

The Role of Artificial Intelligence in Venture Capital: From Gut Feelings to Data-Driven Approaches in Startup Valuation and Decision-Making

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Abstract

Valuing startups is a critical yet inherently uncertain aspect of venture capital (VC) investing, characterized by high risk, limited financial data, and reliance on qualitative judgments. Traditional valuation methods—such as the Venture Capital Method, Scorecard, and Discounted Cash Flow—are widely used but often depend on heuristic estimates and subjective assumptions. Recent advances in Artificial Intelligence (AI), particularly in machine learning and Large Language Models (LLMs), have introduced innovative approaches to support and enhance the VC decision-making process. This paper reviews the foundational valuation frameworks in VC and explores how AI is currently being applied to improve deal sourcing, founder assessment, and predictive analytics. By synthesizing recent academic studies and industry practices, we provide insights into the evolving intersection of AI and venture capital, highlighting opportunities to reduce bias and increase the scalability of startup evaluations.

Keywords: Venture Capital, Startup Valuation, Artificial Intelligence, Machine Learning, Predictive Analytics, LLMs, Deal Sourcing, Due Diligence, Automation

1 Introduction

Valuing early-stage startups remains one of the most complex and subjective tasks in venture capital (VC). Unlike established firms, startups typically lack historical financial records, operate in volatile markets, and pursue innovative, untested business models. This intrinsic uncertainty forces venture capitalists to rely on qualitative judgments—such as the capabilities of the founding team, the scalability of the product, and perceived market opportunities—rather than robust quantitative data.

Traditional valuation methodologies, including the Venture Capital Method, Scorecard, and Berkus frameworks, have been widely adopted despite their reliance on heuristic-based assumptions and personal intuition. These approaches, while practical, often lack consistency and are prone to cognitive biases, making the VC investment process both art and science.

In recent years, advances in Artificial Intelligence (AI), particularly in machine learning and Large Language Models (LLMs), have begun to offer novel tools to augment human judgment in VC. AI-driven systems are being explored for tasks such as startup success prediction, founder evaluation, and automated due diligence, promising to reduce subjectivity and increase efficiency. Studies by Gao et al. (2025) [1], Maarouf et al. (2024) [2], and Ronco & Barontini (2025) [37] demonstrate how AI can process vast, unstructured data sources to identify patterns that correlate with successful outcomes.

This paper provides a critical review of traditional startup valuation methods and investigates the current applications of AI in VC. By analyzing recent developments and real-world implementations, we aim to highlight how AI is reshaping valuation practices, and what potential it holds for transforming decision-making in venture capital.

2 The Venture Capital Landscape: Trends and Market Dynamics

Venture Capital (VC) plays a key role in the financing of early-stage, high-growth companies, particularly in technology-driven sectors. Defined by *Borsa Italiana* as “institutional investments in the equity of start-up companies not listed with high growth potential,” VC differs from traditional private equity by focusing on innovation and scalability rather than operational restructuring. In addition to capital, VC firms provide strategic guidance and networks, making them essential partners for startups excluded from conventional financing due to risk and limited track record.

The data and insights presented in this section are based on a comprehensive review of recent reports, industry publications, and academic sources. All information is supported by the references listed at the end of the document, including those from Crunchbase, Bain, KPMG, AIFI, and SSRN among others [20] [21] [22] [23] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39]

2.1 Venture Capital Market: some key info and insights

Quantifying VC funding worldwide can prove to be a difficult task, as different reports from various companies often provide fundamentally different data. However, all sources agree that in recent years the global venture capital (VC) landscape has been marked by significant volatility, with periods of record highs followed by sharp contractions.

According to CrunchBase data, annual funding increased from \$294.8 billion in 2019 to \$300 billion in 2020. In 2021, the total of venture investments soared to approximately \$643 billion. This peak was followed by a contraction 35% to \$445 billion in 2022, and a further decline to \$285 billion in 2023, the lowest annual total since 2018 and a decrease 38% from the previous year. However, this downturn proved temporary: by 2024, global VC investment had rebounded to \$314 billion. Many sources attribute this recovery to a surge in investments in AI companies.

Looking ahead, the IMARC Group forecasts that the market will expand at a compound annual growth rate (CAGR) of 17.9% between 2024 and 2032, potentially reaching approximately \$1.31 trillion by 2032.

2.2 Global Venture Capital Industry Overview

According to Bain *Global Venture Capital Outlook Q4 2024*, the 2024 rebound unfolded unevenly across global regions, shaped by the strengths of each sector and the policy environment of each market.

- **North America** remained the clear front runner, capturing roughly 70% of the amount invested in Q4 2024. Major generative AI rounds, such as those involving OpenAI and Anthropic, contributed to a 24% quarter-over-quarter increase, reinforcing the US’s leadership in high-growth tech sectors.
- **Europe** experienced strong double-digit sequential growth, driven by deals in biotech, financial services, and AI. The European Commission’s five-year plan to streamline regulations and boost innovation financing played a key role in attracting capital.
- **Asia-Pacific** recorded its lowest funding levels since 2019, constrained by geopolitical uncertainty and China’s sustained economic slowdown. Nevertheless, government-backed investments in electric vehicles and clean technologies served as bright spots, reflecting a regional shift in capital allocation.

This regional divergence underscores how local sector dynamics and regulatory frameworks shaped the pace of VC recovery in late 2024, as illustrated in Figures 1, 2, and 3.

In terms of deal characteristics, there appears to be a global increase in deal size regardless of investment stage (compared to prior quarterly and yearly performance) while the overall number of deals has experienced a slight decline.

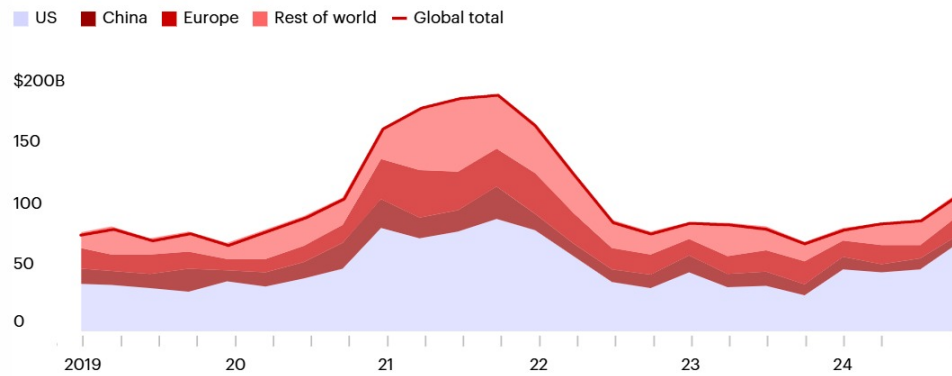


Figure 1: **Global Venture Capital Investment by Region (2019–2024)**. The chart illustrates VC funding volumes by region, showing a significant spike in 2021 followed by a contraction and partial recovery in 2024.

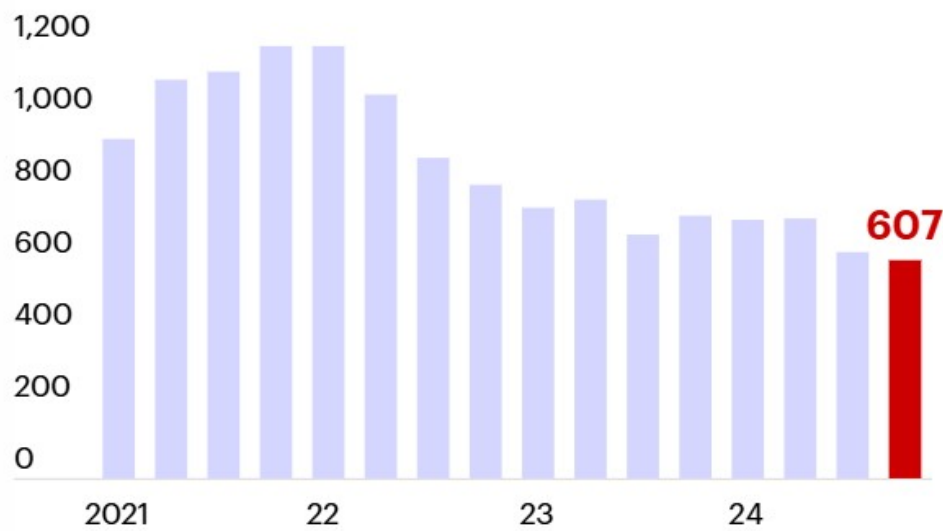


Figure 2: **Number of Corporate and CVC-Backed Deals per Quarter**. Deal activity peaked in 2022 and declined steadily through 2023, before a mild rebound in late 2024.



Figure 3: **Average Deal Size by Funding Stage (Indexed to Q1 2022)**. The figure shows fluctuations in deal sizes across seed, early, and late-stage investments.

2.3 New Trends in The Private Equity Industry

In 2025, the venture capital (VC) landscape is undergoing a significant transformation, marked by several emerging trends that are reshaping investment strategies and priorities.

- **Artificial Intelligence (AI)** continues to be a dominant force in VC investments. Global venture capital funding in generative AI reached approximately \$45 billion in 2024, up from \$24 billion in 2023, highlighting AI's transformative potential across various industries such as healthcare, finance, and manufacturing.
- **Sustainability and Green Tech** have emerged as key focus areas for VCs. Investments are increasingly directed toward renewable energy, carbon capture, and sustainable agriculture, reflecting a commitment to environmental sustainability and aligning with global efforts to combat climate change.
- **Rise of Boutique and Micro VC Funds** is another notable trend. These smaller funds focus on very early-stage startups, often involving smaller investment sums, which allows for personalized support and attention to founders. This approach offers benefits beyond capital, such as mentorship and strategic guidance, and enables investors to adapt quickly to market changes.
- **Private Wealth as a Source of Capital** is increasingly significant. High-net-worth individuals and family trusts are allocating substantial portions of their portfolios into private markets, providing emerging venture capital firms with the necessary funding to support innovative startups.
- **Expansion into Emerging Markets** is gaining momentum. VC investors are exploring opportunities in regions like Africa, Latin America, and Southeast Asia, which present significant growth potential, particularly in sectors such as fintech and renewable energy.

These trends indicate a dynamic shift in the VC industry, with a focus on technological innovation, sustainability, personalized investment approaches, diversified funding sources, and global market expansion.

2.4 Artificial Intelligence in the VC Industry

In recent years, scholars and industry observers have documented a growing role for artificial intelligence in venture capital. Academic studies (2023–2025) confirm that **VCs are increasingly deploying AI to augment decision-making**. For example, Ronco & Barontini (2025) report **sharply rising AI adoption since 2022**, with **AI-driven deal screening** emerging as the most common application. Other research employs machine learning to forecast startup outcomes: one **deep learning model trained on CrunchBase data** for Series B/C rounds predicted key success milestones—such as IPOs, unicorn status, and M&A events—with high accuracy, and back-tested to a **14× capital gain** on a simulated VC portfolio. Similarly, an **LLM-based study (2024)** found that **automatically extracted founder characteristics** can improve success predictions, suggesting that AI may aid in **founder assessment**.

These findings imply that **AI can support critical VC tasks** such as valuation and predictive analytics. However, they also highlight the need for caution: for instance, Lyonnet & Stern (2024) show that VCs often **overweight stereotypical founder traits**—such as elite education, gender, and location—relative to their actual impact, indicating that **AI models must be interpreted carefully** to avoid reinforcing biases.

In parallel, many global VC firms have embraced AI tools. Stockholm's EQT Ventures, for example, uses its proprietary *Motherbrain* AI engine to score and track millions of startups, **crediting it with over \$100 million in investments**. Silicon Valley's SignalFire similarly uses AI across all deal stages—including sourcing, due diligence, and portfolio monitoring—by **processing massive data streams** to guide investments in companies like Grammarly and Ro. Emerging funds such as Roosh Ventures and J&T Ventures also publicly rely on **AI assistants** (e.g., ChatGPT, Claude), **AI-enabled CRMs** (e.g., Affinity), and **custom analytics platforms** to streamline deal flow and portfolio management.

Widely available platforms like **Tracxn**—an AI-powered tracker of over 3 million startups—and **Grata**—an ML/NLP search tool operating on extensive private-company data—are now leveraged globally to **automate deal sourcing and monitoring**. Together, these academic and real-world developments suggest that **AI is rapidly becoming integral to venture capital investing**, underpinning a broader shift toward **data-driven and predictive investment strategies**.

3 Current Methods of Startup Valuation

Before exploring how Artificial Intelligence is being applied to enhance the venture capital process, it is essential to understand the traditional methods used to value startups. This section outlines the main valuation frameworks that have shaped early-stage investing over the past decades.

3.1 Venture Capital Method

The Venture Capital Method (VC Method) is one of the most widely recognized valuation techniques in the venture capital industry, especially for early-stage startups. Introduced by William A. Sahlman in 1987 [5], this method was designed to address the unique challenges faced when valuing young, high-growth companies with limited financial history. Unlike traditional valuation methods that rely heavily on historical performance, the VC Method focuses on estimating the future potential of a startup, emphasizing exit scenarios and investor return expectations [6].

Historical Context

During the 1980s, the rise of venture capital as a formalized investment strategy highlighted the need for tailored valuation frameworks. Traditional corporate finance tools, such as the Discounted Cash Flow (DCF) model, proved inadequate for startups due to the inherent uncertainty and lack of reliable data. The VC Method emerged as a practical solution, grounded in the logic of projecting a company's value at a future liquidity event and working backwards to determine a fair entry price for investors [5].

Application and Use Cases

The VC Method is primarily used in early-stage investments, typically during seed or Series A funding rounds, where financial forecasts are speculative at best [14]. It is especially useful when:

- The startup lacks consistent revenue or profitability.
- Investors focus on potential exit value rather than interim performance.
- Quick, intuitive valuation is needed to support investment decisions.

Investors use this method to determine how much they should invest today to achieve a target return, given an expected future value of the company. It is commonly applied in high-growth industries such as technology, biotechnology, and fintech, where exit multiples can be substantial [7].

Mathematical Formulation

The method calculates the present value (PV) of a future exit value (FV) by discounting it using a required rate of return (r) over a specific investment horizon (n).

$$PV = \frac{FV}{(1 + r)^n} \quad (1)$$

Where:

- PV = Present Value, or the maximum price the investor should pay today.
- FV = Future Value, representing the anticipated valuation at exit.
- r = Required rate of return, typically between 30% and 70% for early-stage ventures.
- n = Number of years until the exit event.

Interpretation of the Formula

This formula encapsulates two critical concepts:

1. **Time Value of Money:** Money today is worth more than money in the future, hence future returns must be discounted.
2. **Risk Compensation:** The higher the risk associated with the startup, the higher the expected return (r), and thus the lower the present value.

A higher required rate of return (r) or a longer time to exit (n) significantly reduces the present value, reflecting the elevated uncertainty in early-stage investing. This helps investors safeguard their capital by investing only when the expected returns justify the risks.

Conclusions

The Venture Capital Method offers a pragmatic approach to startup valuation in uncertain environments. It simplifies complex financial forecasting into a manageable calculation centered on exit potential and investor expectations. Despite its simplicity, it remains a foundational tool in the venture capital industry, valued for its focus on future outcomes rather than speculative current performance. However, its reliance on estimated future values and subjective return rates necessitates cautious application, often complemented by other qualitative assessments during the due diligence process [6, 14].

3.2 Scorecard Method

The Scorecard Method, also known as the Bill Payne Method, is a qualitative approach developed to address the challenges of valuing early-stage startups where financial data is scarce or unreliable. This method helps standardize the inherently subjective process of early-stage investing by using weighted qualitative criteria to adjust an average pre-money valuation [13].

Historical Context

The Scorecard Method was conceptualized by angel investor Bill Payne in the early 2000s, during a time of rapid growth in the startup ecosystem, particularly in technology and internet-based ventures. Traditional valuation methods like the Discounted Cash Flow (DCF) model and Market Multiples often proved inadequate for these young companies due to a lack of historical data and financial predictability [7]. Payne, leveraging his extensive investment experience, identified that qualitative factors—such as the strength of the founding team, market opportunity, and competitive positioning—played a crucial role in determining a startup's potential.

Before the introduction of this method, early-stage valuations were often inconsistent, relying heavily on investor intuition. The Scorecard Method introduced a structured framework that allowed investors to benchmark startups against comparable ventures in the same sector or region, providing a more disciplined approach. This method gained popularity among angel investors and became a standard tool in early-stage investing, supported by organizations such as the Angel Capital Association [13].

Application and Use Cases

The method is widely used by angel investors and early-stage VCs when:

- There is insufficient financial history for quantitative models.
- Investors seek a quick, comparative assessment relative to market norms.
- The focus is on evaluating qualitative strengths (team, product, market).

The process involves benchmarking against average valuations in a specific sector or region, then adjusting that valuation based on a weighted score of the startup's specific attributes.

Mathematical Formulation

Valuation Formula:

$$PV = BV \times S \quad (2)$$

Where:

- PV = Adjusted Present Value,
- BV = Benchmark Valuation (regional/sectoral average),
- S = Score multiplier based on qualitative assessment.

Scoring Function:

$$S = \sum_{i=1}^n w_i \cdot s_i \quad (3)$$

Where:

- w_i = Weight assigned to factor i ,
- s_i = Startup's score relative to average for factor i .

Explanation of the Formula

The benchmark valuation reflects the average deal size in the given context. The score multiplier adjusts this baseline to reflect the specific strengths and weaknesses of the startup. Typical weights w_i might include: team (30%), market size (25%), product (15%), competition (10%), marketing/sales (10%), and other factors (10%) [13, 8].

Conclusions

The Scorecard Method provides a semi-quantitative framework that brings structure to subjective judgments. It is particularly effective for standardizing valuations across different startups and helps investors align decisions with market expectations. While it lacks the precision of financial models, its practical utility in early-stage investing remains high, especially when used alongside other qualitative assessments [7].

3.3 Berkus Method

The Berkus Method is a valuation framework tailored for pre-revenue startups. It provides a milestone-based approach that assigns monetary value to qualitative risk-reducing achievements.

Historical Context

The Berkus Method was developed by Dave Berkus, a prolific angel investor and entrepreneur, in the late 1990s. Berkus, having invested in over 200 early-stage companies, observed that many startups were being overvalued based on unrealistic revenue projections, especially in the dot-com era. His goal was to establish a pragmatic and conservative method that would avoid speculative forecasts, focusing instead on tangible progress made by the startup. The method emerged as a response to the lack of financial data in pre-revenue companies and the need for a structured yet simple approach to early-stage valuation [11].

Initially introduced in his book "Better Than Money," Berkus proposed assigning fixed monetary values to specific milestones that reduce risk. These milestones typically include having a sound idea, a prototype, a strong management team, strategic relationships, and product rollout or sales. Each milestone adds incremental value, with a suggested cap of \$2.5 million to maintain realistic expectations. The method quickly gained popularity among angel investors for its clarity and emphasis on risk reduction rather than speculative growth [7, 8].

Application and Use Cases

Used primarily in very early-stage, pre-revenue investments where:

- There are no financials to project.
- Tangible milestones can be identified (prototype, team, etc.).
- Investors want to cap valuations conservatively.

This method is best suited for:

- Seed-stage startups.
- Sectors where product development precedes monetization (e.g., biotech, hardware).
- Founders seeking transparent valuation logic in early funding discussions.

Mathematical Formulation

Valuation Formula:

$$PV = \sum_{i=1}^n V_i \quad (4)$$

Where:

- PV = Present Value,
- V_i = Assigned value to milestone i ,
- n = Number of milestones (typically 5).

Explanation of the Formula

Each milestone, such as the existence of a prototype or a strong management team, is valued independently. Berkus originally suggested these five milestones with a value of up to \$500,000 each:

1. Sound Idea (\$500,000)
2. Prototype (\$500,000)
3. Quality Management Team (\$500,000)
4. Strategic Relationships (\$500,000)
5. Product Rollout or Sales (\$500,000)

The sum of these values represents a fair pre-money valuation. The simplicity of assigning values ensures that investors avoid overestimating future potential in the absence of financial metrics.

Conclusions

The Berkus Method avoids over-reliance on financial forecasts and focuses on progress milestones, making it a conservative but fair method for evaluating very young startups. Its simplicity and risk-awareness make it popular among angel investors. However, it may undervalue startups with rapid early traction or those in emerging markets with higher capital needs. As such, while it provides a strong foundation for initial discussions, it is often supplemented with other valuation techniques as more data becomes available.

3.4 Market Multiples Method

The Market Multiples Method values a startup by comparing it to similar companies, using financial multiples derived from market data.

Historical Context

The Market Multiples Method originates from public equity markets, where valuation by multiples such as Price/Earnings (P/E) and Enterprise Value/Revenue (EV/Revenue) is a common practice [12]. As venture capital matured during the 1990s and early 2000s, VCs began adopting these techniques to evaluate later-stage startups that exhibited revenue generation and operational stability. The method gained popularity due to its simplicity and alignment with market sentiment, enabling investors to make rapid decisions based on comparative benchmarks rather than speculative forecasts [7, 6]. It evolved further with the proliferation of sector-specific data, allowing refined multiples by industry (e.g., SaaS, fintech) and stage.

Application and Use Cases

Common in later-stage startups or sectors with well-defined benchmarks:

- The startup has existing revenue or EBITDA.
- Industry comparables are available.
- Quick, market-aligned valuation is needed.

Mathematical Formulation

$$PV = X \times M \quad (5)$$

Where:

- PV = Present Value,
- X = Startup's financial metric (e.g., Revenue),
- M = Industry Multiple.

Explanation of the Formula

Multiples reflect market norms (e.g., SaaS companies at 5x revenue) [7, 12]. Adjustments are made for growth, profitability, and market risks, often through discounts or premiums applied to the base multiple depending on how the startup compares to peers.

Conclusions

Market multiples offer speed and realism but can oversimplify unique startup risks. They are best used with mature startups or when industry benchmarks are reliable [6, 8].

3.5 First Chicago Method

The First Chicago Method combines scenario analysis with present value concepts, accommodating uncertainty via probability-weighted outcomes.

Historical Context

Originating from First Chicago Corporation in the 1980s, this method was developed by the bank's venture capital division to address the unpredictability inherent in private equity investments. Traditional valuation approaches like DCF or multiples often failed to reflect the range of possible outcomes for startups or high-growth companies, which could either fail completely or achieve substantial exits. The First Chicago Method introduced a way to model best-case, base-case, and worst-case scenarios, each assigned with probabilities to generate a balanced valuation. It became a key approach for investors who required more structured ways to account for risk beyond single-point estimates [10, 6].

Application and Use Cases

Used when:

- Startups face multiple plausible growth paths with significant variance.
- Investors seek to balance optimistic and pessimistic projections.
- Scenario planning is critical to decision-making.

It is particularly suitable for:

- Later-stage startups with partial financial visibility.
- Sectors with binary outcomes (e.g., biotech approvals).

Mathematical Formulation

$$PV = \sum_{i=1}^n P_i \cdot FV_i \quad (6)$$

Where:

- PV = Present Value,
- P_i = Probability of scenario i ,
- FV_i = Future Value of scenario i .

Explanation of the Formula

Each scenario is typically discounted using a DCF approach, and the weighted sum of these values provides the overall valuation. For example:

- Best Case: €20M exit with 20% chance.
- Base Case: €10M exit with 50% chance.
- Worst Case: €0 with 30% chance.

$$PV = 0.2 \cdot 20M + 0.5 \cdot 10M + 0.3 \cdot 0 = 9M \quad (7)$$

Conclusions

This method is robust and nuanced but relies on subjective probabilities. Best for later-stage or high-variance startups where multiple outcomes need to be accounted for with probabilistic thinking [10, 7].

3.6 Discounted Cash Flow (DCF)

The DCF method projects future free cash flows and discounts them to the present, based on a risk-adjusted rate.

Historical Context

A staple in corporate finance since the early 20th century, the DCF method gained prominence with the development of modern financial theory, particularly after the work of John Burr Williams in the 1930s. In venture capital, its adoption is more recent and limited to later-stage startups where some level of revenue and cost predictability exists. The method assumes that a company's value is the sum of its future cash flows, appropriately discounted to reflect time and risk [6, 9].

Application and Use Cases

Used when:

- The startup has stable or predictable cash flows.
- Detailed projections are possible based on market and operational data.
- Investors require a quantitative basis for valuation.

It is commonly used in:

- Growth-stage startups with revenue visibility.
- Capital-intensive sectors with clear investment-return cycles.

Mathematical Formulation

$$PV = \sum_{t=1}^n \frac{FCF_t}{(1+r)^t} \quad (8)$$

Where:

- FCF_t = Free Cash Flow in year t ,
- r = Discount rate (reflecting cost of capital and risk),
- n = Projection horizon (typically 5-10 years).

Explanation of the Formula

DCF integrates both time value of money and risk. Key challenges include:

- Estimating realistic FCF_t , especially for startups with volatile performance.
- Choosing an appropriate r , often higher for startups (20%-40%).

Conclusions

The Discounted Cash Flow (DCF) method is widely regarded as one of the most precise and theoretically sound valuation techniques, as it directly ties a company's value to its ability to generate future cash flows. However, its practical application is highly contingent on the availability of reliable data and realistic financial forecasts, which makes it more suitable for mature startups that have established revenue streams and a degree of market stability.

For early-stage startups, the inherent uncertainty surrounding future revenues, costs, and market dynamics significantly undermines the effectiveness of DCF. Forecasting long-term free cash flows in such volatile environments often leads to speculative assumptions, rendering the output less credible. Additionally, selecting an appropriate discount rate becomes problematic, as the high risk associated with startups would demand an elevated rate, further reducing the present value and potentially undervaluing the venture.

Despite these limitations, DCF remains a valuable tool for later-stage investors who require a quantitative and rigorous approach to valuation. It is often used in conjunction with other methods to validate assumptions and triangulate a fair valuation, especially in industries where capital expenditure and cash flow generation are more predictable. As startups evolve and gain financial maturity, the DCF method becomes increasingly relevant, providing a structured way to assess long-term value based on solid financial metrics. [6, 9].

3.7 Visual Overview of Traditional Valuation Methods

To better understand the differences between the most commonly used startup valuation methods, we present a visual comparison based on their degree of subjectivity and typical stage of application. This visualization is synthesized from various sources that discuss both qualitative and quantitative aspects of early and late-stage startup valuation, notably the work by Damodaran [6], OpenVC [7], and Berkus [11].

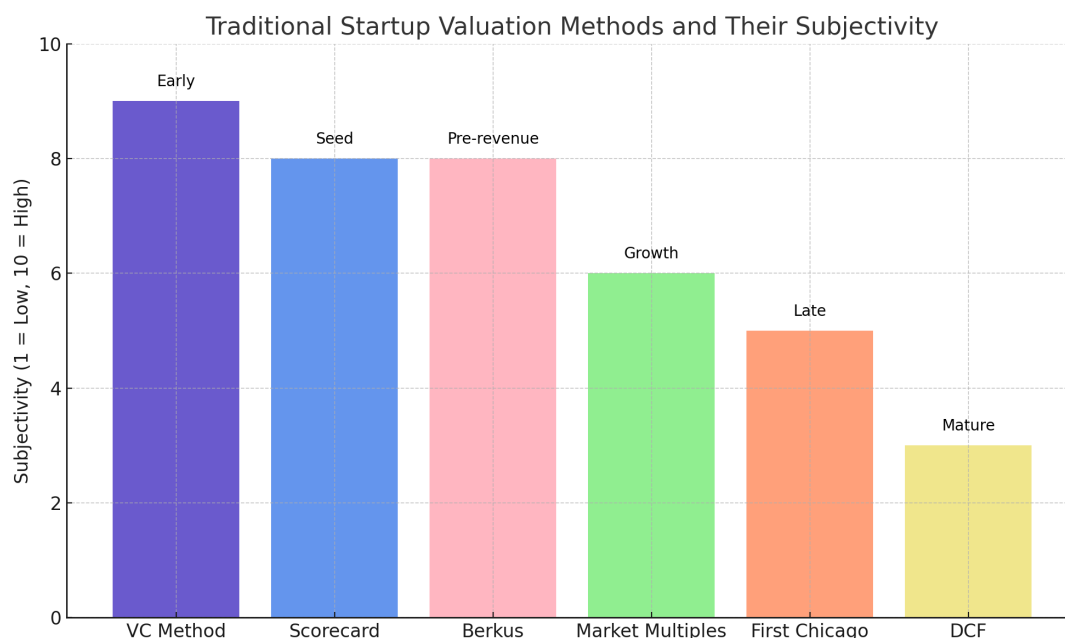


Figure 4: Subjectivity and Application Stage of Traditional Startup Valuation Methods. Higher values indicate greater reliance on subjective judgment.

Interpretation of the Chart

The chart illustrates that early-stage valuation methods such as the VC Method, Scorecard, and Berkus are heavily reliant on subjective assessments due to limited financial data and high uncertainty. These methods prioritize qualitative factors like team strength, market potential, and milestones, often benchmarking against industry norms or investor experience.

In contrast, methods like Discounted Cash Flow (DCF), Market Multiples, and the First Chicago Method, typically applied to more mature startups, offer greater objectivity. These approaches depend on more concrete financial projections and market comparables, allowing for a more data-driven valuation framework.

This visual emphasizes the challenge faced by venture capitalists when valuing startups in their early phases and highlights the potential for AI to reduce subjectivity in such contexts by providing data-enhanced insights and supporting more consistent decision-making.

4 The Current State of AI in Venture Capital

Artificial Intelligence (AI) is progressively shaping the venture capital (VC) landscape, offering novel tools that aim to enhance decision-making, streamline workflows, and uncover patterns often missed by traditional approaches. While venture capital has long relied on qualitative assessments, personal networks, and the so-called "gut feeling," recent advances in machine learning, natural language processing (NLP), and large language models (LLMs) have opened new avenues for data-driven investing.

This section provides a comprehensive overview of the current applications of AI in VC, drawing from recent academic research and real-world implementations by leading investment firms. We explore how AI is being utilized in deal sourcing, founder evaluation, startup success prediction, due diligence automation, portfolio monitoring, and strategic forecasting. Each subsection highlights not only the technological developments but also the practical challenges and limitations faced by VC firms adopting AI.

By mapping the current landscape, we aim to clarify the actual state of AI adoption in venture capital, moving beyond the hype to present a grounded understanding of where the industry stands today.

4.1 Deal Sourcing

Deal sourcing is widely regarded as one of the most fundamental yet resource-intensive activities in the venture capital (VC) ecosystem. Traditionally, venture capitalists have relied heavily on personal networks, industry events, warm introductions, and inbound startup pitches to uncover potential investment opportunities. While this network-centric approach has its strengths, it is inherently limited by the scope of the investor's connections and may lead to missed opportunities—especially among under-the-radar or non-traditional founders.

Artificial Intelligence (AI) is now revolutionizing how deal sourcing is conducted, providing a scalable and data-driven alternative to the conventional approach. By leveraging machine learning (ML) and natural language processing (NLP), AI systems can analyze massive volumes of unstructured data from diverse sources, enabling VCs to detect early signals of promising ventures more efficiently and objectively.

How AI is Transforming Deal Sourcing

AI-powered deal sourcing platforms aggregate and process data from a multitude of digital touchpoints, including news articles, patent filings, startup databases, social media activity, job postings, and web traffic analytics. Sophisticated algorithms sift through this information to identify companies that align with an investor's thesis, ranking them based on factors such as market momentum, team composition, funding signals, and product innovation.

Prominent examples include:

- **Motherbrain** by EQT Ventures: This proprietary AI platform continuously monitors the digital ecosystem to surface high-potential startups. According to Ronco and Barontini (2025) [37], Motherbrain has already driven over \$100 million in investment decisions, proving its strategic value.
- **Beacon** by SignalFire: Beacon tracks over 80 million companies globally, using data points such as hiring trends, online engagement, and product releases to forecast growth trajectories [18].
- **Grata** and **Tracxn**: These commercial AI tools offer VCs access to curated startup intelligence, enriched with real-time analytics and predictive ranking algorithms [19].

Benefits and Limitations

The integration of AI in deal sourcing offers several compelling advantages:

- **Speed and Scale**: Automating the discovery phase allows investors to scan a broader universe of startups in less time.
- **Enhanced Discovery**: AI can uncover promising companies beyond traditional circles, improving diversity in deal flow.
- **Custom Filters**: Algorithms can be tailored to specific sectors, geographies, or growth indicators, aligning with the fund's strategic focus.

Yet, challenges persist:

- **Data Quality**: The effectiveness of AI relies heavily on the reliability and completeness of its data sources.

- **Algorithmic Bias:** AI systems can inherit biases from historical data, potentially reinforcing existing inequalities.
- **Workflow Integration:** Adopting AI requires careful alignment with existing decision-making processes to maximize impact.

Gao et al. (2025) [1] emphasize that AI-powered sourcing is most effective when used to augment—rather than replace—human expertise, enabling VCs to focus on high-value analysis rather than time-consuming scouting.

Conclusion

AI-enhanced deal sourcing represents a significant leap forward in the venture capital toolkit. By systematically analyzing vast datasets, AI enables investors to identify high-potential startups earlier and with greater confidence. While human intuition and relationship-building remain critical, AI serves as a powerful enabler, broadening access to opportunities and elevating the strategic edge of forward-thinking VC firms.

4.2 Founder Evaluation

In the world of venture capital, the founder—or founding team—is often considered the single most critical factor in determining a startup’s success. Especially at early stages, where product-market fit is yet to be achieved and financial data is sparse, VCs make investment decisions largely based on their assessment of the entrepreneur’s vision, leadership ability, resilience, and capacity to execute.

Historically, this evaluation has been deeply subjective, rooted in face-to-face meetings, referrals, and investor intuition. While experienced VCs develop a “gut feel” for spotting talent, such judgments are inherently prone to cognitive biases, including those related to gender, background, and culture.

Artificial Intelligence is now offering tools to bring more structure and objectivity to founder evaluation. By analyzing behavioral data, linguistic patterns, and professional history, AI can help investors assess founders more consistently and fairly.

How AI Assesses Founders

AI applications in founder evaluation typically leverage:

- **Background Analysis:** Mining data on prior entrepreneurial experience, education, previous exits, and industry expertise.
- **Linguistic and Sentiment Analysis:** Evaluating public statements, interviews, social media posts, and pitch decks for indicators of confidence, coherence, and leadership traits.
- **Network Mapping:** Assessing the founder’s professional network strength, including connections to key stakeholders, talent, and advisors.

Ozince and Ihlamur (2024) [3] describe the use of Large Language Models (LLMs) to analyze founders’ communication styles, linking certain linguistic features to higher probabilities of success based on historical datasets. Similarly, Ronco and Barontini (2025) [37] highlight AI systems that evaluate founders’ ability to attract and retain high-quality team members as a predictive metric.

Strengths and Pitfalls

Strengths:

- **Consistency:** AI enables standardized evaluations across different deals and teams.
- **Bias Reduction:** Algorithms can help mitigate human biases by focusing on objective data points.
- **Scalability:** Investors can screen a larger number of founders without sacrificing depth of analysis.

Pitfalls:

- **Historical Bias:** Training data may reflect past inequities, perpetuating systemic issues.
- **Nuance Blindness:** AI may miss qualitative factors such as vision, charisma, or adaptability.
- **Ethical Concerns:** Use of personal data raises privacy and consent challenges.

Maarouf et al. (2024) [2] argue for a hybrid approach, where AI serves as a decision-support system rather than a final arbiter, enriching the investor’s perspective without displacing human judgment.

Conclusion

AI is poised to reshape how venture capitalists evaluate founders, introducing greater rigor and scalability to a process long dominated by intuition. By combining data-driven insights with human experience, VCs can make more informed and equitable decisions, unlocking potential in founders who might otherwise be overlooked.

4.3 Startup Success Prediction

One of the most ambitious frontiers in applying Artificial Intelligence to venture capital is the prediction of startup success. Unlike traditional methods that rely heavily on qualitative assessments and historical analogies, AI-driven success prediction aims to forecast outcomes such as fundraising milestones, market traction, and exit probability using data-driven techniques. While no algorithm can fully capture the chaotic nature of startup evolution, recent advances in machine learning, especially in the context of ensemble models and Large Language Models (LLMs), are beginning to show promise in reducing uncertainty.

From Descriptive to Predictive Modeling

Startup success prediction typically starts with aggregating diverse datasets—ranging from founding team bios, social media sentiment, hiring trends, and investor networks, to product reviews, web traffic, and prior funding rounds. These data points are then structured and fed into machine learning algorithms trained to recognize patterns linked to historical startup outcomes.

Gao et al. (2025) [1] propose a multi-layer ensemble model combining decision trees, gradient boosting, and logistic regression to predict exit events, achieving notable improvements over baseline heuristics. Their model incorporates over 200 variables, including founder experience, funding history, and LinkedIn activity, demonstrating that even sparse signals can contribute meaningfully to forecasting.

Maarouf et al. (2024) [2] introduce a novel approach using fused LLMs that analyze unstructured data such as founder interviews and pitch decks. These models interpret linguistic and semantic features to extract markers of confidence, coherence, and strategic clarity—traits that correlate with successful founders.

Opportunities and Constraints

Opportunities:

- **Early Risk Detection:** Predictive models can flag high-risk ventures before a capital commitment is made.
- **Prioritization:** Algorithms help prioritize which startups deserve deeper due diligence or faster follow-up.
- **Scalability:** Unlike human analysts, AI systems can score thousands of startups simultaneously.

Constraints:

- **Noisy Ground Truth:** Success is often ill-defined—does it mean reaching Series B, achieving a \$100M exit, or simply surviving 5 years?
- **Outcome Bias:** Models may overfit to historical patterns that no longer apply in shifting market conditions.
- **Black Box Risks:** Many ML models, particularly deep learning architectures, suffer from low interpretability, reducing trust among investors.

Conclusion

While still in its early stages, AI-based startup success prediction is gradually moving from experimental to practical use in VC. When combined with human expertise, these tools can offer meaningful improvements in deal triage and portfolio optimization. However, expectations must be tempered—no model can guarantee accuracy in such a volatile domain. The real value lies in reducing noise, not in removing uncertainty altogether.

4.4 Due Diligence Automation

Due diligence is a critical phase in the venture capital (VC) investment process, involving a thorough assessment of a startup's business model, legal compliance, market potential, financial health, and technical capabilities. Traditionally, this process is time-consuming and resource-intensive, requiring analysts to manually review documents, conduct interviews, and verify claims. In fast-paced deal environments, delays in due diligence can lead to missed opportunities or rushed decisions based on incomplete information.

Artificial Intelligence (AI) is now being leveraged to automate and accelerate key components of due diligence. By integrating natural language processing (NLP), machine learning (ML), and document intelligence technologies, VC firms can extract, analyze, and summarize vast amounts of unstructured data from pitch decks, legal agreements, financial statements, and online sources.

Key Applications of AI in Due Diligence

AI systems assist due diligence through:

- **Document Parsing and Summarization:** NLP models extract key terms from contracts and financial reports, flagging risk factors, inconsistencies, or missing data.
- **Market and Competitive Analysis:** AI tools scan web content, social media, and industry databases to generate real-time competitor maps and market trend summaries [37].
- **Technical Assessment:** Code analysis tools evaluate product repositories (e.g., GitHub) to assess development activity, code quality, and technology stack alignment [2].
- **Risk Identification:** ML classifiers trained on historical investment data can flag red flags, such as unusual cap table structures or regulatory exposure [3].

Advantages and Limitations

Advantages:

- **Speed:** Reduces due diligence time from weeks to days, enabling faster decision cycles.
- **Consistency:** Standardizes the evaluation process across deals, improving internal benchmarking.
- **Breadth:** Allows screening of more deals by lowering the cost per diligence process.

Limitations:

- **Contextual Gaps:** AI may miss nuance or context-specific insights crucial for certain verticals (e.g., medtech regulation).
- **Training Data Bias:** Risk of drawing incorrect inferences if historical data used to train models reflects past selection bias.
- **Overreliance Risk:** Full automation may overlook subtleties that only expert human judgment can detect.

Conclusion

AI-powered due diligence tools are augmenting the capabilities of VC firms, especially in early-stage and high-volume dealflow environments. By automating repetitive and document-heavy tasks, they enable investors to focus their expertise where it matters most—strategic insight and founder alignment. However, the most effective implementations treat AI as a co-pilot, not an autopilot, ensuring that final decisions reflect both data and domain expertise [37, 2, 3].

4.5 Portfolio Monitoring

Once an investment has been made, effective portfolio monitoring becomes essential for venture capital (VC) firms to support startup growth, manage risk, and optimize returns. Traditionally, this process has relied on periodic financial reporting, board meetings, and informal updates from founders. While these methods offer qualitative insights, they are often reactive, time-consuming, and limited in scope.

Artificial Intelligence (AI) is increasingly being adopted to bring real-time, data-driven visibility into portfolio company performance. Through the integration of machine learning (ML), natural language processing (NLP), and predictive analytics, AI enables VCs to proactively monitor startups, flag potential issues early, and provide value-added support.

AI-Powered Monitoring Tools

Modern portfolio monitoring platforms harness data from multiple structured and unstructured sources, including accounting software, CRM systems, social media, web traffic, employee reviews, and customer feedback platforms. These tools process the data to identify trends, anomalies, and growth signals across portfolio companies.

For instance:

- **Motherbrain** by EQT Ventures not only aids in deal sourcing but also tracks key growth signals across portfolio startups in real-time [37].
- **SignalFire's Beacon** uses proprietary data to provide continuous updates on team expansion, product launches, and customer sentiment, enhancing investor engagement and reducing blind spots [18].
- Custom in-house dashboards, often built using APIs and LLMs, now allow real-time synthesis of founder updates, KPIs, and market news into actionable summaries [3].

Benefits of AI in Monitoring

Proactive Oversight: By detecting deviations in growth patterns or negative sentiment trends, AI systems can alert investors to potential problems before they escalate.

Time Efficiency: Automated data extraction and summarization reduce the need for manual tracking and reporting, allowing analysts to focus on strategic support.

Enhanced Collaboration: Interactive dashboards and AI-generated insights can be shared across investment teams and with founders to improve alignment and transparency.

Benchmarking: ML models can benchmark portfolio companies against peer sets to identify outliers or underperformers.

Challenges and Limitations

Despite its potential, AI-based monitoring presents challenges:

- **Data Integration:** Not all startups use standardized tools or share data uniformly, limiting the comprehensiveness of monitoring systems.
- **Privacy and Governance:** Monitoring sensitive internal data raises ethical and regulatory questions around consent and data ownership.
- **Signal-to-Noise Ratio:** Not all flagged anomalies are material; human oversight is still necessary to contextualize insights.

Conclusion

AI-driven portfolio monitoring represents a paradigm shift in how VC firms engage with their investments post-funding. By moving from reactive to proactive oversight, AI enables more timely interventions, smarter support strategies, and deeper visibility into portfolio dynamics. However, its effectiveness depends on the quality of data, the willingness of startups to participate, and the integration of AI into the firm's broader decision-making processes [37, 3].

4.6 Strategic Forecasting

Strategic forecasting plays a crucial role in venture capital (VC) by helping investors anticipate market trends, adjust investment theses, and position their portfolios for long-term success. Traditionally, this process has relied on macroeconomic analysis, expert intuition, and historical precedent. However, the increasing complexity and pace of technological change make purely human-led forecasting insufficient. Artificial Intelligence (AI), particularly through machine learning (ML) and Large Language Models (LLMs), is emerging as a transformative tool in this domain.

How AI Supports Strategic Forecasting

AI enables venture capitalists to process and synthesize vast volumes of structured and unstructured data, from financial statements and patent databases to social media, academic publications, and geopolitical news. These capabilities enhance foresight by:

- **Identifying Emerging Trends:** NLP-powered trend detection systems can surface signals from research publications, startup job postings, and industry news, allowing investors to spot nascent technologies earlier than competitors [37].
- **Thematic Mapping:** AI models cluster companies, technologies, and markets into thematic maps that highlight emerging domains such as synthetic biology, quantum computing, or regenerative AI [2].
- **Scenario Simulation:** Generative models can simulate possible future scenarios, stress-testing portfolio allocations and helping GPs prepare for a range of macroeconomic or technological developments [1].
- **Market Sentiment Analysis:** LLMs trained on real-time news and social media help detect shifts in investor sentiment or consumer behavior, informing fund strategy or reallocation.

Case Examples

- **Andreessen Horowitz (a16z)** reportedly uses proprietary AI tools to track global discourse across podcasts, blogs, and technical forums to anticipate movement in developer ecosystems.
- **Sequoia Capital** has invested in AI systems that support thematic forecasting by correlating shifts in public market performance with early-stage private signals [37].

Opportunities and Risks

Opportunities:

- **Thesis Refinement:** AI allows funds to continuously refine their investment theses based on evolving market signals.
- **Contrarian Insights:** LLMs can uncover under-discussed or contrarian views in niche forums and technical literature, potentially identifying overlooked sectors.
- **Cross-Disciplinary Signals:** AI excels at connecting dots across domains—e.g., linking breakthroughs in material science to potential disruptions in EV batteries.

Risks:

- **Overreliance on Trends:** AI may amplify hype cycles by highlighting the most-discussed themes, crowding investors into the same areas.
- **Data Validity:** Forecasts based on noisy or biased inputs can mislead strategic decisions.
- **Opaque Reasoning:** The complexity of LLMs can obscure the rationale behind a suggested trend, limiting trust among decision-makers [3].

Conclusion

Strategic forecasting, once a domain of gut instinct and macro analysis, is being redefined by AI's capacity to process weak signals and synthesize broad datasets into actionable foresight. While not infallible, these systems can dramatically enhance a VC firm's ability to navigate uncertainty and position capital where future growth is most likely to occur. Human judgment remains essential, but it is increasingly empowered by AI-generated foresight [37, 1].

Synthesis Table

Table 1 summarizes the main areas where AI is currently being applied in venture capital. It compares the AI techniques involved, the key benefits observed, and the most relevant limitations, offering a holistic view of how each function is being transformed by automation and data-driven insights.

Table 1: Comparison of AI Applications in Venture Capital

Application Area	Main AI Techniques	Benefits	Limitations
Deal Sourcing	NLP, ML classifiers, web scraping	Scalability in scanning vast datasets; discovery of under-the-radar startups ; supports thesis-driven filtering and increases diversity in deal flow.	Heavily reliant on data quality and coverage ; false positives may emerge without human cross-checking; integration into existing workflow can be complex.
Founder Evaluation	LLMs, sentiment analysis, professional network mapping	Enables consistent evaluation across founders; potential for bias mitigation ; scalable analysis of linguistic and behavioral traits .	Risk of reinforcing historical biases in training data; may overlook soft traits like charisma or resilience; privacy concerns over personal data use.
Success Prediction	Ensemble models, LLMs on unstructured data	Allows for early risk detection and smarter deal triage ; improves portfolio construction ; identifies signals of momentum before market consensus.	Noisy or ambiguous outcomes make training hard; potential for overfitting to historical trends; lack of interpretability in complex models.
Due Diligence Automation	NLP, document classification, entity recognition	Speeds up analysis of legal, financial, and technical documents; enhances workflow efficiency ; helps standardize evaluations across deals.	Context sensitivity is difficult to automate; domain-specific nuances may be lost; risk of legal exposure if misinterpreted outputs are trusted blindly.
Portfolio Monitoring	Predictive analytics, anomaly detection, dashboarding	Enables proactive intervention ; supports real-time performance tracking and alerts; helps detect leading indicators of failure or growth.	Dependent on up-to-date and reliable inputs ; possible signal-to-noise imbalance ; dashboards may become overwhelming without prioritization .

5 Conclusion

The intersection between venture capital and artificial intelligence is rapidly becoming one of the most dynamic and promising areas of innovation in financial decision-making. This paper set out to examine the current state of AI adoption within the venture capital industry, with a particular focus on how it is complementing—rather than replacing—traditional methods of startup valuation and investor judgment.

We began by analyzing foundational valuation frameworks such as the Venture Capital Method, Scorecard, and Discounted Cash Flow. These traditional techniques, while still widely used, exhibit significant limitations in early-stage contexts due to high uncertainty, lack of historical financial data, and reliance on subjective heuristics. We then explored the growing application of AI technologies—such as machine learning, natural language processing, and large language models—in key areas of the VC process, including deal sourcing, founder evaluation, success prediction, due diligence automation, portfolio monitoring, and strategic forecasting.

Throughout this analysis, it became evident that AI is not aiming to substitute human expertise but to expand and refine it. Venture capital, often described as a blend of art and science, is increasingly benefitting from the data-enhanced insights made possible by AI. Yet, while the potential is vast, the actual implementation across the industry remains uneven, with most firms still in experimental or hybrid phases of integration. As such, this paper provides not a conclusion to the discussion, but a snapshot of a field in transition—one where intuition is being augmented, not displaced.

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