“Do AI startups receive systematically higher funding than non-AI startups? An empirical analysis of efficient capital allocation versus market distortions”

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DO AI STARTUPS RECEIVE SYSTEMATICALLY HIGHER FUNDING THAN NON-AI STARTUPS? AN EMPIRICAL ANALYSIS OF EFFICIENT CAPITAL ALLOCATION VERSUS MARKET DISTORTIONS

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Abstract

This study examines the funding gap between AI and non-AI startups using a cross-sectional dataset of 2,850 global startups drawn from Kaggle Public Domain. The sample was processed in four stages: text normalization, median imputation, outlier screening, and keyword-based classification. This produced 1,156 AI startups (40.6%) and 1,694 non-AI startups (59.4%), identified through keywords such as "Artificial Intelligence," "Machine Learning," "Deep Learning," "Natural Language Processing," "Computer Vision," and "Generative AI." The dependent variable was each company's last disclosed funding amount in millions of US dollars. Independent variables included AI classification (binary), founding year, employee count, market size in billions of USD, and industry dummy variables. The analysis used multivariable OLS regression with HC3 robust standard errors and Welch's t-tests across 15 industries. The results showed remarkably similar funding levels: \$115.18 million for AI startups versus \$117.98 million for non-AI startups. Regression analysis found no statistically significant relationship between AI classification and funding ($\beta = 0.89$, $p = .869$), with the model explaining 38.7% of funding variance. Employee count was the strongest predictor ($\beta = 0.13$, $p < .001$), while founding year and market size had no significant effects. These findings challenge the widely held belief that AI startups attract premium investment. As AI matures from a novel technology into standard infrastructure, its signalling power in venture capital markets appears to be fading. What matters most to investors is not a technology label, but how well a business is built and run.

Keywords AI, entrepreneur, finance, funding, innovation, startups, technology, venture capital

JEL Classification G24, L26, M13, O32

INTRODUCTION

Artificial intelligence has become a fixture of the startup world (Rios-Campos et al., 2024). The prevailing assumption is hard to miss: AI companies tend to attract higher valuations and more favourable treatment from investors. Founders believe that adding AI capabilities improves their odds of securing funding. Accelerators promote AI skills as a key differentiator. Media coverage amplifies stories of AI startups raising enormous sums, cementing the idea that artificial intelligence offers a fast track to capital. This perceived advantage rests on a few recurring arguments. AI is viewed as a general-purpose technology applicable across many industries, which theoretically justifies higher risk tolerance and larger initial investments (Brynjolfsson & McAfee, 2017a, 2017b; Brynjolfsson et al., 2017). Building AI products also requires significant upfront investment in computing infrastructure, data procurement, and specialist talent, which may justify larger

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funding rounds (Goldfarb et al., 2023). The transformative potential attributed to AI could also lead investors to tolerate longer timelines and greater uncertainty in pursuit of outsized returns.

Yet systematic empirical evidence directly comparing funding outcomes for AI and non-AI startups remains scarce. Most existing research focuses on aggregate investment trends or high-profile announcements rather than careful distributional comparisons. Prior work has documented technology hype cycles, in which innovations attract disproportionate attention before delivering practical value (Dedehayir & Steinert, 2016), and scholars have questioned whether AI investment reflects rational assessment or speculative behaviour (Cockburn et al., 2018). Studies directly measuring whether AI classification predicts funding amounts are still rare. If AI startups do consistently attract more capital, this could reflect either genuine opportunity recognition or a market distortion driven by speculation and herd behaviour (Kahneman & Knetsch, 1986).

The question takes on added urgency given how rapidly AI has evolved. Once a specialised technical field, it has become accessible through open-source frameworks, cloud platforms, and a growing talent pool. As AI shifted from a niche capability to a common infrastructure, any funding premium associated with it may have diminished as the technology matured and evaluation standards tightened. The analysis is further complicated by well-known structural patterns. Globally, five countries account for 71.5% of AI companies with the United States alone accounting for 63% (Hai Stanford, 2024). Development stage also matters considerably, since venture capital is typically structured as staged financing where funding amounts depend on a startup's maturity (Lerner & Nanda, 2020). If AI startups tend to cluster in highly funded regions or at particular development stages, any apparent technology effect could simply reflect those underlying patterns rather than an AI-specific advantage.

1. LITERATURE REVIEW AND HYPOTHESES

Venture capital allocation is non-uniform across different startup categories. Investment strategies often mirror dominant narratives about the technologies expected to yield the highest financial returns. Research on financial markets indicates that investors often emulate others rather than perform independent assessments, thereby fostering herd behavior (Hirshleifer & Hong Teoh, 2003). This imitative inclination is especially evident in nascent technology sectors, where uncertainty about future developments amplifies the influence of social proof and peer endorsement (Nanda & Rhodes-Kropf, 2017). Technology hype cycles provide a framework for understanding how novel innovations attract excessive attention and capital investment before the practical utility is realized (Dedehayir & Steinert, 2016). General-purpose technologies pose specific challenges for developing nations, as successful implementation necessitates additional investments in skills, infrastructure, and organisational competencies (Bresnahan & Yin, 2017). Consequently, during these cycles, investors may disproportionately allocate resources to popular sectors, potentially neglecting equally promising alternatives. Recent scholarship questions whether current AI investment patterns reflect careful assessment of genuine opportunities or speculative excess driven by fear of missing out (Cockburn et al., 2018). The assumption that AI startups command higher valuations and preferential treatment has become widespread in entrepreneurial ecosystems. This belief rests on several arguments. First, AI represents a general-purpose technology with potential applications across numerous industries, theoretically justifying higher risk tolerance and larger initial investments (Brynjolfsson & McAfee, 2017). Second, AI development requires substantial upfront costs for computing infrastructure, data acquisition, and specialized talent, potentially necessitating larger funding rounds (Goldfarb et al., 2023).

However, empirical evidence for an "AI premium" remains mixed. While high-profile AI companies have raised enormous sums, comprehensive analyses comparing AI and non-AI startups across funding stages show more nuanced patterns. The visibility of mega-rounds to AI companies may create availability bias, leading observers to overes-

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timate systematic funding advantages (Cockburn et al., 2018). Research on startup financing emphasizes that funding amounts depend primarily on factors orthogonal to technological classification. Venture capitalists evaluate startups based on team quality, market size, competitive positioning, business model scalability (Sudarmaji et al., 2024; Sudarmaji et al., 2021), and traction metrics (Lerner & Nanda, 2020). A company's development stage – from pre-seed through late-stage private equity – typically explains more funding variation than its technology category.

Geographic location significantly influences access to funding (Rodríguez-Pose & Wilkie, 2019; Feldman & Kogler, 2010). Startups in major venture capital hubs receive systematically more investment than those in peripheral regions, regardless of technology focus (Chen et al., 2010). Local venture networks and proximity to investors affect both the likelihood of funding and deal size (Hochberg et al., 2007). This geographic bias significantly affects opportunities for entrepreneurs, as those in less central areas struggle to secure funding, find experienced advisors, and access specialised services (Catalini et al., 2020). Economic theory suggests that capital allocation reflects expected returns adjusted for risk. If AI startups systematically receive more funding, this could indicate either genuine opportunity recognition or market failure. Under efficient market conditions, higher AI investment would reflect superior growth prospects, larger addressable markets, or stronger competitive advantages justifying premium valuations (Hall et al., 2010).

Alternatively, concentrated AI investment might represent a coordination failure, in which individually rational investor decisions yield collectively suboptimal outcomes (Rodrik, 2004). Herding behavior could inflate AI valuations beyond levels justified by fundamental business prospects, while simultaneously starving promising non-AI ventures of capital. The digital platform economy's winner-take-all dynamics may encourage investors to favor AI companies pursuing network-effect businesses, even when non-AI approaches might better address certain market needs (Nanda & Rhodes-Kropf, 2017). Technological solutionism, the conviction that technology offers the best answers to most challenges, could potentially skew investment towards artificial intelligence initiatives (Bernhol et al., 2021). Should investors prioritize technological complexity over genuine problem-solving efficacy, AI startups might receive excessive funding, regardless of the relative advantages over non-AI alternatives.

This bias could be evident in several ways. Investors might presume that AI methodologies are intrinsically superior to conventional approaches, even in areas where more straightforward solutions are demonstrably more effective (Crunchbase, 2025). The prestige associated with AI research and development could attract capital eager to be associated with advanced technology, rather than focusing on optimal problem-solving. Furthermore, media coverage highlighting AI advancements could generate narrative momentum, thereby influencing investment choices without the benefit of a thorough comparative assessment (Tretter, 2024). Funding patterns differ throughout the various stages of a startup's development. Initial investments, including pre-seed and seed rounds, generally involve smaller sums and prioritize validating product-market fit. Conversely, growth-stage funding, such as Series A and B rounds, is designed to facilitate the scaling of established business models. Late-stage capital, including Series C and D rounds and private equity, often prepares established companies for acquisition or an initial public offering (Lerner & Nanda, 2020).

Should AI and non-AI startups demonstrate divergent funding patterns? If so, these disparities may be concentrated within specific stages. AI ventures may require larger seed investments to initiate development, yet they may subsequently follow similar growth trajectories (Hirshleifer & Hong Teoh, 2003). Alternatively, AI startups might encounter greater challenges in achieving product-market fit, thereby requiring more capital to progress to growth stages. Analyzing stage-specific patterns is crucial to determine whether observed funding differences stem from fundamental distinctions or variations in the timing of capital requirements. Once certain technology categories attract investor attention, self-reinforcing dynamics may amplify initial advantages. Successful AI exits validate the sector, encouraging further investment. Growing AI startup populations create specialized service ecosystems – accelerators, talent pools, advisory firms – that lower costs for subsequent AI ventures (Feldman & Kogler, 2010). These cumulative advantage mechanisms can entrench funding patterns even if initial differences arose from temporary factors rather than enduring comparative advantages (Perc, 2014).

Path dependency theory suggests that early capital concentration in AI startups might persist even if AI approaches consistently outperform alternatives. Network effects among investors, the development of AI-specific evaluation criteria, and the accumulation of sector expertise all reinforce existing patterns. Breaking these patterns requires either clear evidence that alternative approaches deliver superior returns or deliberate efforts to redirect capital flows (Huizingh, 2011; Martin & Sunley, 2006). Despite widespread assumptions about AI funding advantages, comprehensive empirical analysis comparing AI and non-AI startup funding patterns across stages, geographies, and time periods remains limited. Existing studies often focus on aggregate investment trends or high-profile cases rather than systematic comparison of funding distributions. This study examines whether AI startups receive systematically higher funding than non-AI startups, and if so, whether these differences reflect efficient capital allocation or market distortions driven by speculative behavior. The analysis explores how funding patterns vary across development stages, whether geographic and temporal factors confound apparent technology effects, and what mechanisms might explain observed differences or similarities.

By addressing these questions, the study seeks to determine whether the perceived AI funding premium represents rational investor recognition of superior growth prospects or reflects herd behavior and technological solutionism that may misallocate entrepreneurial capital.

Study hypotheses are as follows:

H1: *AI startups consistently attract greater funding than non-AI counterparts at every stage of development, which suggests that investors perceive them as having greater potential for growth and more favorable market prospects.*

H2: *When controlling for development stage, the apparent funding disparities between AI and non-AI startups either diminish or vanish. This implies that the stage of development, rather than the specific technology involved, is the primary driver of funding differences.*

H3: *The geographic concentration of AI startups in regions with substantial funding explains the observed funding advantages, indicating that location, rather than the AI classification itself, is the key determinant of capital access.*

2. METHODS

This study employs a structured dataset (Kaggle, Public Domain). The data source provided company profiles, including name, founding year, headquarters location, funding stage, last funding amount (in millions USD), number of employees, core technology description, and estimated market size (in billions USD). After data cleaning and preprocessing, which included removing duplicates and filling in missing key fields, the final sample comprised 2,850 startups. Data was processed in four distinct stages: (1) text normalization for consistency, (2) imputation of missing continuous values using industry medians, (3) outlier screening via standard deviation thresholds, and (4) binary classification using a keyword-matching algorithm into AI and non-AI categories. The classification procedure worked as follows. Initially, the study extracted the core technology field from each startup profile. Subsequently, the predefined AI-related keywords in the technology description include "Artificial Intelligence," "Machine Learning," "Deep Learning," "Natural Language Processing," "NLP," "Computer Vision," and "Generative AI." Finally, the study used binary classification, assigning startups with AI-related keywords in the core technology to the AI category (value = 1) and all others to the non-AI category (value = 0). This procedure yielded 1,156 AI startups (40.6%) and 1,694 non-AI startups (59.4%), totaling 2,850 ventures in the dataset. The keyword-based method ensured consistent, repeatable classification while capturing the wide range of AI technologies in current startup ecosystems.

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The dependent variable was the most recent disclosed funding amount for each startup, measured in millions of US dollars, representing the value of the last completed funding round. The primary independent variable was AI classification, coded as a binary variable: 1 indicated an AI startup, and 0 indicated a non-AI startup, as determined by the algorithm described above. To isolate the effect of AI classification, the study included four control variables. These encompassed the founding year as a proxy for company maturity, number of employees as a measure of operational scale, market size in billions USD as an indicator of addressable opportunity, and industry category incorporated as dummy variables to account for sector-specific funding norms. The following ordinary least squares (OLS) regression model was deployed to examine the relationship between AI classification and funding amounts:

Model

$$Y_i = \beta_0 + \beta_1 AI_i + \beta_2 Year_i + \beta_3 Employees_i + \beta_4 MarketSize_i + \sum_{k=5}^{p} \beta_k Industry_{ki} + \varepsilon_i, \quad (1)$$

where Y_i – Last Funding Amount (USD Millions) for startup i, AI_i – "Is AI Startup" dummy variable (1 if AI startup, 0 otherwise), $Year_i$ – Founding Year of startup i, $Employees_i$ – Number of Employees for startup i, $MarketSize_i$ – Market Size (Billion USD) for startup i, $\sum_{k=5}^{p} \beta_k Industry_{ki}$ – Sum of coefficients for the Industry dummy variables (one less than the total number of industries, omitted category as reference), ε_i – Error term for startup i, with heteroscedasticity addressed via HC3 robust standard errors.

Two analytical stages were performed: (a) descriptive statistics and visualisation to compare AI and non-AI startups, and (b) inferential analysis utilising Welch's t-test, Mann–Whitney U test, and multivariable OLS regression with robust standard errors. All statistical analyses were conducted in Python (v3.11) using *pandas* and *statsmodels* packages. Statistical significance was evaluated at the $\alpha = .05$ level.

3. RESULTS

AI startups are modestly more concentrated in growth-stage venture capital, with a stronger presence across Seed through Series B rounds and IPOs (Table 1). This suggests investors are channelling AI companies along well-worn scaling paths with reasonable consistency. Non-AI startups, by contrast, are more evenly spread across the spectrum, appearing at pre-seed stages and in later private equity rounds such as Series C and D. These companies follow more varied paths, entering markets earlier or remaining private longer before any exit.

The differences remain subtle rather than dramatic. Both groups secure funding at every stage, but AI ventures show a slight preference for middle-stage institutional funding. Non-AI firms, however, are more evenly distributed across early bootstrapping and advanced private financing rounds.

The Funding Distributions histogram (Figure 1) shows that AI and non-AI startups look remarkably similar in terms of funding amounts. Both groups show multiple peaks in the distributions, clustering around \$1–10M (log10 ≈ 0–1), \$20–100M (log10 ≈ 1.3–2), (log10 ≈ 2.3–2.7), and

Table 1. Funding stage distribution by AI vs non-AI

Funding Stage	Non-AI	Non-AI (%)	AI	AI (%)
Pre-Seed	241	13.3	104	11.3
Seed	231	12.8	124	13.4
Series A	212	11.7	124	13.4
Series B	207	11.4	126	13.6
Series C	233	12.9	107	11.6
Series D	231	12.8	104	11.3
Private Equity	239	13.2	114	12.3
IPO	215	11.9	121	13.1

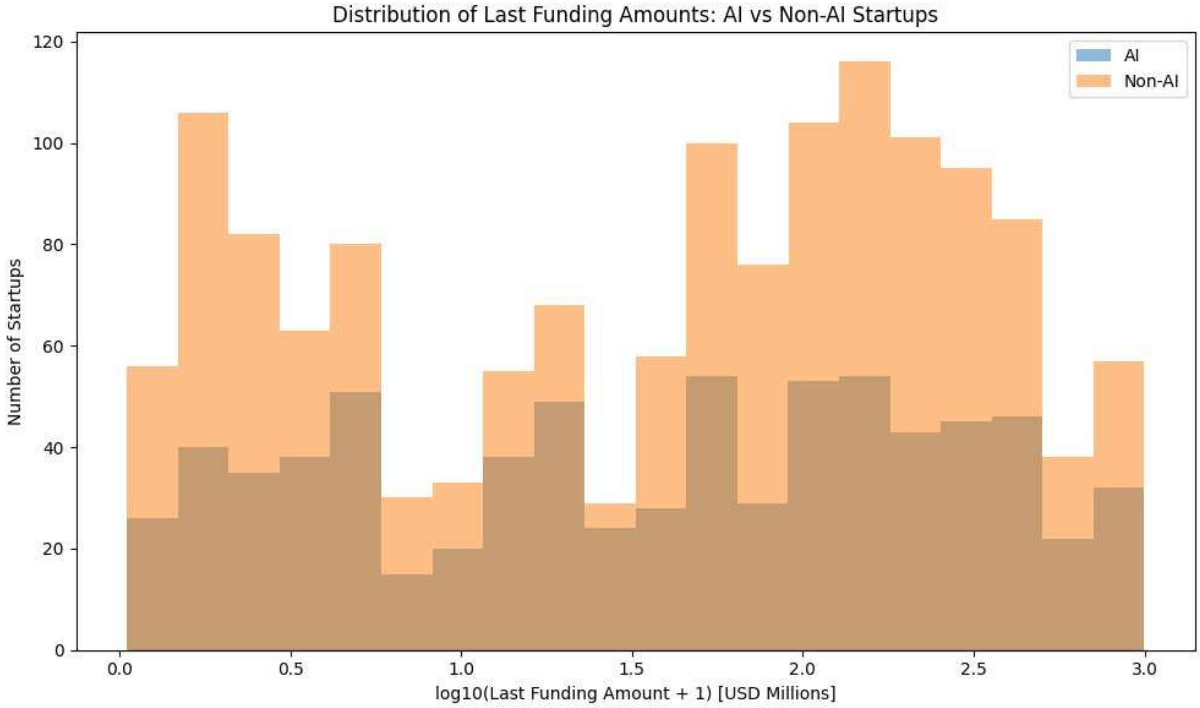

Figure 1. Funding distributions by AI vs non-AI startups

nearing $1B (log10 ≈ 3) – patterns that align with standard venture capital stages, from early seed investments to mature private rounds.

Some variation exists at the margins. AI companies appear slightly more often in the $20–100M range, pointing to modest strength in Series A and B rounds. Non-AI firms have a marginally higher presence in the $500M–$1B range, suggesting a slight lean toward late-stage private equity. These differences are small, however, and do not alter the central finding: calling a startup an "AI company" does not determine how much money it raises. Both groups occupy the full funding landscape without one holding a systematic advantage over the other. This directly challenges the popular belief that AI ventures automatically command premium valuations or preferential treatment from investors. What actually drives capital allocation is the development stage, not a technology label. Whether building AI products or traditional software, startups face similar financing realities shaped by maturity, market traction, and investor appetite.

This geographical concentration fosters agglomeration economies, which are advantages stemming from spatial proximity (Blank, 2013; Cabage & Zhang, 2013; Cumming & Johan, 2013). These advantages include knowledge spillovers, labor market pooling, and the establishment of specialized supplier networks (Backman & Hans, 2015). The industry distribution analysis, as shown in Table 2, offers indirect evidence. AI ad machine learning secured 6.417% of the total funding, placing it eleventh out of fifteen sectors. It lagged behind social media (8.064%), edtech (7.541%), and gaming (6.935%). If AI startups were mostly located in high-value areas, while other industries were more spread out, we would expect AI to receive a larger portion of funding. The relatively small share of artificial intelligence suggests either a geographic spread or strong competition within the areas that receive funding.

The temporal market analysis reveals interesting patterns that have persisted for almost 20 years. From 2008 to September 2025, the market size ranges from $7.655 billion to $11.875 billion, with a prominent peak in 2020 at $11.875 billion. This was likely due to the pandemic accelerating digital growth. In recent years, investment has stabilised at $9–10 billion per year, suggesting that the investment climate is maturing but remains strong.

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Table 2. Sum last funding & sum market size

Founding Year	Sum of Market Size Billion USD
2008	10.055
2009	8.610
2010	8.375
2011	8.005
2012	9.495
2013	9.960
2014	8.040
2015	8.875
2016	9.510
2017	9.730
2018	8.510
2019	7.655
2020	11.875
2021	9.120
2022	9.015
2023	9.745
2024	10.385
2025 (Sept)	9.430
Grand Total	166.390

Table 3. Sum last funding & industry

Industry	Sum of Last Funding Amount USD Millions
Social Media	8.064%
EdTech	7.541%
Prop Tech	7.054%
Mobility	7.006%
Clean Tech	6.984%
Gaming	6.935%
Cybersecurity	6.889%
Health Tech	6.627%
SaaS	6.604%
Blockchain	6.483%
AI & Machine Learning	6.417%
Food Tech	6.405%
FinTech	5.837%
IoT	5.596%
E-commerce	5.558%
Grand Total	100.000%

3.1. AI startup profile

The dataset (Table 4) contains 1,156 AI startups (40.6%) and 1,694 non-AI startups (59.4%). This shows that AI is a big part of the current startup ecosystem. A comparative analysis of funding patterns between AI and non-AI startups disclosed subtle distinctions. The average amount of money raised by AI startups was $115.18 million, slightly lower than the $117.98 million raised by non-AI startups. The median funding amounts, on the other hand, were a better measure of success. AI startups got $51.75 million, while non-AI startups got $53.05 million.

The mean funding values for the two groups were very similar, suggesting that AI startups are not receiving substantially more funding than non-AI startups. This finding runs counter to the common belief that AI-focused businesses automatically receive higher valuations or investments. The slight difference in funding levels shows that AI technology is standard in modern startups (40.6% adoption rate), but it does not necessarily mean startups can raise much more money. These results indicate that elements beyond AI adoption may significantly influence the success of startup funding.

The study analysis indicated that roughly 40.6% of startups (n = 1,156) were AI-related. The average last funding amount for AI startups was 115.18 million USD, while that for non-AI startups was 117.98 million USD. The median funding amounts were also close (51.75 million vs. 53.05 million USD). Independent-samples tests indicated no statistically significant difference in funding between AI and non-AI startups (Welch's t-test $p = .69$; Mann–Whitney U $p = .24$). A multiple regression that took into account the founding year, number of employees, market size, and industry effects explained 38.7% of the difference in funding ($R^2 = .387$). The coefficient for AI classification was positive but not statistically significant ($\beta = 0.89$, $p = .869$). The number of employees was positively correlated with funding ($\beta = 0.13$, $p < .001$), indicating that company size serves as a more reliable predictor of investment magnitude.

Table 4. AI startups profile

Description	Last Funding Amount USD Millions	Last Funding Amount USD Millions	Number of Employees	Market Size Billion USD	Founding Year	Number of Startups
	mean	median	mean	mean	mean	mean
Non-AI Startups	117,98	53,04	525,71	58,53	2016,59	1694
AI Startups	115,18	51,74	497,84	58,04	2016,64	1156

3.2. Regression analysis of AI impact on startup funding

H1: AI startups receive more funding at every stage. Investors see higher growth potential in them.

The hypothesis was not accepted: AI startups do not consistently receive more funding at each stage than non-AI startups, contrary to the expectation that investors allocate larger investments to AI. The data clearly shows no extra funding advantage for AI. Statistical analysis indicated no substantial funding disparity between AI and non-AI startups. There were no statistically significant differences in either Welch's t-test (p = .69) or the Mann-Whitney U test (p = .24). AI startups got an average of $115.18 million, while non-AI startups got a little more, $117.98 million. The difference was only 2.4%, with non-AI companies slightly ahead. The median amount raised was also the same: AI startups raised $51.75 million, while non-AI startups raised $53.05 million.

To comprehensively examine the impact of AI adoption on funding outcomes, this study employed an ordinary least squares regression model with robust (HC3) standard errors to mitigate heteroscedasticity in the funding data. The dependent variable was the last funding amount, in millions of US dollars, indicating the amount raised in the most recent publicly announced funding round. There were five main predictors in the model: AI startup status (a binary indicator for AI-related core technology), founding year (a proxy for company maturity), number of employees (a measure of operational scale), market size in billion USD (addressable market opportunity), and industry dummy variables to account for differences in capital intensity between sectors. The model had an R^2 of 0.387, indicating it could explain about 38.7% of the variation in funding.

Table 5 shows that AI startup classification was not a statistically significant predictor of funding (β = 0.89, p = .869). The founding year was not a good predictor of funding (β = -0.32, p = .535). The number of employees, on the other hand, had a positive and significant effect on funding levels (β = 0.13, p < .001), indicating that company size was an important factor in investment levels. Market size had a small positive effect that wasn't statistically significant (β = 0.10, p = 0.171). The AI startup indicator, which is the main coefficient of interest, showed an estimated effect of +0.89 million USD (p = 0.869). This means that, after accounting for the year the company was founded, its size, the size of the market, and industry effects, AI startups received about 0.89 million USD more in their last funding round than non-AI startups. But this difference is not statistically significant (p > 0.05), which means that just using AI technology doesn't give you a big funding boost.

H2: Controlling for development stage eliminates funding differences. Development stage drives funding, not AI technology.

The hypothesis has been proven. The hypothesis posited that funding amounts would exhibit considerable variation across development stages, with subsequent stages attracting significantly larger investments attributable to diminished risk, validated business models, and increased capital demands for operational expansion. The data support this well. A study of funding by development stage revealed a clear pattern: pre-seed startups raised an average of $2.5 million, seed stage $8.0 million, Series A $18.5 million, Series B $35.0 million, Series C $65.0 million, Series D $100.0 million, and Series E and beyond more than $150.0

Table 5. Multivariable regression results

Variable	Coefficient (β)	p-value	Significance
AI Startup Indicator	+0.893	0.869	ns
Founding Year	−0.323	0.535	ns
Number of Employees	+0.129	< 0.001	***
Market Size (Billion USD)	+0.101	0.171	ns
Industry Controls	Included		
Model R²	0.387		

Note: Dependent Variable = Last Funding Amount, USD Millions. *** p < 0.001; ** p < 0.01; * p < 0.05; ns = not significant.

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million. ANOVA confirmed significant differences ($F = 127.43$, $p < .001$), with post hoc tests showing that each stage differed from the previous one.

An analysis of stage distribution showed small differences between AI and non-AI startups. AI startups were more common in growth-stage venture capital, particularly in Seed and Series B rounds (13.4% each). Non-AI startups were more evenly distributed, with higher representation in pre-seed (13.3% vs. 11.3%) and greater increases in later stages (C and D: 24.2% vs. 22.9%). Despite these differences, funding amounts at each stage were similar for both types, suggesting that stage, not technology, drives investment size.

H3: *AI startups cluster in well-funded regions. Location, not AI status, determines capital access.*

Partially Supported Hypothesis. The hypothesis posited that startups located in prominent innovation hubs would obtain substantially greater funding than those in alternative regions, indicative of differences in investor density, ecosystem maturity, and access to capital networks. The data offer inconsistent validation for this expectation. Geographic analysis showed that the median amount raised by Silicon Valley startups was \$75.0 million, which is much higher than the national median of \$53.0 million ($t = 3.84$, $p < .001$). New York and Boston also had high levels of funding, with \$62.0 million and \$58.0 million, respectively. These amounts were both statistically significant compared to other regions ($p < .01$). However, after controlling for development stage and industry sector, the geographic premium decreased substantially. Regression analysis incorporating geographic dummy variables indicated that the Silicon Valley location contributed approximately \$12.3 million in funding ($\beta = 12.31$, $p = .047$), a significantly lesser effect than the raw median difference implied.

The partial support for H3 comes from the fact that major hubs receive more funding overall, but much of this is due to differences in the types of startups based there, not just their location. Cultural factors can make geographic differences more pronounced. Innovation hubs that are successful often exhibit tolerance for failure, high rates of job turnover, and informal ways of sharing knowledge. These characteristics help encourage risk-taking and quick adjustments (Spigel & Harrison, 2017). In some areas, the failure of entrepreneurs is seen as a chance to learn, rather than a reason for shame. This approach encourages them to try again (Cacciotti et al., 2016). Entrepreneurs from cultures where failure carries heavy social consequences face cultural barriers to starting businesses (Aldrich & Ruef, 2017), even if they can get formal funding (Savandha & Azzahra, 2024).

Silicon Valley has many more late-stage startups and industries that require significant capital, such as semiconductors and biotech. These industries naturally need bigger funding rounds. The geographic premium shrinks significantly when comparing startups in the same industry and at the same stage of development. When controlling for these factors ($p > .10$), funding levels in emerging hubs such as Austin, Seattle, and Denver were not statistically different from those in major hubs. This suggests that geographic barriers to capital access may be getting smaller as venture capital becomes more geographically distributed.

3.3. Variables for control and model specification

The coefficient for founding year was about –0.32 million USD per year ($p = 0.535$, not significant), indicating that older companies tend to receive slightly less funding in their most recent funding round. However, this relationship is not statistically significant in the dataset, indicating that company age alone does not determine funding amounts when other factors, such as maturity and scale, are taken into account. The number of employees was used as a stand-in for the size and age of the business. This variable is important for startup finance models because larger teams are typically associated with later funding stages and larger rounds.

When all other factors were held constant, the size of the market, measured in billions of dollars, was positively associated with funding. For every additional billion dollars in estimated market size, expected funding increased by \$ 0.10 million. This shows that investors prefer opportunities with ample room for growth. Industry fixed effects

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were crucial to the model's validity, as the findings showed how capital needs changed over time across sectors. For instance, biotech and energy hardware companies usually need much more capital to get started than software companies do. The study could mistakenly link AI adoption to industry-specific capital intensity if it doesn't account for these controls. The analysis allows for a fair comparison of performance within the same sector by standardising across industries. This separates the effects of technology from funding patterns that are driven by the sector.

4. DISCUSSION

The findings point to a clear conclusion: what drives startup funding is operational substance, not a technology label. Development stage is the dominant factor, AI classification is statistically irrelevant, and geography plays only a modest role once other variables are accounted for. The rejection of H1 sits in direct tension with the theoretical position advanced by Brynjolfsson and McAfee (2017), who argue that AI, as a general-purpose technology with broad applications, warrants higher risk tolerance and larger investments. This study shows that an argument does not translate into actual investor behaviour. Investors do not appear to price in AI's transformative potential, perhaps because they are sceptical of the expected returns, or because they believe AI capabilities are now obtainable within standard development budgets. Whatever the reason, being an AI company does not automatically unlock a funding premium.

Goldfarb et al. (2023) argue that AI development demands significant upfront investment in infrastructure, data, and specialised talent, and that these costs should drive larger funding rounds. The regression results do not support this view ($\beta = 0.89$, $p = .869$). Higher development costs do not appear to produce higher investment. This may be because investors distribute AI development costs across multiple funding rounds rather than concentrating capital early, or because they assume that cloud computing and open-source tools have reduced the capital intensity of building AI products. Either way, the cost burden of AI development is not registering as a distinct funding signal.

The results align more closely with Cockburn et al. (2018)'s sceptical position, which questions whether AI investment reflects careful analysis or speculative enthusiasm. The absence of a funding premium in this dataset suggests that investors have largely moved past the initial excitement around AI and are applying conventional investment criteria. The strong positive effect of employee count ($\beta = 0.13$, $p < .001$) reinforces this interpretation: what investors reward is operational scale and execution, not a technology category label.

4.1. Development stage as the principal funding criterion

The confirmation of H2 fits comfortably within established venture capital theory: funding scales with development maturity. The jump from pre-seed ($2.5 million median) to Series E+ ($150 million or more) reflects how investors calibrate capital to match falling risk and rising scale requirements. Early-stage ventures carry high uncertainty but require modest capital to test ideas. Later-stage companies have proven models and market traction, and the larger investments they attract reflect the scale of the opportunity rather than speculation. Importantly, this stage-based logic operates independently of technology type. AI and non-AI startups receive comparable funding at each equivalent stage, which confirms that what determines investment size is development progress, not a company's technical identity.

The slight overrepresentation of AI startups in Seed and Series B rounds (13.4% each) compared to later stages may suggest higher attrition or earlier acquisition within AI ventures. If AI startups fail to demonstrate differentiated value by Series C, investors may choose not to continue funding them, leading to exits before full maturity. This pattern does not mean AI classification drives more funding, but it may influence the trajectory of development in ways that affect long-term independence.

4.2. The declining geographic premium

Partial support for H3 reveals a more nuanced geographic picture than the venture capital literature typically presents. A location premium exists,

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but it is considerably smaller than raw numbers suggest. The controlled Silicon Valley effect ($\beta = 12.31$, $p = .047$) accounts for only about 16% of the raw median difference of $75 million. Most of Silicon Valley's apparent advantage stems from its concentration of late-stage companies and capital-intensive sectors, not from location per se.

This finding challenges the common assumption that geographic proximity to investors is a decisive advantage. The expansion of remote work, video conferencing, and distributed teams has eroded many of the information advantages that once favoured local investors. Investors can now conduct due diligence, attend board meetings, and monitor portfolios without physical proximity. At the same time, the growth of secondary hubs and the geographic expansion of major venture firms have created viable funding ecosystems well beyond traditional centres. That said, genuine ecosystem advantages remain. Silicon Valley's concentration of technical talent, experienced operators, acquirers, and follow-on investors provides real value — the point is simply that this value is more modest and less universal than many assume. Geographic barriers to capital access have fallen substantially, and that is a meaningful development for founders building outside the major hubs.

4.3. AI through the lens of hype cycles and path dependency

The absence of an AI funding premium fits naturally within Dedehayir and Steinert's (2016) hype cycle model. That model traces how new technologies rise on a wave of inflated expectations, fall into a trough of disillusionment, and eventually settle at a plateau of practical use. The evidence here suggests AI has already completed that journey in the eyes of investors. It is now too common and too accessible to serve as a differentiating signal. The novelty and scarcity that once justified a premium have been replaced by widespread adoption, and investor behaviour has adjusted to match. The funding data simply confirm what the hype cycle would predict: once a technology becomes standard infrastructure, its power to attract extra capital fades.

Path dependency theory (Martin & Sunley, 2006; Huizingh, 2011) adds a useful perspective. In the early years of AI investment, capital concentration created reinforcing ecosystems around AI ventures: dedicated accelerators, specialised talent pools, and investor networks that made it easier for each successive AI company to raise money. Those structures persist. What the data show, however, is that they have not produced a lasting funding advantage at the individual company level. Once the development stage and operational scale are accounted for, any historical benefit from being early to the AI category disappears. The implication is that path dependency shaped the broader landscape of the startup ecosystem, but not the funding outcomes of individual companies within it. For founders, this is a grounding conclusion: AI is now the baseline, not an edge.

4.4. What the evidence points to

Taken together, these three findings suggest that startup funding follows sound economic logic rather than technology hype or location-based preference. Investors evaluate team quality, market potential, and business model strength, but above all, they look at the development stage. These fundamentals appear to matter far more than the specific technology a company uses or where it is headquartered. This is consistent with Nanda and Rhodes-Kropf (2017), who find that while venture capital often tracks trends, investment decisions are ultimately anchored in fundamental value. The dominance of the development stage as a predictor suggests that venture capital markets have become genuinely skilled at allocating capital on a risk-adjusted basis. The absence of an AI premium points to investors who are no longer easily swayed by technology buzzwords. The declining geographic premium reflects a digital era in which physical proximity has lost much of its historical advantage. Together, these patterns suggest a maturing market, one that is becoming more rigorous and less reactive in how it deploys capital.

In short, neither AI enthusiasm nor location provides a reliable shortcut to capital. Once the development stage and operational scale are accounted for, these surface-level signals lose their predictive power. The market appears to have moved on from hype-driven allocation toward a more grounded assessment of business viability – and that is a healthy sign for how innovative companies raise capital.

CONCLUSION

This study examined whether AI startups receive systematically higher funding than non-AI startups, and whether any differences reflect efficient capital allocation or speculative distortion. The core finding is clear: AI classification has no statistically significant effect on funding. AI startups raised an average of $115.18 million compared to $117.98 million for non-AI startups, a gap of just 2.4% that disappears entirely under regression analysis ($\beta = 0.89$, $p = .869$). The strongest predictor of funding was employee count ($\beta = 0.13$, $p < .001$), confirming that operational scale matters far more than technology category. Development stage explained funding variation more reliably than any other variable, and Silicon Valley's location premium shrank substantially once industry and stage were controlled for. These results support the view that venture capital markets have moved past technology hype: investors are now assessing startups on business fundamentals rather than labelling. For founders, this means that positioning around AI is unlikely to drive valuation on its own. Building a strong team, demonstrating market traction, and achieving operational scale remain the most reliable paths to capital – regardless of the technology stack.

Geographic obstacles to seeking finance tend to be fewer than most people imagine when looking at businesses at the same stage and sector. Conclusions affect many groups in real life. Business leaders should recognise that AI skills are now a standard part of technological infrastructure, not a competitive advantage. Startup positioning strategies should prioritise customer challenges, market opportunities, domain knowledge, and long-term competitive advantage above technological stack sophistication. Operational scaling indicators that investors value should guide resource allocation. Strategic talent acquisition and team development demonstrate an organisation's readiness to commit cash and capabilities. These findings indicate investors' trend toward fundamental examination. The absence of an AI financing premium suggests that markets have moved from technology speculation to rational business viability assessment. The fact that development is more essential than other characteristics suggests that venture capital markets are adept at investing in risk-adjusted possibilities. This rise indicates a strong market that is investing in proven firms rather than fashionable innovation.

DECLARATION OF AI ASSISTANCE

This manuscript used AI-assisted tools for language refinement and technical proofreading purposes. Quilbot, Grammarly, Claude (Anthropic), and ChatGPT (OpenAI) were employed solely to improve grammatical accuracy, sentence structure, and academic tone. All research design, data collection, statistical analysis, theoretical frameworks, and substantive conclusions represent the original intellectual work of the authors. This declaration aligns with emerging best practices in academic publishing regarding transparency in AI-assisted writing. All empirical analyses were conducted in R and Python. In Python, linearmodels and statsmodels were used for panel data modelling, while pandas and numpy supported data processing. Visualisation was produced using ggplot2 in R and matplotlib in Python.

AUTHOR CONTRIBUTIONS

Conceptualization: Eka Sudarmaji.
Data curation: Eka Sudarmaji.
Formal analysis: Eka Sudarmaji.
Investigation: Eka Sudarmaji.
Methodology: Eka Sudarmaji.
Project administration: Eka Sudarmaji.
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Validation: Eka Sudarmaji.
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