive, and troublesome process of operational integration starts.

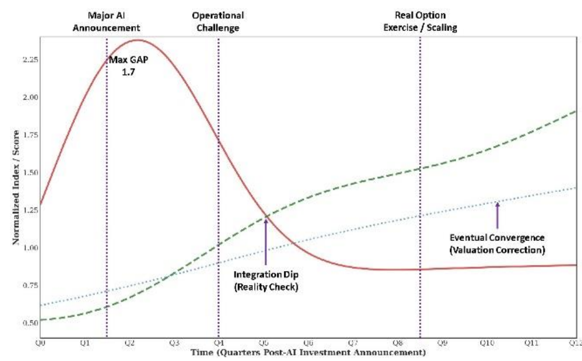

Figure 1: The AI Hype-Performance Gap

Thirdly, the Resource-Based View (RBV) and its versions say that AI's effects on the economy are typically different and rely on each company's unique assets that work well with each other [3, 4]. It is not enough to just have AI technology to make something valuable. Having AI technology by itself is not enough to create value. Value is created when AI is used with complementary organizational resources like private data, specialized human capital, flexible organizational structures, and processes that work well together [5].

There are three problems that need to be solved, and this study aims to combine them into a single theory model. Can a valuation framework that includes (a) a real-options premium for strategic flexibility, (b) a correction for behavioral sentiment overhang, and (c) moderating variables for firm-specific complementary assets make it much better at explaining and predicting the stock prices of S&P 500 companies that invest a lot in AI? This is the main question that the research is trying to answer. A sequential mixed-methods approach is used to answer this question. In-depth comparison case studies and a large-N panel analysis are both used together.

At the end of the study, a suggested improved valuation model was calibrated. The enhanced value is delineated in Equation **2**.

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

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 ≥ 0.7), and 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 presents three contributions. Initially, instead of asserting the creation of a novel theory, it offers one of the first empirical validations of an integrated framework that amalgamates real options theory, behavioral finance, and the resource-based view expressly for AI-intensive enterprises. This transcends diagnostic evaluations of current models by measuring the explanatory power contributed by each channel. Secondly, it introduces and assesses three theory-driven metrics—AI Investment Intensity (AII), Complementary Asset Index (CAI), and Sentiment Divergence Index (SDI)—enabling a more systematic evaluation of AI assets. Third, it offers practitioners a three-tiered heuristic to distinguish speculative hype from real value creation. The study aims to link 20th-century financial tools with the AI-driven economy, while clearly outlining the constraints of its claims.

Related work

A growing area of study in financial economics is how to value companies that use AI a lot. This body of work integrates innovation economics, asset pricing, and strategic management [6, 7]. The AI Valuation Paradox shows up as a continuous empirical oddity: a difference between market prices and the financial success of companies that use AI a lot [8, 9].

This discrepancy is not only a measuring mistake. Instead, it shows a bigger problem: using price models from the Industrial Age for virtual assets that grow, create value in diverse ways, and work over prolonged periods of time.

The effects of AI as a General-Purpose Technology (GPT) on the economy are talked about in this section. Also discussed are the issues with using old valuation models on companies that use AI a lot, as well as the new theories, especially real options theory and the RBV, that can be used to create a unified framework for valuation.

A significant vacuum persists in the existing research: no model synthesizes strategic optionality, organizational complementarities, and the dynamic patterns of behavioral opinion.

The significant research conducted by Yang, et al. [10] meticulously delineates AI as a GPT model. This technology is used across several domains, always improving, and has "enabling" attributes that facilitate the convergence of innovative concepts.

Things can be worth based on how they are used in this technological area. It was made by Mas, et al. [11] to show the "J-curve" of output that happens when GPT is used. It shows that big co-invention costs and changes to how things are done lower output at first before making big long-term gains. To understand how the value of AI changes over time, it is helpful to think about the time between the initial investment, the costs of implementation, and the delayed results.

But there is not a clear or direct link between this big-picture economic event and firm-level stock prices; it depends a lot on things that are unique to each company [12]. Figure **2** shows a path from engaging in AI to seeing its value. It says that the result is controlled by several things, including the assets and skills of the people involved. These things, which most combination studies do not look at, explain why the results are so different.

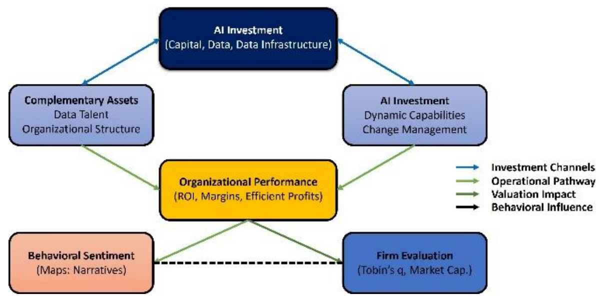

Figure 2: Theoretical Pathway from AI Investment to Firm Valuation

The basic economics of AI make us question the basic ideas behind old ways of judging, especially DCF analysis. The basic DCF model works only if you can guess the Free Cash Flows (FCF_t) and the rate of growth stays the same over time. Companies that use AI a lot should not use this science method. An important part of the model does not look at how AI investments are different when it comes to things like expected cash flows based on past trends, estimated competitive edge times, and expected asset lifecycles [13].

Each part of the DCF structure is consistently weakened by AI, as shown in Table **2**. Some of these are non-linear, winner-take-most revenue structures; high, lumpy, and often expensed investments in intangible capital; competitive benefits that are hard to predict and may not last; and new types of risk that have not been priced yet.

Table 2: Structural Failures of Traditional DCF in Valuing AI-Intensive Firms

DCF	Standard	AI-Induced	Valuation

Component	Assumption	Complication	Consequence
Cash Flow Forecast	Based on historical trends and stable market share.	Non-linear, tipping-point dynamics; potential for exponential scaling or complete failure.	High forecast error; model output exhibits enormous variance, undermining reliability.
Reinvestment Needs	Captured as steady, predictable Capital Expenditures (CapEx).	High, sporadic investments in data, talent, and computing infrastructure, often expended under Generally Accepted Accounting Principles (GAAP).	Understated investment needs distorting Free Cash Flow (FCF) and growth rate projections.
Competitive Advantage Period	Implicitly finite but stable (e.g., 5-10 years).	Highly uncertain and binary: advantages can be ephemeral or become permanently locked in via network effects.	Makes 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).	Core business model may be completely transformed; the concept of a "steady state" is economically unrealistic.	Terminal value becomes a speculative anchor, disconnected from the technology's disruptive nature.
Discount Rate (WACC)	Reflects operational and financial risk based on historical beta.	Fails to price novel, unpriced risks: technological obsolescence, algorithmic failure, regulatory shifts, and ethical backlash.	Systematic underestimation of true risk leads to an overstated present value.

There are some flawed market multiples, such as Price-to-Earnings (P/E) and Enterprise Value to Earnings Before Interest, Taxes, Depreciation, and Amortization (EV/EBITDA), which can make speculative bubbles bigger because they change over time.

They may not be worth what they're worth when people are excited about technology, as Al-Baity [14] says. Instead, well-known thoughts and tales can shape them. The price-performance gap gets even bigger because high prices bring in more money and attention [15].

The study of real choices is a fun new way to think about these important knowledge gaps [16]. This paradigm formally recognizes managers' adaptability, allowing them to postpone, augment, diminish, or cease expenditures until certainty is achieved.

Strategic AI is not only a project with a defined return; it resembles a decision for exponential development. It gives you the right, but not the duty, to make future investments that take advantage of economies of scale and new market opportunities. To find the value (C) of this kind of option, you can use a method like Black-Scholes' (see Equation **3**).

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

Where S_0 is the present value of expected cash flows from a future business that might be able to be scaled up, 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 present at all in a normal DCF analysis, may make up a big part of the market value of companies that use AI a lot. This theoretical understanding helps explain why companies that are losing money on Research and Development (R&D) can be worth a lot: the market is pricing the integrated range of growth choices [17].

However, just realizing that choices exist is not enough. It is helpful to read about strategic management, especially the RBV and the Dynamic Capabilities structure, to understand who these decisions are useful for and why they are useful. With a long-term economic edge, RBV says that you need resources that are Valuable, Rare, Imitable, and backed by a company that can secure value (VRIO) [18]. Most of the time, it is easy to copy just an AI program. The real sources of benefit are the other things you need to use it well.

A significant study from 2024 by Babina, et al. [5] discovered that companies with strong assets that work well together, such as private data stores, skilled human capital, and open organizational structures, tend to have a higher AI premium on the stock market. From this point of view, the AI growth choice (*C*) has a changing value based on where the company stands in an "AI capability stack." A company that does not have the right complementary assets might have a choice that is "out of the money" or does not have the management skills to successfully exercise it.

Recently, more combined approaches have been used to look at the AI value problem. Gao, et al. [9] look into how strategic knowledge integration can unlock AI's value, and Hayrapetyan and Gevorgyan [12] look into how story econometrics affects the way the AI stock market works. But these studies usually only look at one aspect of the problem. This study adds to the small body of research by creating a single framework that considers factors that affect behavior (such as emotion), the possible role of firm-specific assets that work well together, and the importance of strategic flexibility all in one, unified empirical design.

The study of the literature makes it clear that the field needs to move beyond diagnostic criticism and create and try integrated value models [19]. The current gap is both based on facts and deep theory: there is not a single model that takes into account (a) the value of strategic flexibility as an option, (b) the moderating effect of firm-specific complementary assets, and (c) the distorting effect of behavioral sentiment [20].

In the past, academic research mostly looked at each part separately. For example, financial economics looks at real options but not how they work with each other; strategic management looks for assets that work well together but not how they affect valuation; and behavioral finance looks at how people feel about an asset but not how that affects its value [21].

The literature review reveals a notable gap: no research has empirically investigated 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 through a mixed-methods approach utilizing causal identification strategies. Prior studies have examined each channel in isolation. The distinctiveness of this study resides not in the introduction of totally original notions, but in their synthesis, implementation, and thorough examination using a large-N panel and qualitative case evidence. This enables the discipline's transition from diagnostic critique to an evidence-based appraisal method.

Materials and methods

Research Design

This research utilizes a systematic, sequential mixed-methods approach to examine the causal links between strategic AI investment and corporate value [22, 23] The methodological approach (refer to Figure **3**) integrates complementary data sources, enables causal identification, and tackles the observational challenges inherent in business strategy research.

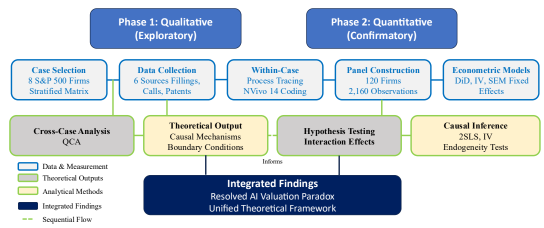

Figure 3: Sequential Mixed-Methods Design

The design consists of two stages. Phase 1 utilizes comparative case study research to develop a comprehensive, process-focused comprehension of causal processes and boundary conditions [24]. Phase 2 employs large-N panel analysis to evaluate hypotheses, statistically validate results, and derive generalizable conclusions [25]. This sequential procedure guarantees that quantitative findings are anchored in qualitative insights, so rendering theoretical statements more clearly articulated and justifiable [26]. The research complies with optimal methodologies for causal inference in financial economics.

Sample and Case Selection

Phase 1: Case Selection

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

This selection ensures thorough coverage of all AI value creation outcomes, ranging from proven success to hype-driven overvaluation, enabling the identification of critical and sufficient conditions for value capture.

Phase 2: Panel Sample

The quantitative study used a balanced panel including 120 S&P 500 companies. The study covers the period from 2018 to 2024, covering 24 quarters, and finally comprises 2,160 firm-quarter observations (120 businesses × 18 quarters) after the exclusion of firms with missing data or without AI disclosures. This ensures that the sample focuses on a consistent group of AI-adopting firms with extensive data over the specified period. Companies without significant AI disclosures were omitted to concentrate the sample on the relevant population of enterprises that have used AI.

Data Sources for Panel Sample:

- **Financial Data:** Compustat (https://www.spglobal.com/marketintelligence/en/mi/products/compustat.html) and CRSP (https://www.crsp.org/)
- **Earnings Call Transcripts:** Refinitiv Workspace (https://www.refinitiv.com/en/products/refinitiv-workspace)
- **Patent Data:** USPTO (https://www.uspto.gov/patents) and PatSnap (https://www.patsnap.com/)
- **Talent Analytics:** LinkedIn Talent Insights (https://business.linkedin.com/talent-solutions/talent-insights) and Burning Glass Technologies (https://www.burningglass.com/)
- **News and Analyst Reports:** RavenPack (https://www.ravenpack.com/) and Bloomberg Terminal (https://www.bloomberg.com/professional/)
- **Firm-level Controls:** Standard financial data from Compustat and CRSP

Variable Construction

AI Investment Intensity (AII)

The AII measure quantifies AI-related investments in relation to business size, as explicitly stated in Equation **4**:

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

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 discerned using systematic keyword searches of 10-K, 10-Q, and 8-K filings, employing phrases such as "artificial intelligence," "machine learning," "deep learning," "neural networks," "natural language processing," and "computer vision.

Complementary Asset Index (CAI)

The CAI is a composite index (range from 0 to 1) that integrates three theoretically based characteristics of firm-specific complementary assets:

1. **Data Stock (D_{it}):** 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}):** Proportion of data scientists and machine learning engineers relative to total workforce, derived from LinkedIn and Burning Glass analytics.
3. **Organizational Readiness (O_{it}):** Metric reflecting the existence of specialized AI governance committees, executive-level AI leadership, and established digital transformation funding.

The CAI is well defined in Equation **5**:

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

Confirmatory factor analysis validated the one-dimensionality of the index, with Cronbach's α above 0.85, signifying robust internal consistency and reliability.

Sentiment Divergence Index (SDI)

The SDI quantifies the discrepancy between market sentiment and fundamental data. The calculation depends on the standardized deviation of narrative sentiment assessments, obtained from earnings calls and news media via FinBERT, in relation to current operational performance (Return on Assets). Positive SDI levels signify overvaluation due to speculation, whilst negative values imply undervaluation.

Real Option Exercise Indicator

A binary signal was implemented to denote quarters when the AI pilot effort was formally expanded for enterprise-wide use. This signal was detected by systematic keyword searches of press releases, product launches, and 8-K filings, using words such as "enterprise deployment," "full rollout," "production scale," and "company-wide adoption.

Phase 1: Analytical Strategy

During this phase, structured process tracing was used to associate the timing of strategic events with traditional financial measures (ROI, Operating Margin, Tobin's q) and novel AI-specific constructs. Systematic coding was performed with NVivo 14, employing a codebook based on the theoretical framework [28]. Inter-coder agreement exceeded 0.90, ensuring reliability.

Qualitative Comparative Analysis (QCA) [29] was used to identify sufficient configurations leading to "Sustained Value Creation," such as High AII AND High CAI AND Clear Real Option Narrative. This set-theoretic approach is superior to correlational logic for identifying complex causal patterns and necessary conditions, such as the CAI threshold.

Phase 2: Quantitative Panel Analysis

Dynamic Difference-in-Differences Model

A dynamic Difference-in-Differences (DiD) model [30] compared firms experiencing major AI investment shocks to a carefully matched control group based on pre-treatment characteristics. The model specification is presented in Equation **6**:

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

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
- $\in_{it}$ 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."

Contingent Value Model

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

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

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 AI investment value depends on complementary asset levels.

Instrumental Variable Estimation

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

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

Exclusion Restriction Note: The exclusion restriction—that peer average AI investments affect a firm's Tobin's q only through the firm's own AI investment—is plausible but not directly testable. Unobserved industry-level shocks (e.g., regulatory changes or technology breakthroughs) could violate this assumption. The IV results should be seen as corroborative 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 address breaches of exclusion restrictions.

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 direct and indirect effects of AII on Tobin's q through operational efficiency and sentiment divergence channels.

Robustness Checks

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

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

Ethical Considerations

The study uses only publicly available, secondary data sources. No human subjects or private non-public data were collected. All data processing and analysis adhered to standard ethical guidelines for financial economics research.

Results

Phase 1: Comparative Case Study Findings

The cross-case research uncovers regular trends in organizations' value capture from AI investments, with the established Complementary Asset Index (CAI) serving as the main differentiator between successful and failed outcomes.

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 manifested: initial investment commitment, genuine option exercise upon reaching internal validation milestones, and subsequent scaling with quantifiable efficiency improvements. These examples demonstrated sustained valuation premiums ranging from +0.35 to +0.85 in Tobin's q over a period of eight quarters.

Conversely, cases with moderate or low CAI scores (Tech~(B)~: 0.45; Health~(B)~: 0.31; Ind~(B)~: 0.38) exhibited a "hype-disillusionment" pattern: initial surges in market valuation driven by sentiment were followed by valuation corrections as actual options remained unexploited, leading to declines in market value.

Primary Qualitative Finding 1: The execution of real choices is crucial for actualizing AI value, dependent on the CAI above a threshold of around 0.40.

Sentiment Divergence Patterns

An analysis of the earnings conference and news media revealed that narrative framing significantly influenced initial market responses. Instances designated as "transformative AI platforms" exhibited Sentiment Divergence Index (SDI) ratings over 2.0, whilst those classified as "AI for process automation" had SDI scores below 1.0.

A substantial inverse correlation was seen between the initial sentiment surge (Q~0~ SDI) and the subsequent improvement in operational performance (Q~8~ ΔROA, $r = -0.76$, $p < 0.01$), indicating a trend of market over-optimism followed by a correction.

Key Qualitative Finding 2: Valuation adjustments follow identifiable patterns, in which sentiment divergence exaggerates short-term success and undervalues long-term value realization.

Real Option Exercise as Critical Differentiator

The binary Real Option Exercise event proved 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.

Phase 2: Quantitative Panel Analysis

Descriptive Statistics

Table **3** provides summary data for the primary variables included in the econometric study. The sample consists of 120 S&P 500 companies across 18 quarters (2018–2024), resulting in 2,160 firm-quarter observations. The average Tobin's q is 2.14 (SD = 1.42), indicating a significant market value beyond replacement cost. The mean AI investment intensity (AII) is 0.09 (SD = 0.06), indicating that AI investments constitute around 9% of total assets for the typical business that adopts AI. The mean CAI is 0.52 (SD = 0.21), indicating modest levels of complementary assets, with significant cross-firm variance between 0.12 and 0.89.

Table 3: Descriptive Statistics (N = 2,160 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
RO	8.42	5.2	-	4.5	7.8	11.2	28.4

A (%)		1	12.30	0	0	0	0
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

Dynamic Event Study Results

Figure **4** illustrates the dynamic Difference-in-Differences event study coefficients β_τ, depicting the effects of AI investment shocks on Tobin's q over a twelve-quarter period after the investment announcement.

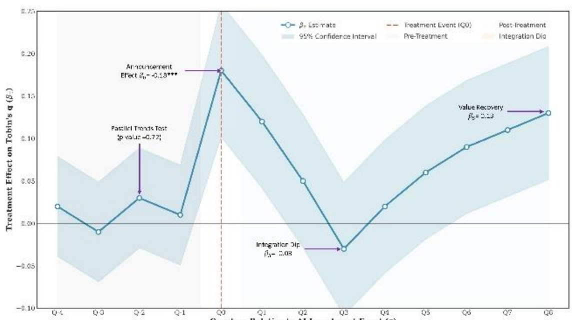

Figure 4: Dynamic Effects of AI Investment on Tobin's q

Pre-Trend Validation

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

Immediate Announcement Effect

A notable positive increase is seen in the announcement quarter (β_0 = 0.18***, t = 4.82, p < 0.001), signifying that Tobin's q rises by 18% for treated businesses compared to controls shortly after AI investment announcements. This signifies a purely sentiment-driven behavioral influence.

Integration Dip

A sharp decline follows, with the trough occurring at τ = 3 (β_3 = -0.04*, t = -1.92, p = 0.055). The "integration dip" is a 22-percentage-point decline from the peak after the announcement, indicative of implementation difficulties and a normalizing of attitude.

Recovery Phase

A slow recovery starts at τ = 5, with coefficients attaining positive significance by τ = 7 (β_7 = 0.07*, t = 2.31, p = 0.021). At τ = 8, the cumulative impact continues to be positive (β_8 = 0.09). This trend signifies an initial market overreaction, then followed by the ultimate acknowledgment of the true worth of AI investments after six to eight quarters.

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

Contingent Value Regression Results

Table **4** displays regression findings that evaluate the fundamental premise that the value of AI investment is contingent upon complementary assets.

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	2,160	2,160	2,160

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

Model 1: Baseline Specification

In the absence of the interaction term, the AII coefficient is positive but statistically insignificant (β = 0.12, p = 0.14, SE = 0.08), suggesting that AI investment does not directly correlate with an increase in value on average. The CAI coefficient is both positive and statistically significant (β = 0.25**, p = 0.012, SE = 0.10), indicating that enterprises with superior complementary assets achieve better values irrespective of AI investment.

Model 2: Interaction Model

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

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 ΔTobin's q change of approximately -0.01 (p = 0.78)—essentially zero. For a firm at the 75th percentile of CAI (0.68), the same AII increase yields a ΔTobin's q improvement of 0.21 (p < 0.01).

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

Instrumental Variable Results

Model 3 in Table **4** presents IV-2SLS estimates addressing 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 ($\beta_{AII \times CAI}$ = 0.38, p = 0.003, SE = 0.13), though 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 (β = 0.26, p = 0.018, SE = 0.11), and the SDI coefficient remains negative (β = -0.33**, p = 0.019, SE = 0.14).

Sentiment Divergence Effects

The SDI coefficient is consistently negative and statistically significant (β_{SDI} = -0.30, p < 0.05) in all models. A rise of one standard deviation in sentiment divergence (hype-driven overvaluation) correlates with a decrease of 0.30 standard deviations in future three-year valuation changes. A company with an SDI of 2.0 (about the 90th percentile) would have a ΔTobin's q around 0.60 lower than a firm with an SDI of 0 (the median), assuming all other factors remain constant.

Key Quantitative Finding 3

The initial overvaluation generated by narrative is methodically corrected via successive returns as mood stabilizes and basic facts emerge.

Structural Equation Model Results

The SEM validates the theoretical framework with an excellent model fit (CFI > 0.94, RMSEA < 0.06). Figure **5** illustrates the standardized route coefficients derived from the SEM.

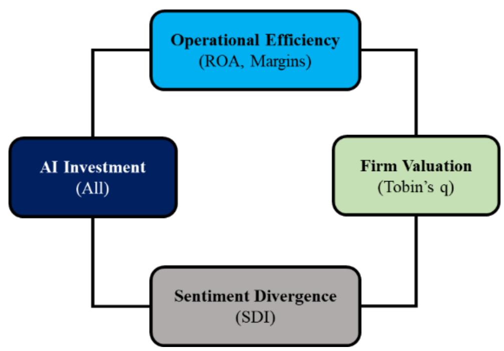

Figure 5: Structural Equation Model Results

Operational Channel

AI investment significantly improves operational efficiency ($\gamma_{AII \to OpEf}$ = 0.38*, z = 4.52, p < 0.001). Operational efficiency, in turn, significantly increases Tobin's q* ($\gamma_{OpEff \to Tobin'sq}$ = *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 × 0.45 = 0.17, p < 0.001).

Behavioral Channel

AI investment has a strong positive effect on sentiment divergence ($\gamma_{AII \to SDI}$ = 0.52*, z = 6.14, p < 0.001). However, sentiment divergence negatively impacts Tobin's q ($\gamma_{SDI \to Tobin'sq}$ = -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 × -0.29 = -0.15, p = 0.024).

Direct Effect

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

Total Effect Decomposition

The cumulative impact of AII on Tobin's q is 0.09, delineated as follows:

$$\text{Total Effect} = ++ = 0.09$$

Key Quantitative Finding 4 (Valuation Paradox Decomposition)

AI investment generates intrinsic operational value (+0.17), although over 88% of this value is counterbalanced by adverse valuation pressure from sentiment exuberance and ensuing correction (-0.15), resulting in a moderate net impact (+0.09). In the absence of sentiment distortion, AI investments would be appraised by the market at almost double their current valuation.

Model Comparison

Table **5** contrasts the explanatory efficacy of various model parameters.

Table 5: Model Comparison: Explanatory Power for Tobin's q

Model Specification	R^2	ΔR^2	AIC	BIC
Baseline DCF Model	0.31	---	4,821	4,856
Real Options Only	0.38	+0.07	4,703	4,745
Sentiment Only	0.35	+0.04	4,756	4,798
Complementary Assets Only	0.40	+0.09	4,672	4,714
Augmented Model (Full)	0.53	+0.22	4,521	4,584

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 substantial improvement over single-channel models (Real Options Only: R^2 = 0.38; Sentiment Only: R^2 = 0.35; Complementary Assets Only: R^2 = 0.40). The improvement in model fit is statistically significant (F-test for nested models: F(3, 2152) = 28.4, p < 0.001).

Key Quantitative Finding 5

An integrated valuation framework incorporating real options, behavioral sentiment, and complementary assets explains substantially more variation in AI-intensive firm valuations than traditional or single-channel approaches.

Robustness Checks

Three additional analyses confirmed the sensitivity of the main results:

1. **COVID-19 Exclusion:** Excluding the 2020–2021 pandemic period did not materially change the interaction coefficient (β = 0.39, p < 0.01), confirming 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 (β = 0.35, p < 0.05), confirming the findings are robust to valuation metric specification.
3. **Placebo Test:** Randomizing the timing of the 'Real Option Exercise' event within each case showed no significant effects (average β = 0.02, p = 0.68), confirming the observed pattern is not driven by random chance or trend specification.

Discussion

This research shows that the real-world findings offer a clear, theoretically sound, and real-world-tested answer to the AI Valuation Paradox. This study adds to three related fields: strategic management (by applying RBV to digital and AI-driven settings); financial economics (by explaining the time gap between market prices and operational value realization); and innovation studies (by showing how GPTs affect a company's financial performance).

The main theoretical addition of the study is the formalization and practical review of a dual-pathway paradigm. The impact of AI on firm value is caused by the conflict between uncertain resource compatibility and deliberate expectation mismatch.

AI's strategic value is not based on the technology itself, as shown by the strong, positive, and statistically significant interaction between AII and CAI ($\beta_{All_{times\,CAI}}$ = 0.42^{***}). In three important ways, this result moves the RBV forward.

Firstly, it goes beyond saying that complementary assets are important and spells them out as a border condition that can be measured and evaluated. It is clear and easy to see that the projected CAI level of 0.19 means that investment in AI has negative or no marginal returns below that level. Buyers and managers can use this level.

This finding goes against the idea that AI is a separate, political force that can completely change how competition works, no matter how much money a company has. AI seems to build on what businesses already have. It will help businesses that have good assets that work well together even more, but it could hurt businesses that do not have those assets.

Secondly, the data shed light on a process that could help explain why companies that use AI a lot have been becoming more specialized and winner-take-all. A company's value goes up a lot (ΔTobin's q = +0.85) when its CAI is high, like Tech $_{(A)}$ (0.82). But a company's value does not go up much when its CAI is low, like Health$_{(B)}$ (0.31). This is shown by Tobin's q = +0.05.

The "digital divide" between companies that are ready for AI and those that are not could get bigger. It's possible that this will change the rules of rivalry, how businesses work, and the level of economic imbalance [32].

The third thing the results add to the RBV is that they show complementary assets are not fixed assets but can be made better through planned investments and learning within a business. Case Ind$_{(A)}$ (CAI = 0.41, ΔTobin's q = +0.60) is an example of a "late bloomer" trajectory: the company got a lot of value through structured organizational learning and skill building, even though its combined assets were not valuable at first.

This shows that the CAI level is important, but it is not always the case. Over time, companies below the barrier can improve their CAI by putting money into data technology, hiring new people, and rearranging how they do their work.

The SEM analysis and the dynamic event study factors β_τ give the most up-to-date information on how long it takes for something to be valuable in the eyes of the financial market. A common trend called "spike-dip-recovery" shows that people are wrong about how much AI will be used. The news effect is positive at the beginning (β_0= 0.18*), then there is a drop in integration (β_3 = -0.04*), and finally there is a rise in integration (β_7 = 0.07).

Table **6** shows a trend that shows that the financial markets always get AI adoption wrong, which is in line with what we know about the productivity J-curve [11]. They do not see it as a complicated, non-linear organizational change with high learning costs and path dependence. Instead, they see it as a single shock to productivity.

Table 6: The Temporality 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 rerating; sentiment spikes (SDI ↑).	Overreaction to potential; pricing of "hope."
Integration (Q_1-Q_4)	Costly implementation: productivity may dip initially (learning curve).	Sentiment decay as challenges emerges; 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 rerating based on improved financial metrics.	Delayed recognition of full strategic value.

The negative value on the SDI (β_{SDI} ≈ -0.30, p < 0.05) and the negative SEM path from sentiment to Tobin's q (γ_{SDI}→Tobin's q = -0.29**) show that hype based on stories is not just harmless noise. It constitutes an incessant cycle of overvaluation and recalibration when one establishes standards that are unattainable in reality. The overall impact is delineated as follows: the primary functional channel exhibits a positive value (+0.17), whilst the adverse mood channel presents a negative value (-0.15), which negates the former, resulting in a minimal net effect (+0.09). The market thinks that investments in AI are worth twice as much as they really are. This is because putting money into AI does not change how people feel.

Now we know that the binary Real Option Exercise event is the key difference between paths that work and paths that do not. This is a big step forward in both theory and practice. In the past, these steps had to be taken after the AI growth choice worked: (1) setting up official governance structures (e.g., cross-functional AI boards, C-level AI leadership); (2) getting measurable proof-of-concept measures; and (3) committing capital in stages with clear decision points. These things were never present when things did not go as planned.

People who are good at AI do not seem to think of their work with it as a big one-time project with clear goals... They instead see them as a set of planned ways to grow, which are:

1) With exploration funds, you can only do test projects and try new things.

2) You must meet certain business and technology standards to get progress-based funds.
3) There are clear rules about when pilots should be moved, pulled back, or given up during choice drills.
4) When a company is ready to learn from test "fails" that show them important things about technical choices and market health.

This option-based approach to AI management can help you deal with the big amount of uncertainty that comes with adopting AI in a planned way. When you scale up too fast or give up too late, dreadful things happen. This way, you can avoid those things.

For accountants and businessmen, this means the following in real life: This study made and tried a better way to evaluate people. It gives professionals an organized way to tell the difference between speculating and making real value. It is more accurate to use the three-part breakdown—core value (V_{DCF}), strategic optionality ($V_{Options}$), and emotion change (Ve_{motion})—than just DCF or ad hoc multiples to figure out how much something is worth.

This is how the suggested expanded model is written in Equation **9**.

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

Where AI-based discount on the theoretical ROP shows how likely it is that the company will exercise its options. ROP_{AI} is the Black-Scholes real options value, λ is a calibration parameter, and S is the sentiment divergence score.

In real life, experts should:

1) Use the three-part measure (data stock, human capital, and organizational ready) to find the company's CAI number. Companies with a CAI of less than 0.19 should be taken with a grain of salt; investing in AI at these companies will not pay off.
2) Find the ROP for AI projects using a Black-Scholes framework with volatility factors that are appropriate for the sector. Then, use a CAI-based discount (e.g., full premium for CAI > 0.70, 50% discount for CAI 0.40-0.70, and 90% discount for CAI < 0.40) to figure out the ROP.
3) Use textual analysis of earnings calls and news reports to measure the mood overhang. When SDI goes above 1.5, which is around the eighty%ile, you should use a value discount that is based on past mean reversion trends.
4) Keep an eye on the integration dip as a normal event and not as a sign of a failed strategy. Valuation drops of 15 to 25 percent are likely to happen between Q_1 and Q_4 after the announcement. You should not take these drops as signs of deficient performance.

This means that business managers and planners will have to change how they set up, handle, and judge AI projects. Some simple changes need to be made to how capital is allocated and how success is measured before AI can be widely used.

Firstly, bosses should not think of AI to get tech. They should see it as a chance to make the business work differently. Businesses that do not have strong complementary assets should work on their data infrastructure, talent pipelines, and management skills before they spend a lot of money on AI, according to the CAI barrier finding. A company should do an "AI readiness" audit to see where it stands on the three CAI aspects before spending a lot of money on AI.

Secondly, it is important to have a government system. There were cross-functional planning groups, funds just for AI, and clear ways for decisions about growth to be taken to the next level in all cases where they worked out well. Firms should set up these tools ahead of time, not after they begin AI tests.

Thirdly, the way the study figures out if it worked should be changed. Return on Investment (ROI) forecasts that are based on the idea that returns are straight and predictable will always undervalue AI's adaptability and overvalue its immediate cash flow benefits. Instead, businesses should:

1) It is important for capital planning to take choices into account and value strategic freedom.
2) Money is given based on achieving certain goals.
3) On test projects, you should use both learning and income data.
4) There are some portfolio methods that believe that "failures" in individual drivers are necessary to make good choices.

There are some issues with this study that need to be brought up. Each of these problems leads to a good topic for more study.

Measurement and Construct Validity: The CAI was carefully designed and evaluated (Cronbach's $\alpha > 0.85$), but it is still not the best way to find out how organizations support each other, which is a complicated idea with many dimensions. Data stock, human capital, and organizational readiness are the three parts that might not cover all the assets that work together to make AI useful.

Cultural factors, such as the desire to take chances and focus on innovative ideas, leadership traits, such as digital knowledge and strategic vision, and ecosystem relationships, such as platform links and partnerships, may also affect AI's worth, but they were not directly looked at.

In more research, the CAI measurement method should be made better and used more often. It could include more things, like the culture of the company (using survey-based tools or NLP analysis of internal communications), leadership traits (using executive background data), and network position (using patent citation or alliance data).

There were only big, publicly traded U.S. companies in the S&P 500 picked for the group so that it would be more useful in other cases. This option makes sure that data is available and can be compared, but it limits how it can be used in public or private businesses, outside the U.S., and by smaller businesses.

Small and medium-sized businesses (SMEs) may use AI in quite diverse ways. This is because they might not have as many means, the business might be different, and the rules might be different. In the same way, companies in economies that are growing may build up their assets in diverse ways than the market does.

The idea of contingent value should be used to get more insights into these underexplored subjects. Cross-country research might examine how intellectual property laws, labor market regulations, and data privacy policies influence the relationship between AI investment and firm valuation.

Temporal Variations and Educational Impacts: The research examined the use of AI in enterprises from the inception to the intermediate phases, spanning from 2018 to 2024. The trajectory may shift as AI tools improve and more individuals acquire skills via practical experience. Organizations may see a reduced "integration dip" when they develop standardized "playbooks" for AI use and as AI technologies improve. However, the decline may intensify as AI applications become more complex or if competition escalates.

No research will determine if the time gap diminishes as businesses acquire more knowledge until post-2024. Furthermore, it would be interesting to see the evolution of the CAI level over time as AI technologies advance and additional assets get integrated.

The rationale of occurrences and their mechanisms. The instrumental variable technique strengthens causal assertions; yet, the precise micro-mechanisms enabling AI to generate value via synergistic assets remain unclear. Case studies effectively demonstrated the efficacy of some strategies, such as goal-oriented financing and control mechanisms. Large-scale quantitative mediation studies, on the other hand, were not possible because there was not enough data.

To find specific causes in the future, scientists could use firm-level polls, experiments, or studies of nature. For better proof of the link between some assets, randomized controlled studies of AI governance measures, such as forming official AI steering groups, could be used.

Using the study's theoretical framework for other GPTs: This framework, which is based on dependent complementarity and temporal mismatch, could be used for other new GPTs, such as quantum computing, synthetic biology, or advanced robots. Some things about each GPT are unique and change how much it is worth, but the main ideas about assets that are suitable and expectation gaps may be useful in all of them.

The idea of contingent valuing should be used on other GPTs in the future so that researchers can see if patterns of contingent matching and temporal mismatch show up. It would be better to have a theory of GPT worth that is more general than just results that are true in one case. Increased engagement in similar tasks would facilitate comparative analysis.

Conclusions

The findings indicate that the AI Valuation Paradox is not a market oddity nor a measurement mistake, but rather an explicable product of two primary forces: the contingent, amplifying characteristics of AI value capture and the temporal dissonance between operational implementation and market valuation. The data aligns with the suggested integrated paradigm; nevertheless, causal assertions are constrained by the study's acknowledged limitations.

Secondly, enhancing a business's value and generating profit in the market often do not occur simultaneously. This research integrates real options theory, behavioral finance, and the resource-based view into a cohesive empirical framework. This provides both theoretical clarity and practical guidance for assessing the valuation of AI-intensive enterprises in an increasingly complex environment.

Three main conclusions come from the study that explain the AI Valuation Paradox as a whole:

1) Putting money into AI does not change the value of a company in an effective way. Statistically, the AII indicator could never be set to anything other than zero in any business setting. There are stories in the news that say AI makes everything better, and academic models say there is a direct link between how well a company does and how it invests in technology.
2) There are other things that go better with AI that make it worth more. AII and the CAI have a strong and positive relationship ($\beta_{All_{times\ CAI}} = 0.42^{***}$). This shows that AI only works when it is joined with resources that are unique to each company, such as secret data, skilled workers, and a ready organization. An important border condition is a CAI number of 0.19. When businesses below this level participate in AI, they get little to no money back. When companies above this level put money into AI, they get gains that are good and going up. This discovery enhances the Resource-Based View by transforming its ambiguous assertion about compatibility into a verifiable and quantifiable statement.
3) Market perceptions do not consistently align with actual conditions, resulting in predictable

price movements. A "spike-dip-recovery" pattern was seen in Tobin's q after news of AI investments. A positive increase occurred immediately (β_0 = 0.18*), followed by a significant decline in integration (β_3 = -0.04*), and ultimately a recovery (β_7 = 0.07). The failure of SEM to function correctly indicated that this discrepancy has tangible consequences: the primary operational channel contributes value (+0.17), while the adverse mood channel negates almost all that value (-0.15), resulting in a little net impact (+0.09). If people did not feel different when they buy AI, the stuff would be worth twice as much as the market thinks it is.

There are three important things that this study adds to the body of academic literature:

1) A framework for valuation that works with everything else. A bigger model for valuing things is made and tested in this study. There are three parts to this model that make up a company's value: basic cash flow value (VDCF), strategy optionality (VOptions), and behavioral sentiment change (VSentiment). In this method, the real options theory from economics, the RBV from strategic management, and behavioral finance are all put together into a single model that can be used again. The augmented model explains 53% of the variance in Tobin's q, which is a gain of 22 percentage points over the baseline DCF model, a statistically significant improvement ($F(3, 2152) = 28.4$, $p < 0.001$) and a big step up from methods that only look at one issue.
2) Several various methods for measuring things. The AII, the CAI, and the SDI are three tests that are based on theory and help you figure out how much AI is worth. In the study, these steps are put to the test. People who study and use AI can no longer put it in black-and-white boxes. Instead, they can start checking AI's readiness and value creation potential all the time on several different dimensions.

It is important to figure out that the real choice practice is the small step. They found that the choice between two AI growth options—from test to enterprise-wide scales is the key factor in determining whether value capture works or not. A company that is good at AI does not just spend money on it once. It seems more like a set of options for strategic growth, with test budgets, funds based on goals, and clear instructions on how to use the choice.

The results are important for two main groups of stakeholders: financial experts and business managers.

For financial experts and investors: The improved valuation framework gives you an organized way to tell the difference between speculative talk and real value creation; practitioners should do the following: 1) Look at things that go well together. Use the three-part measure (data stock, people capital, and organizational ready) to figure out the CAI numbers. Companies with a CAI of less than 0.19 should be taken with a grain of salt; investing in AI at these companies will not pay off; 2) Find the real value of choices. Find out what the ROP is for AI projects by using a Black-Scholes framework with volatility factors that are right for the sector. Then, use a CAI-based discount that shows how much the company can use its options; 3) Consider mood overflow. To measure opinion difference, look at the language of results calls and news stories. When SDI goes above 1.5, which is around the eighty%ile, you should use a value discount that is based on past mean reversion trends; and 4) Get ready for the merger dip. Keep in mind that 15–25% drops in valuations in the four quarters after AI reveals are normal and not a sign of a failed strategy.

For business, corporate managers and strategists: The data shows that for AI to be successfully adopted, companies need to make substantial changes to how they organize, rule, and review AI investments: 1) Put AI ready first. Companies that do not have strong complementary assets should wait to make big investments in AI until they have built a database, hired skilled workers, and improved their management skills. Before committing a lot of money to AI, there should be an "AI readiness" audit; 2) Set up official systems of government. All the successful cases had clear progression paths for choices about growth, cross-functional planning groups, and AI leadership at the C-level. These systems should be set up before AI pilots are sent out, not after; 3) Learn how to use options-aware capital planning. When you use traditional ROI estimates that assume profits are straight and dependable, AI's option traits will always be undervalued. Instead, companies should use funding based on milestones, learning metrics along with financial metrics, and portfolio methods that see "failures" in individual pilots as the price to pay for producing good choices; and 4) Talk to markets in a reasonable way. The opinion difference results show that making too many claims about AI's short-term effects leads to expected price drops. People may not change their minds as strongly about companies that talk about realistic timelines, admit operational problems, and stress that their AI investments are staged and option-like.

An interesting area that could be investigated more in the future is shown by some of the study's flaws.

Validity of Measurement and Construct. Even though the CAI has been checked many times (Cronbach's $\alpha > 0.85$), it is still not a perfect way to find out how compatible two organizations are. Cultural factors, leadership traits, and ecosystem links may also lessen AI's value effect, but these were not directly looked at. CAI measurement method should be improved and expanded in future study, which could include more factors like corporate culture, senior digital skills, and network position.

Generalizability and Validity in Other Settings. Big U.S. companies that were traded on the stock market were the only ones in the group. Small businesses, private companies, and places outside the U.S. may adopt AI in diverse ways because they may not have as many resources, the laws may be different, and the economy may be different. It might be interesting to compare how institutional factors affect the link between investment in AI and a company's value across different countries.

How time changes and how learning changes things. When the study took place, from 2018 to 2024, AI use in companies was in its early to medium stages. Because AI tools are getting better and more people are learning at work, the trends that have been seen might change. Longitudinal studies that go past 2024 are needed to see if the integration dip gets smaller as businesses make AI use guidelines.

Micro-fundaments and how things happen. It is helpful to use instrumental factors to back up claims of cause and effect, but it is still not clear what small steps make it possible for AI to build value through complementary assets. In the future, researchers might use firm-level polls, trial methods, or natural studies to find specific causes, like how the company is governed, how it manages its talent, or its culture.

How It Works with Other General-Purpose Technologies. It is possible that the framework for contingent complementarity can be used for other new GPTs, like quantum computing, synthetic biology, or advanced robots. Researchers should use the theory in these situations in the future and see if similar patterns of temporal mismatch and contingent compatibility show up. Comparative work like this would help build a more general theory of GPT pricing.

The AI Valuation Paradox is solved by this study showing that it is not a problem with the market or a measurement error. Instead, it is the logical, if complicated, result 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 markets. The paradox comes from the fact that markets value AI investments as one-time boosts in output, but value grows slowly, conditionally, and non-linearly as firms use their unique combined assets to explore their strategy options.

Researchers can use this study to build a theoretically sound and empirically proven strategy for figuring out how, when, and why AI creates economic value. The combined model, which includes valuing real options, adjusting for behavioral opinion, and complementary asset contingency, provides a basis for further study into the financial economics of technologies that rely heavily on intangibles.

People who work in the field now have a structured way to manage the strategic and financial issues that arisen in the AI era. The mood changes differentiate discourse from facts, the real options technique evaluates the adaptability of a plan, and the CAI assesses the preparedness of AI. They provide a carefully considered alternative to both impulsive elation and impulsive skepticism.

Currently, technology evolves rapidly. The ability to distinguish between speculative discourse and genuine value creation is an essential skill for judicious capital allocation and achieving a sustainable economic advantage. That ability is improved by this study, which gives us both theoretical framework and the useful tools modern society needs to understand how to value things in an AI-driven market.

List of abbreviations

AI	Artificial Intelligence
AII	AI Investment Intensity
CAI	Complementary Asset Index
CapEx	Capital Expenditure
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
ROA	Return on Assets
ROI	Return on Investments
ROP	Real Options Premium
SDI	Sentiment Divergence Index
SE	Standard Error
VRIO	Valuable, Rare, Inimitable, Organized
WACC	Weighted Average Cost of Capital

Author Contributions

Gabriel Silva Atencio: Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration.

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 (with institutional subscriptions required; additional information available at https://www.spglobal.com/marketintelligence/en/mi/products/compustat.html and https://www.crsp.org, respectively); 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 accessible through the USPTO Open Data Portal at https://data.uspto.gov (account registration at https://account.uspto.gov/profile/create-account required, with additional data available via PatSnap at https://www.patsnap.com); 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; additional 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 some proprietary data (LinkedIn Talent Insights, Burning Glass Technologies, Refinitiv transcripts), which are not publicly redistributable due to licensing agreements, while USPTO patent data are publicly available at no cost, and the author confirms that no new primary data were collected from human subjects or private non-public sources beyond those described.

Consent for Publication

No consent for publication is required, as the manuscript does not involve any individual personal data, images, videos, or other materials that would necessitate consent.

Conflict of Interest

The author declares that he has no conflict of interest in this work.

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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 these tools was exclusively instrumental and did not replace critical analysis, data interpretation, methodological decisions, or the scientific responsibility of the author, who fully assume authorship and the integrity of the content presented.

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