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NECESSITY CONDITIONS AND THE USE OF ARTIFICIAL INTELLIGENCE (AI) BY STARTUPS FOR ATTRACTING INVESTORS

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Contents

Tables

Figures

Introduction

Artificial intelligence (AI) has become a powerful force throughout innovation ecosystems in determining the identity and perceived legitimacy of startups. AI is commonly used as a symbol of technological sophistication, scalability, and market readiness in investor presentations and pitch decks. The widespread use of AI, however, does not always correspond with the technical content it suggests, according to recent industry analyses and scholarly commentary. Instead of signifying significant technological distinction, AI has frequently turned into a strategic buzzword; a symbolic term used by founders to strengthen their investment narrative [1]; [2]; [3].

As investor interest in emerging technologies has increased, so too has the marketing of AI. Despite lacking any observable proprietary models or algorithmic infrastructure, almost half of seed-stage startups in industries such as real estate, wellness, and finance mentioned AI in some capacity in their investment materials, according to a 2021 CB Insights survey [4]. This is indicative of a larger trend: AI is no longer a novelty in startup narratives, but rather an expectation. Founders commonly use it to build legitimacy in markets with early-stage risk and information asymmetry, in addition to explaining product features.

This trend is demonstrated by well-known instances. In its investor documents before its disastrous 2019 initial public offering (IPO), the real estate startup WeWork used terms like "AI-driven occupancy analytics" and "machine learning-enabled efficiency," despite its focus on physical infrastructure [5]. Post-IPO disclosures showed little significant AI capabilities, even though such language may have helped position the company as a tech-centric enterprise rather than a conventional real estate operator. Similar to this, Compass, another real estate company, highlighted features like "predictive pricing engines" and a "AI-powered video studio" to strengthen its positioning prior to its IPO, even though a large portion of this functionality was obtained from outside software providers [6].
Fintech companies have adopted a similar rhetorical strategy. For instance, Clearco (formerly Clearbanc) positioned its capital offerings as data-driven substitutes for conventional venture capital funding and promoted its algorithmic underwriting model as "AI-based." Analysts

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[1] Dan Faggella, "Enterprises Don't Fear AI – But Fear Is Their Greatest Motive in Adopting It," 2020, https://emerj.com/fear-motive-adopting-ai/.
[2] CB Insights, "State of AI : Global Data and Analysis on Dealmaking, Funding, and Exits Private Market AI Companies," 2021.
[3] Jinghan Zeng, "Securitization of Artificial Intelligence in China," *Chinese Journal of International Politics* 14, no. 3 (2021): 417–45, https://doi.org/10.1093/cjip/poab005.
[4] Insights, "State of AI : Global Data and Analysis on Dealmaking, Funding, and Exits Private Market AI Companies."
[5] Matthew Zeitlin, "Why Wework Went Wrong," *The Guardian*, 2019, https://www.theguardian.com/business/2019/dec/20/why-wework-went-wrong.
[6] TechCrunch, "As Compass Downsizes Its IPO, Signs of Weakness Appear for High-Growth Companies," 2021, https://techcrunch.com/2021/03/31/as-compass-downsizes-its-ipo-signs-of-weakness-appear-for-high-growth-companies/.

pointed out that although the company did use simple machine learning models, its focus on AI was probably strategically increased to stand out in a crowded fintech market [7]; [8]

Similar to previous waves of "greenwashing" in sustainability discourse, these examples are indicative of what some commentators refer to as "AI-washing", a phenomenon in which businesses exaggerate or vaguely define their use of AI to draw in investors [9]. This narrative inflation goes beyond anecdotal evidence. According to a Stanford AI Index report from 2022, 61% of startups that stated in their funding announcements that they were "AI-driven" were unable to provide evidence of AI use during further due diligence [10]. Moreover, "AI-augmented startups" are positioned at the pinnacle of exaggerated expectations in Gartner's 2023 Emerging Tech Hype Cycle, indicating a saturation of claims that might surpass true capabilities [11].
For founders and investors as well, the ramifications are profound. On the one hand, AI references, regardless of technical complexity, can increase initial visibility and perceived valuation, particularly in industries that need digital transformation [12]. But, as due diligence gets more stringent and investor heuristics change, an over-reliance on AI buzzwords without measurable backend infrastructure runs the risk of undermining investor trust.

A key research question is raised by this conflict between the operational substance of AI and its symbolic power:

RQ: ***Is AI a necessity condition for a start-up to secure funding? is it a funding success probability raiser? Or is it just one of many possible signals that can be replaced by other factors of legitimacy?***

In more specific terms, this thesis investigates whether companies without AI can still obtain significant funding and whether other elements, like the credibility of the founder, market traction, or a distinct product vision, could make up for the lack of AI.

Two major trends raise the stakes of this investigation. The first is the increasing sophistication of investors: venture capital firms are using in-house AI evaluators or technical experts to verify claims in pitch materials [13]. Secondly, investors are prioritizing verifiable business models and execution capabilities as the venture landscape becomes more selective due to tightening capital

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[7] Faggella, "Enterprises Don't Fear AI – But Fear Is Their Greatest Motive in Adopting It."
[8] TechCrunch, "Recapitalization, $60M Series D Support Growth of e-Commerce Financier Clearco," 2023, https://techcrunch.com/2023/10/04/clearco-60m-e-commerce-financier/.
[9] TechCrunch.
[10] Jack Clark and Ray Perrault, "Introduction to the AI Index Report 2022," *Human-Centered AI Institute, Stanford University,* 2022, 230, https://aiindex.stanford.edu/wp-content/uploads/2022/03/2022-AI-Index-Report_Master.pdf.
[11] Lori Perri, "What's New in Artificial Intelligence from the 2023 Gartner Hype Cycle," 2023, https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2023-gartner-hype-cycle.
[12] Zeng, "Securitization of Artificial Intelligence in China."
[13] Xianling Mu et al., "Policy Induction: Predicting Startup Success via Explainable Memory-Augmented In-Context Learning" 2, no. 1 (2025), http://arxiv.org/abs/2505.21427.

markets and rising interest rates [14]. These changes imply that AI's signaling capabilities might be contingent and time-sensitive rather than constant or universally effective.

This thesis seeks to close a significant gap in light of this. Few studies have looked at the narrative use of AI in early-stage startup capital acquisition, despite the fact that existing literature has examined how AI affects firm performance and process efficiency. Fewer still have used a multi-method approach that incorporates investor viewpoints, funding data, and comparative case analysis. Thus, this study adds to the empirical mapping of AI's function in startup ecosystems as well as to more general debates in the sociology of valuation, technology legitimacy, and entrepreneurial signaling theory [15].

To address these issues, the study is structured around three hypotheses:

1. **H1**: AI functions as a necessity condition for securing venture capital.
2. **H2**: AI increases the probability of securing funds but is not essential.
3. **H3**: Other signals (e.g., founder quality, product clarity, traction) can substitute for AI in determining funding outcomes.

These hypotheses are investigated using a triangulated mixed-methods design that includes:
(1) a **quantitative analysis** of funding patterns across 36 startups grouped by AI usage type,
(2) a **comparative case study** of nine high-profile firms from three strategic archetypes (AI-core, AI-pitch, and non-AI), and
(3) **semi-structured interviews** with Venture capitalists and innovation leaders to explore real-world investor heuristics.
The thesis makes theoretical and practical contributions in the process. It helps investors better determine the credibility of AI signals in the face of uncertainty and offers founders advice on navigating capital markets and crafting compelling narratives. In a broader sense, the work contributes to the scholarly understanding of how emerging technologies operate in early-stage innovation economies as instruments of performance and persuasion in addition to being tools of production

[14] Crunchbase, "Artificial Buildup: AI Startups Were Hot In 2023, But This Year May Be Slightly Different," 2024, https://news.crunchbase.com/ai/hot-startups-2023-openai-anthropic-forecast-2024/.
[15] Michael Spence, "*The MIT Press, Job Market Signaling*," *The Quarterly Journal of Economics* 87, no. 3 (1973): 355–74.

Chapter 1 : Theoretical Background

1.1 Venture Capital Investment Criteria

Venture capitalists and accelerators follow a structured approach to evaluating startups, assessing key factors that determine a startup's potential for success. Traditionally, these evaluations focus on entrepreneurial opportunity, team characteristics, business model viability, market opportunity, financial performance, and credibility. Each element plays a crucial role in determining whether a startup is investment-worthy.[16]

1.1.1 Entrepreneurial Opportunity

A startup's potential begins with the problem it seeks to solve and the innovation it brings to the market.

- **Specific Problem and Innovation:** Investors and accelerators prioritize startups that address well-defined problems with innovative solutions. As [17] highlight, entrepreneurial opportunity is assessed based on the problem's clarity, the solution's uniqueness, and the overall value proposition. Startups that leverage breakthrough technologies and offer rapid product development timelines are particularly attractive. Additionally, having a working prototype is often a key indicator of a startup's readiness for market entry.
- **Market Potential:** Beyond the innovation itself, the startup's market potential is critical to investment decisions. According to [18], accelerators analyze market size, customer base, and scalability. Investors seek startups that operate in large and rapidly growing markets with strong demand. Studies by [19] emphasize that a startup's growth prospects and competitive positioning also play a vital role in its attractiveness. Similarly, [20] highlight that targeting expansive and scalable markets significantly increases a startup's investment appeal.

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[16] Ian C. Macmillan, Robin Siegel, and P. N.Subba Narasimha, "Criteria Used by Venture Capitalists to Evaluate New Venture Proposals," *Journal of Business Venturing* 1, no. 1 (1985): 119–28, https://doi.org/10.1016/0883-9026(85)90011-4.
[17] Berna Beyhan, Semih Akçomak, and Dilek Cetindamar, "The Startup Selection Process in Accelerators: Qualitative Evidence from Turkey," *Entrepreneurship Research Journal* 14, no. 1 (2024): 27–51, https://doi.org/10.1515/erj-2021-0122.
[18] Beyhan, Akçomak, and Cetindamar.
[19] José Carlos Nunes, Elisabete Gomes Santana Félix, and Cesaltina Pacheco Pires, "Which Criteria Matter Most in the Evaluation of Venture Capital Investments?," *Journal of Small Business and Enterprise Development* 21, no. 3 (2014): 505–27, https://doi.org/10.1108/JSBED-10-2013-0165.
[20] Abrori Ahmad Noor Esa and Yunieta Anny Nainggolan, "What Factors Attract Venture Capital And Angel Investor Funding: Case Of Indonesia," *Journal Integration of Social Studies and Business Development* 1, no. 2 (2023): 70–79, https://doi.org/10.58229/jissbd.v1i2.92.

1.1.2 Team Characteristics

Even with a strong business idea, the quality of the team often determines whether a startup secures funding.

- **Entrepreneur:** As [21] argue, the entrepreneur is the most critical factor in investment decisions. Investors often prioritize leadership ability, experience, and resilience over the startup's product or financial projections. Studies by [22] further emphasize that an entrepreneur's credibility is essential, particularly in crowdfunding platforms where reducing uncertainty is key. Venture capitalists not only assess a startup's technical and commercial potential but also their ability to experiment, learn, and develop iteratively. Teams are seen as lower-risk investments when they exhibit resilience and adaptability through test-and-learn methodologies, which are frequently in line with Lean Startup principles.[23][24][25]
- **Full-Commitment:** A founder's dedication to their vision significantly influences investor confidence. [26] note that strong enthusiasm and perseverance are key indicators of a startup's long-term success.
- **Coachability:** Successful founders must be open to mentorship and feedback. Accelerators favor teams that demonstrate adaptability and a willingness to refine their approach based on expert guidance [27].
- **Diversity and Cooperation:** Investors recognize that diverse teams bring varied perspectives, which can enhance decision-making and innovation. Startups with team members from different educational and professional backgrounds are often viewed as more resilient and dynamic [28].
- **Balanced Skill Set:** A startup's team must have a well-rounded mix of technical expertise, business acumen, and customer engagement skills. This balance ensures that the company is not only capable of building a product but also effectively positioning it in the market [29].

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[21] Macmillan, Siegel, and Narasimha, "Criteria Used by Venture Capitalists to Evaluate New Venture Proposals."
[22] Shuangfa Huang et al., "Signalling Entrepreneurs' Credibility and Project Quality for Crowdfunding Success: Cases from the Kickstarter and Indiegogo Environments," *Small Business Economics* 58, no. 4 (2022): 1801–21, https://doi.org/10.1007/s11187-021-00477-6.
[23] Paul Gompers et al., "Performance Persistence in Entrepreneurship," *Journal of Financial Economics* 96, no. 1 (2010): 18–32, https://doi.org/10.1016/j.jfineco.2009.11.001.
[24] Xiao Ping Chen, Xin Yao, and Suresh Kotha, "Entrepreneur Passion and Preparedness in Business Plan Presentations: A Persuasion Analysis of Venture Capitalists' Funding Decisions," *Academy of Management Journal* 52, no. 1 (2009): 199–214, https://doi.org/10.5465/AMJ.2009.36462018.
[25] Beyhan, Akçomak, and Cetindamar, "The Startup Selection Process in Accelerators: Qualitative Evidence from Turkey."
[26] Beyhan, Akçomak, and Cetindamar.

- **External Relationships:** Beyond internal team dynamics, a startup's external relationships can influence investor interest. [30] highlight that industry attractiveness, the strength of the founding team, and strategic partnerships all contribute positively to a startup's valuation.

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1.1.3 Business Model Viability and Scalability

For long-term success, a startup must demonstrate that its business model is both viable and scalable.

- **Product-Market Fit:** Venture capitalists analyze how well a startup's product aligns with customer needs. [31] emphasize that a strong product-market fit increases the likelihood of sustainable revenue generation. Venture capitalists give this a good deal of thought. Early on in a start-up, they try to determine when they can reach it, and in the late stages, they try to determine whether they have already achieved it or not.[32]
- **Traction Indicators:** Evidence of traction, such as monthly revenue, life time value, churn rate, user growth, sales figures, and customer engagement, serves as a validation of the business model. Investors look for clear signs that a startup has momentum and market acceptance [33].

1.1.4 Market Opportunity and Competitive Landscape

A startup's ability to thrive depends on the broader market environment and its competitive positioning.

- **Market Size and Growth:** A startup's potential is heavily influenced by the market it operates in. Investors prioritize industries with high growth potential and strong demand [34]; [35]. [36] further confirm that startups targeting expanding markets with scalable products are more likely to attract funding.

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[30] Tarek Miloud, Arild Aspelund, and Mathieu Cabrol, "Startup Valuation by Venture Capitalists : An Empirical Study To Cite This Version :" 14, no. July (2014): 151–74.
[31] Esa and Nainggolan, "What Factors Attract Venture Capital And Angel Investor Funding: Case Of Indonesia."
[32] Clement Gastaud, Theophile Carniel, and Jean-Michel Dalle, "The Varying Importance of Extrinsic Factors in the Success of Startup Fundraising: Competition at Early-Stage and Networks at Growth-Stage" 3 (2019): 1–14, http://arxiv.org/abs/1906.03210.
[33] Esa and Nainggolan, "What Factors Attract Venture Capital And Angel Investor Funding: Case Of Indonesia."
[34] Carlos Nunes, Gomes Santana Félix, and Pacheco Pires, "Which Criteria Matter Most in the Evaluation of Venture Capital Investments?"
[35] John Hall and Charles W. Hofer, "Venture Capitalist' Decision Criteria in New Venture Evaluation," *IEEE Engineering Management Review* 21, no. 2 (1993): 49–58.
[36] Esa and Nainggolan, "What Factors Attract Venture Capital And Angel Investor Funding: Case Of Indonesia."

- **Differentiation and Intellectual Property:** Standing out in a crowded market is essential. Investors look for startups with unique value propositions, proprietary technology, which is a key factor in investment appeal, as it creates barriers to entry, reduces the risk of imitation, and signals long-term scalability, and intellectual property that allows a startup to differentiate itself from competitors, making it more attractive to potential investors and providing a competitive advantage. [37].

1.1.5 Financial Performance and Projections

A solid financial foundation is crucial for investor confidence.

- **Financial Forecasts and Fund Usage:** Startups are expected to provide realistic financial projections and a clear roadmap for how they will use investor funding [38].
- **Go-to-Market Strategy:** A well-defined go-to-market strategy increases investor confidence. [39] note that accelerators evaluate whether a startup has a feasible plan for acquiring customers and achieving sustainable growth.

1.1.6 Referrals and Credibility

A startup's reputation and network can influence its evaluation. Referrals from credible sources can significantly enhance a startup's attractiveness to investors. [40] found that accelerators are more likely to favor proposals that come through trusted networks, as these endorsements reduce perceived investment risks.

1.2 The Rise of AI as a Critical Factor in Startup Branding

In addition to the traditional criteria used by venture capitalists, such entrepreneurial opportunity, team characteristics, business model viability, market opportunity, financial performance, and credibility, AI has emerged as a powerful new factor influencing startup evaluations and investment decisions. Over the past few years, AI has become a central theme in startup branding and investor pitches, often serving as a key differentiator that attracts funding and market attention. A striking 86% of startup founders report that AI positively impacts their go-to-market strategies, and AI adoption among startups has skyrocketed by 270% in just four years [41][42].

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[37] Esa and Nainggolan.
[38] Carlos Nunes, Gomes Santana Félix, and Pacheco Pires, "Which Criteria Matter Most in the Evaluation of Venture Capital Investments?"
[39] Esa and Nainggolan, "What Factors Attract Venture Capital And Angel Investor Funding: Case Of Indonesia."
[40] Hall and Hofer, "Venture Capitalist' Decision Criteria in New Venture Evaluation."
[41] VentureBeat, "No Title," 2025, https://venturebeat.com/ai/ai-fuels-startup-success-86-of-founders-report-positive-impact-hubspot-finds/.
[42] Zipdo, "No Title," 2025, https://zipdo.co/research/ai-in-the-startup-industry-statistics/.

Investors have taken notice, with AI-driven startups collectively raising over $21 billion in 2020 alone, and AI-generated pitch decks proving to be three times more likely to secure funding compared to human-crafted ones[43].

However, as AI claims become increasingly influential in startup valuations, a growing number of companies are exaggerating their AI capabilities to capitalize on investor enthusiasm. A study revealed that 40% of European startups labeled as AI-driven did not actually use AI in a way that was core to their business [44] . This phenomenon is not limited to early-stage startups. Established companies like WeWork and Compass have also strategically positioned themselves as AI-powered disruptors despite relying heavily on traditional business models. WeWork, for instance, marketed itself as a tech-driven workspace innovator, while Compass branded itself as an AI-enhanced real estate platform, even though much of its operations remained dependent on human agents rather than advanced machine learning. These cases highlight how AI branding, rather than substantive AI capabilities, has often been used to enhance company valuations and attract investor interest.

Similarly, emerging startups such as Onyx and OptimHires have secured funding by emphasizing AI-driven automation in their business models, reinforcing the notion that AI claims are now a key factor in investor decision-making [45]; [46]. While AI certainly has the potential to revolutionize industries, these trends suggest that investors must scrutinize AI claims more carefully to distinguish between genuinely innovative AI-driven businesses and those leveraging AI as a marketing strategy. As AI continues to shape the startup landscape, it is becoming an essential factor in how companies are evaluated beyond the traditional metrics used by venture capitalists, adding both opportunities and risks to the investment landscape.

1.3 AI in Business Applications

Artificial Intelligence (AI) has become a transformative force in modern business, offering organizations enhanced efficiency, scalability, and competitive advantages. However, its adoption presents both opportunities and challenges, particularly in startups, where AI-driven capabilities are increasingly positioned as an investment signal. The extent to which AI delivers tangible business value depends on an organization's ability to integrate AI strategically rather than merely adopting it as a branding tool.

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[43] ZDNet, “No Title,” 2025, https://www.zdnet.com/article/gpt-4-generated-pitches-are-3x-more-likely-to-secure-funding-than-human-ones/.
[44] The Verge, “No Title,” 2019, https://www.theverge.com/2019/3/5/18251326/ai-startups-europe-fake-40-percent-mmc-report.
[45] Business and Insider (Onyx), “No Title,” 2025, https://www.businessinsider.com/pitch-deck-ai-agent-startup-onyx-seed-round-2025-3.
[46] Business Insider (OptimHires), “No Title,” 2025, https://www.businessinsider.com/pitch-deck-ai-hiring-agent-optimhires-5-million-seed-round-2025-3.

A systematic review by [47] identifies the key enablers and inhibitors of AI adoption, highlighting that while AI is widely regarded as a catalyst for business growth, many organizations face implementation barriers such as data integration complexities, cross-domain knowledge gaps, and process compatibility issues. The study categorizes AI's business value creation into first-order effects, such as improved process efficiency and data-driven insights, and second-order effects, which encompass financial gains, market competitiveness, and business model innovation. Importantly, the research emphasizes that AI adoption is not solely a technological shift but requires strategic organizational alignment to achieve meaningful long-term benefits.

Similarly, the work of [48] underscores AI's impact across industries, including customer service, finance, healthcare, and marketing. AI-driven automation optimizes operations, reduces costs, and enhances decision-making processes. However, despite its benefits, AI adoption presents risks such **as** data privacy concerns, biases in AI-generated content, and regulatory uncertainties, all of which influence the sustainability of AI-driven businesses. Notably, [49] warns against the over-reliance on AI as a mere investment signal, cautioning that startups leveraging AI without demonstrating real-world business impact may lead to venture capital misallocation. These insights reinforce the need for investors to conduct rigorous due diligence when evaluating AI-powered startups to distinguish genuine technological advancements from superficial market positioning**.**

1.3.1 AI as a Value Driver

AI contributes to business innovation by driving operational efficiency, predictive analytics, and enhanced customer engagement. Scholars have categorized AI's impact into two primary levels**:**

- **First-order effects**: These immediate benefits include process automation, real-time insights, and efficiency improvements that optimize business workflows [50]; [51].
- **Second-order effects**: These encompass broader implications such as enhanced market competitiveness, financial gains, and the emergence of new business models [52]; [53].

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[47] R. Bunod et al., "Artificial Intelligence and Glaucoma: A Literature Review," *Journal Francais d'Ophtalmologie* 45, no. 2 (2022): 216–32, https://doi.org/10.1016/j.jfo.2021.11.002.
[48] Md Arman and Umama Rashid Lamiya, "Exploring the Implication of ChatGPT AI for Business: Efficiency and Challenges," *Journal of Innovation Information Technology and Application (JINITA)* 5, no. 1 (2023): 52–64, https://doi.org/10.35970/jinita.v5i1.1828.
[49] Md Arman and Umama Rashid Lamiya.
[50] Bunod et al., "Artificial Intelligence and Glaucoma: A Literature Review."
[51] Erik Brynjolfsson et al., "Linked References Are Available on JSTOR for This Article : What Can Machines Learn and What Does It Mean for Occupations and the Economy ?," *AEA Papers and Proceedings* 130, no. May (2018): 43–47.
[52] Iain M Cockburn, Rebecca Henderson, and Scott Stern, "NBER WORKING PAPER SERIES - The Impact of Artificial Intelligence on Innovation," *National Bureau of Economic Research WORKING PAPER SERIES* Working Pa (2018), http://www.nber.org/papers/w24449%0Ahttp://www.nber.org/papers/w24449.ack.
[53] Spyros Makridakis, "The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms," *Futures* 90 (2017): 46–60, https://doi.org/10.1016/j.futures.2017.03.006.

For startups, AI serves as both an innovation enabler and an investment magnet**.** AI-powered businesses are often perceived as having higher scalability potential, making them attractive to venture capitalists ([54]; [55]. However, while AI is a valuable asset, its successful integration requires overcoming significant operational and strategic challenges.

1.3.2 Challenges in AI Adoption & Investment Decisions

Despite AI's potential, its implementation is fraught with hurdles that investors must carefully evaluate. Among the most pressing challenges are:

Data Integration Issues: Many startups struggle with data accessibility, quality, and structuring for AI models. Effective AI systems rely on vast, structured datasets, which early-stage companies may lack [56].

Regulatory & Ethical Risks: As AI technologies evolve, concerns regarding algorithmic bias, data privacy, and regulatory compliance become more pronounced. Investors are particularly wary of startups that do not adequately address transparency, fairness, and ethical AI usage [57]; [58].

Hype vs. Reality: The increasing prevalence of **"**AI washing**",** where startups exaggerate their AI capabilities to attract funding poses a significant risk. Some businesses promote AI-driven models without substantial technological differentiation, misleading investors and resulting in misallocated venture capital [59].

Given these challenges, venture capitalists are prioritizing stringent due diligence in assessing AI-driven startups [60]; [61]. While AI can undeniably enhance business performance and market positioning, investors seek verifiable, scalable AI-driven business models rather than those relying solely on AI as a branding strategy.

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[54] David R. Tobergte and Shirley Curtis, "Venture Capital Data: Opportunities and Challenges," *Nber Working Paper* 53, no. 9 (2016): 1689–99.
[55] Ajay Agrawal, Joshua Gans, and Avi Goldfarb, "Economic Policy for Artificial Intelligence," *Innovation Policy and the Economy* 19, no. 1 (2019): 139–59, https://doi.org/10.1086/699935.
[56] Tobergte and Curtis, "Venture Capital Data: Opportunities and Challenges."
[57] Brent Daniel Mittelstadt et al., "The Ethics of Algorithms: Mapping the Debate," *Big Data and Society* 3, no. 2 (2016): 1–21, https://doi.org/10.1177/2053951716679679.
[58] Anna Jobin, Marcello Ienca, and Effy Vayena, "The Global Landscape of AI Ethics Guidelines," *Nature Machine Intelligence* 1, no. 9 (2019): 389–99, https://doi.org/10.1038/s42256-019-0088-2.
[59] Baobao Zhang and Allan Dafoe, *Artificial Intelligence: American Attitudes and Trends*, *SSRN Electronic Journal*, 2019, https://doi.org/10.2139/ssrn.3312874.
[60] Benedetta Montanaro, Annalisa Croce, and Elisa Ughetto, "Venture Capital Investments in Artificial Intelligence," *Journal of Evolutionary Economics* 34, no. 1 (2024): 1–28, https://doi.org/10.1007/s00191-024-00857-7.
[61] Source The, Economic Perspectives, and No Spring, "Author (s): Paul Gompers and Josh Lerner Published by : American Economic Association Stable URL : Http://Www.Jstor.Org/Stable/2696596 The Venture Capital Revolution" 15, no. 2 (2016): 145–68.

1.4 Theoretical Models of Investment Decision-Making

Venture capitalists and startup accelerators play a crucial role in financing early-stage businesses. Their investment decisions are guided by various theoretical models that help them assess startup potential, mitigate risks, and maximize returns [62]. Among these models, signaling theory provides a key framework for understanding how startups communicate their value to potential investors.

1.4.1 Signaling Theory

Signaling theory, first introduced by [63] in the context of job market signaling, was later applied to venture capital decision-making to explain how startups convey credibility to investors. One of the earliest studies incorporating this perspective was conducted by [64], who found that entrepreneurs' characteristics serve as critical indicators of venture success. Their research established a foundation for understanding how investors rely on observable traits, such as leadership experience, industry expertise, and commitment, to mitigate uncertainty and assess startup viability.

1.4.1.1 Signaling Theory in Venture Capital Investment

In early-stage financing, signaling theory helps explain how entrepreneurs communicate the quality and legitimacy of their ventures to potential investors. Startups operate in an environment characterized by high uncertainty and significant information asymmetry, meaning investors often lack full visibility into a startup's actual capabilities, market potential, and long-term viability. To address this challenge, startups use observable signals to convey credibility, reduce investor skepticism, and differentiate themselves from competitors. These signals include:

- **Founding team quality** (industry expertise, leadership track record)
- **Prior entrepreneurial experience** (successful past ventures)
- **Intellectual property** (patents, proprietary technology)
- **Strategic partnerships** (alliances with established firms)
- **Early market traction** (customer adoption, revenue growth)

[62] Jeffrey S. Petty, Marc Gruber, and Dietmar Harhoff, "Maneuvering the Odds: The Dynamics of Venture Capital Decision-Making," *Strategic Entrepreneurship Journal* 17, no. 2 (2023): 239–65, https://doi.org/10.1002/sej.1455.
[63] Spence, "*The MIT Press, Job Market Signaling*."
[64] Macmillan, Siegel, and Narasimha, "Criteria Used by Venture Capitalists to Evaluate New Venture Proposals."

[65] provides a comprehensive review of entrepreneurial signaling, emphasizing the fragmented nature of existing research and the diverse investment contexts in which signals are interpreted, such as crowdfunding, angel investing, and venture capital. He highlights that different types of investors prioritize distinct signals. For example:

- Angel investors focus on founder passion, vision, and behavioral intentions.
- Venture capitalists (VCs) prioritize intellectual property, prior funding, and partnerships.
- IPO investors emphasize corporate governance and financial performance.

Colombo also explores key boundary conditions that affect the effectiveness of signals, such as entrepreneurial track record**,** industry reputation, and startup funding stage. A startup with prior VC backing or a well-known founder is likely to send stronger and more credible signals than a first-time entrepreneur with no funding history. Furthermore, signals evolve based on funding rounds.Early-stage investors focus more on founders, whereas later-stage investors prioritize financial performance and market traction**.**

Building on this, [66] develop a taxonomy of 18 signaling constructs, categorizing signals based on:

- **Identity of the signaler** (startup vs. third-party endorsement)
- **Type of signal** (patents, prior funding, partnerships, media attention)
- **Signal receivers** (VCs, institutional investors, corporate investors)

These insights highlight the nuanced and context-dependent nature of signaling theory in venture capital investment**.**

1.4.1.2 Technology and Innovation as Investment Signals: Risks of Misinterpretation
According to [67], startups leverage observable strategies to strengthen their perceived viability among VCs. These include:

- **Highlighting technological advantages** (cutting-edge AI, deep learning, blockchain, etc.)
- **Securing high-profile endorsements** (investments from top-tier VCs, industry awards)
- **Demonstrating early customer adoption** (enterprise contracts, revenue milestones)

For example, a startup securing a strategic partnership with a leading tech firm sends a strong positive signal that enhances investor confidence. Conversely, a startup with no clear differentiation, unproven leadership, or vague technology claims struggles to attract funding.

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[65] Oskar Colombo, "The Use of Signals in New-Venture Financing: A Review and Research Agenda," *Journal of Management* 47, no. 1 (2021): 237–59, https://doi.org/10.1177/0149206320911090.
[66] Julian Bafera and Simon Kleinert, "Signaling Theory in Entrepreneurship Research: A Systematic Review and Research Agenda," *Entrepreneurship: Theory and Practice* 47, no. 6 (2023): 2419–64, https://doi.org/10.1177/10422587221138489.
[67] Bafera and Kleinert.

However, signals are context-dependent, and their effectiveness varies based on:

- **Market conditions**: Economic downturns push investors to prioritize financial sustainability over aggressive growth signals.
- **Investor experience**: Seasoned VCs leverage industry knowledge to assess signals more accurately, whereas less experienced investors may fall for overhyped claims.
- **Regulatory environment**: Compliance with industry norms strengthens startup legitimacy [68].

[69] highlight that investors often misinterpret signals, particularly in fast-moving tech sectors. Ambiguous signals, such as first-mover advantages or founder charisma, can distort market viability assessments, leading to overvaluation or undervaluation of startups. Additionally, [70] notes that even strong technological signals can be misunderstood, as investors interpret innovations through their own biases.

1.4.1.3 The Risks of AI-Washing

A major concern in AI-driven startups is AI-washing; a phenomenon where companies exaggerate their AI capabilities to attract investment. This creates a credibility crisis, undermining genuine innovation and misleading stakeholders [71].

Examples of AI-washing include:

- **Superficial AI claims**: Startups marketing standard automation tools as "AI-powered."
- **Overpromising technological capabilities**: Companies claiming to use advanced machine learning without demonstrable AI research.
- **Regulatory concerns**: Lack of transparency regarding AI models used, raising ethical and legal risks.

[72] warns that misleading AI claims can lead to regulatory scrutiny and legal consequences. For instance, the Federal Trade Commission (FTC) mandates that AI-based claims must be scientifically validated, ensuring companies do not misrepresent their technology.

[73] argue that while AI is a significant driver of innovation, the hype around AI creates both opportunities and risks. Investors must differentiate between:

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[68] Felix Reichenbach and Martin Walther, "Signals in Equity-Based Crowdfunding and Risk of Failure," *Financial Innovation* 7, no. 1 (2021), https://doi.org/10.1186/s40854-021-00270-0.
[69] Yan Zhou et al., "How Do Innovative Internet Tech Startups Attract Venture Capital Financing?," *Journal of Management and Organization*, 2023, https://doi.org/10.1017/jmo.2023.39.
[70] Mojca Svetek, "Signaling in the Context of Early-Stage Equity Financing: Review and Directions," *Venture Capital* 24, no. 1 (2022): 71–104, https://doi.org/10.1080/13691066.2022.2063092.
[71] Al Haddi, "AI Washing : The Cultural Traps That Lead to Exaggeration and How CEOs Can Stop Them," 2024.
[72] Purvish M Parikh, "Artificial Intelligence: ChatGPT to Artificial Intelligence Washing," *Journal of Mahatma Gandhi University of Medical Sciences and Technology* 8, no. 1 (2024): 1–4, https://doi.org/10.5005/jp-journals-10057-0231.
[73] Cockburn, Henderson, and Stern, "NBER WORKING PAPER SERIES - The Impact of Artificial Intelligence on Innovation."

- **Genuine AI advancements**: Companies developing breakthrough AI models.
- **Hyped AI startups**: Firms using AI as a marketing tactic without substantial differentiation.

[74] emphasizes the need for structural estimation methodologies in AI evaluation. By treating AI developments akin to empirical research, investors can separate real innovations from marketing rhetoric**.**

1.4.2 Heuristics

Herbert Simon's concept of bounded rationality highlights the inherent limitations in human decision-making, emphasizing that individuals often operate under constraints such as cognitive limitations, incomplete information, and time pressures. This perspective challenges traditional models of rational choice, suggesting that rather than seeking optimal solutions, people frequently rely on simplified decision-making processes that reflect real-world complexities [75]. Building on this foundation, heuristics play a crucial role in investment decisions, illustrating how individuals adapt their strategies to navigate uncertainty and complexity, ultimately revealing practical ways to cope with bounded rationality.

Heuristics are cognitive shortcuts or rules of thumb that simplify decision-making, particularly in situations characterized by limited knowledge, time, and resources. These fast and frugal heuristics, such as the recognition heuristic and the take-the-best heuristic, enable decision-makers to navigate complex choices with minimal cognitive effort, often leading to satisfactory outcomes despite uncertainty. Research indicates that individual characteristics, such as personality traits and decision-making styles, significantly influence the selection and application of heuristics, highlighting the need for further exploration of the interplay between decision-making strategies and contextual factors [76].

[77] emphasizes the significance of heuristics in decision-making, describing them as cognitive shortcuts that allow individuals to make judgments and decisions efficiently by drawing on personal experiences rather than exhaustive analysis. However, while heuristics enhance decision-making speed, they can also introduce biases and errors, as they simplify complex situations and may overlook alternative solutions. Key heuristics include the availability heuristic, which assesses the likelihood of events based on how easily instances come to mind, and the representativeness heuristic, which can lead to reliance on stereotypes.

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[74] Mitsuru Igami, "Artificial Intelligence as Structural Estimation: Deep Blue, Bonanza, and AlphaGo," *Econometrics Journal* 23, no. 3 (2020): S1–24, https://doi.org/10.1093/ECTJ/UTAA005.
[75] Lindsay W. McSweeney, "Introduction to a Behavioral Model of Rational Choice," *Competition Policy International* 6, no. 1 (2010): 239–58.
[76] Cristina del Campo et al., "Decision Making Styles and the Use of Heuristics in Decision Making," *Journal of Business Economics* 86, no. 4 (2016): 389–412, https://doi.org/10.1007/s11573-016-0811-y.
[77] Steve Dale, "Heuristics and Biases: The Science of Decision-Making," *Business Information Review* 32, no. 2 (2015): 93–99, https://doi.org/10.1177/0266382115592536.

Understanding these heuristics is essential for recognizing how they influence judgments and improving decision-making processes.

1.4.2.1 Heuristics in Investment Decision-Making

- Heuristics play a fundamental role in the investment decision-making process, particularly for business angel investors with varying levels of experience. These mental shortcuts enable investors to make quicker judgments based on prior experiences and limited information. Two primary heuristics identified in investment decision-making are the availability heuristic and the representativeness heuristic.
- **The availability heuristic** refers to the ease with which instances or experiences come to mind; experienced investors are more likely to recall past investment situations, enhancing their confidence in evaluating new opportunities [78]. As experience increases, investors develop a richer memory base, influencing their decision-making approach.
- **The representativeness heuristic** involves assessing the central features of a category and applying these to specific instances. Experienced investors can quickly identify relevant factors when considering new ventures based on past successes and failures, whereas novice investors tend to focus on a limited set of factors, leading to longer decision-making processes due to a lack of a robust knowledge base [79]. Additionally, learning processes among investors are shaped by past experiences and vicarious learning, which helps mitigate the challenges of limited direct experience. Overall, heuristics significantly shape investment decision-making, with experience level influencing their application and effectiveness.

Business angels employ both predictive and control-oriented decision-making styles. Predictive investors rely on quantitative data and market analysis to forecast potential outcomes, while control-oriented investors leverage their experience to actively shape investment processes. This duality underscores the critical role of heuristics in guiding decisions, as control-oriented investors tend to be more engaged in investment activities, using heuristics to navigate uncertainties effectively [80].

1.4.2.2 Heuristic Biases in Investment Decision-Making

[81] investigated the role of heuristic biases in investment decision-making, focusing on individual equity investors in the Indian stock market. They found that biases such as overconfidence and the availability heuristic significantly influence investors' perceptions of risk and trading behaviors.

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[78] Richard T. Harrison, Colin Mason, and Donald Smith, “Heuristics, Learning and the Business Angel Investment Decision-Making Process,” *Entrepreneurship and Regional Development* 27, no. 9–10 (2015): 527–54, https://doi.org/10.1080/08985626.2015.1066875.
[79] Harrison, Mason, and Smith.
[80] Christophe Bonnet et al., “What Drives the Active Involvement in Business Angel Groups? The Role of Angels’ Decision-Making Style, Investment-Specific Human Capital and Motivations,” *Journal of Corporate Finance* 77, no. March 2021 (2022): 101944, https://doi.org/10.1016/j.jcorpfin.2021.101944.
[81] Jinesh Jain et al., “Heuristic Biases as Mental Shortcuts to Investment Decision-Making: A Mediation Analysis of Risk Perception,” *Risks* 11, no. 4 (2023): 1–22, https://doi.org/10.3390/risks11040072.

Overconfident investors tend to underestimate risks and engage in excessive trading, while those relying on the availability heuristic often prioritize easily accessible information at the expense of comprehensive analysis. Greater awareness of these biases is needed to improve investment decisions and mitigate potential losses in capital markets.

Similarly, [82] explored how heuristic techniques and cognitive biases influence investment decision-making, often leading to systematic errors. Investors use heuristics such as representativeness, availability, and anchoring to simplify financial decisions, but these shortcuts can distort judgment. These biases may lead to overconfidence, mispricing of assets, and suboptimal investment choices. The study highlights the impact of behavioral biases, including overconfidence, narrow framing, and the disposition effect, which reinforce irrational behaviors such as excessive risk-taking or reluctance to sell failing investments. The authors argue that prioritizing financial literacy and investor awareness can help mitigate the negative effects of heuristics and biases, promoting more rational investment choices. Further research is needed to explore how these biases interact with market anomalies and investment decision frameworks in venture capital and startup funding contexts.

1.4.2.3 Investor Psychology in AI Startup Evaluation

Investor psychology plays a critical role in evaluating AI startups, particularly through the mechanisms of overconfidence and self-attribution bias. Overconfidence can lead investors to place excessive trust in their ability to predict the success of emerging AI technologies, often resulting in inflated valuations for startups lacking solid fundamentals or feasible technological solutions. This bias creates a tendency to dismiss critical information and overlook the complexities and risks associated with AI development. Similarly, self-attribution bias may prompt investors to erroneously attribute past successes in technology investments to their own superior insight, fostering unwarranted enthusiasm for new AI ventures without adequate due diligence.

This phenomenon is frequently illustrated by the hype surrounding AI companies during funding rounds, where anecdotal evidence and fear of missing out (FOMO) overshadow rigorous evaluations of technological capabilities and market readiness. These psychological heuristics can significantly impair sound decision-making, contributing to market inefficiencies characterized by the mispricing of AI firms based on trends rather than thorough analysis. Recognizing these biases is essential for investors, as it encourages a more disciplined and rational approach to evaluating AI startups, ultimately leading to improved investment practices and healthier market dynamics [83].

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[82] Jain et al.

[83] Avanidhar Subrahmanyam, “American Finance Association Investor Psychology and Security Market Under- and Overreactions Author (s): Kent Daniel , David Hirshleifer and Avanidhar Subrahmanyam Source : The Journal of Finance , Vol . 53 , No . 6 (Dec ., 1998), Pp . 1839-1885 Publ,” *The Journal of Finance* 53, no. 6 (2016): 1839–85.

1.4.2.4 The Impact of the Representativeness Heuristic on Investments

In their seminal work on judgment under uncertainty, [84]introduced the representativeness heuristic, which explains how individuals assess probabilities based on similarity to existing stereotypes or prototypes. While simplifying decision-making, this mental shortcut can lead to significant misjudgments, particularly in investment contexts. Investors might hastily categorize a company as a potential success based solely on perceived traits that align with successful ventures, neglecting crucial statistical data and base rates that reflect the actual probability of success.

Such reliance on representativeness can result in cognitive biases, including the illusion of predictability, overconfidence in certain predictions, and insufficient diversification of investment portfolios. By favoring similarity over statistical reasoning, investors may be drawn to trends or narratives that reinforce their biases, increasing the risk of financial losses. This highlights the need for awareness of cognitive heuristics in investment decision-making, as an understanding of these biases can lead to more informed and rational investment strategies.[85]

1.4.2.5 Overconfidence Bias in Investment Decisions

Overconfidence bias is a significant psychological phenomenon affecting investors, particularly in complex and rapidly evolving fields such as AI startups. This bias manifests as an inflated sense of understanding and capability, leading individuals to overestimate their knowledge and ability to predict outcomes. As a result, investors often underestimate inherent risks, believing they possess superior insights compared to their peers. This cognitive distortion can lead to poor decision-making, as overconfident investors may disregard critical information or warnings, increasing their vulnerability to financial losses. Understanding the implications of overconfidence bias is essential for developing more effective investment strategies and fostering a more cautious approach to risk assessment in high-stakes environments [86].

1.5 AI in Different Startup Growth Stages (Pre-seed, Seed, Growth, Late stage)

The integration of artificial intelligence (AI) in startups evolves as they progress through different growth stages. AI can be a differentiator at any stage, but its role, application, and impact vary depending on a startup's maturity, available resources, and market positioning. Investors scrutinize AI-driven startups differently at each phase, prioritizing viability, scalability, and strategic use of AI technology. AI also presents unique challenges at each stage, including data accessibility, computational costs, ethical considerations, and regulatory compliance [87]; [88]

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[84] Amos Tversky and Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases. Biases in Judgments Reveal Some Heuristics of Thinking under Uncertainty," *Science* 185, no. 4157 (1974): 1124–31.
[85] Tversky and Kahneman.
[86] James Montier, *Behavioural Investing*, *Behavioural Investing*, 2007, https://doi.org/10.1002/9781118673430.
[87] Felipe A. Csaszar, Harsh Ketkar, and Hyunjin Kim, "Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors," no. March 2025 (2024), https://doi.org/10.1287/stsc.2024.0190.
[88] Ahmad AbuzaidMajida Khalaf Khaleel Alsbou, "No Title," *ResearchGate*, 2024.

1.5.1 Pre-seed Stage (Idea & Concept Development)

At the pre-seed stage, startups are primarily focused on refining their business idea, conducting feasibility studies, and developing early prototypes. AI adoption at this stage is often conceptual, as startups must establish the technological and business viability of their AI-driven solutions.

Key AI Considerations:

- **Concept Validation:** Founders should critically evaluate and demonstrate the necessity of AI in addressing specific entrepreneurial challenges, ensuring it is not merely employed for marketing purposes but is instead integral to achieving desired outcomes in their ventures [89].
- **Early Feasibility Studies:** AI feasibility analysis, theoretical modeling, and proof-of-concept (PoC) studies are critical in gaining investor confidence [90]. Startups that leverage AI research publications or academic collaborations often gain credibility.
- **Data Strategy:** Given that AI models rely on large datasets, startups at this stage need to outline how they will collect, process, and refine data for model training [91]. Data partnerships with institutions or third-party providers can be advantageous.
- **Investment Considerations:** Funding at this stage typically comes from angel investors, accelerators, and deep-tech grants, emphasizing innovation potential over immediate profitability [92]. Investors may also look for early endorsements from AI experts or advisors.

Challenges:

- **Limited Data Access:** Many AI startups struggle with data scarcity, making model development difficult [93]. Synthetic data generation or transfer learning approaches can help mitigate this challenge.
- **Resource Constraints:** High computational costs limit startups' ability to develop AI beyond prototypes [94]. Cloud-based AI development can reduce upfront infrastructure costs.

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[89] Christian Linder, Abhisekh Ghosh Moulick, and Christian Lechner, "Necessary Conditions and Theory-Method Compatibility in Quantitative Entrepreneurship Research," *Entrepreneurship: Theory and Practice* 47, no. 5 (2023): 1971–94, https://doi.org/10.1177/10422587221102103.
[90] Miloš Petković et al., "The Odyssey of Strategic Investing in Artificial Intelligence (AI) Startups," 2023, 131–36, https://doi.org/10.15308/finiz-2023-131-136.
[91] Montanaro, Croce, and Ughetto, "Venture Capital Investments in Artificial Intelligence."
[92] Reichenbach and Walther, "Signals in Equity-Based Crowdfunding and Risk of Failure."
[93] Anna Jobin, Marcello Ienca, and Effy Vayena, "Artificial Intelligence: The Global Landscape of Ethics Guidelines," 2019, http://arxiv.org/abs/1906.11668.
[94] Igami, "Artificial Intelligence as Structural Estimation: Deep Blue, Bonanza, and AlphaGo."

- **Investor Skepticism:** Many investors are wary of AI-washing, where startups exaggerate AI capabilities without substantial backing [95]. Demonstrating a clear AI roadmap can improve credibility.

1.5.2 Seed Stage (Product-Market Fit & Initial Traction)

In the seed stage, startups move beyond theoretical AI concepts and begin developing functional prototypes, gathering real-world data, and acquiring early customers. The focus shifts towards demonstrating AI's impact on product differentiation and customer engagement.

Key AI Considerations:

- **Prototype Development:** Investors expect a working AI prototype that showcases core functionalities and initial real-world application [96]. Open-source AI tools can accelerate development and reduce costs.
- **Data Collection & Model Training:** Early-stage AI models require continuous data acquisition to improve accuracy and reliability [97]. Crowdsourced or federated learning approaches can enhance data availability while addressing privacy concerns.
- **Early User Adoption & Feedback:** AI-driven solutions must demonstrate practical value to users through pilot programs and beta testing [98]. Investor confidence increases with evidence of user retention and engagement.
- **Investor Expectations:** Seed-stage investors prioritize technical feasibility, initial traction, and AI's scalability within the business model [99]. Startups that show AI-driven efficiencies in cost reduction or automation gain an investment advantage.

Challenges:

In the seed stage, some of the various challenges that may be encountered are:

- **Model Optimization:** AI models must improve despite limited initial training data [100]. Active learning techniques can enhance model refinement.
- **Regulatory Considerations:** Startups must navigate data privacy laws and ethical concerns related to AI decision-making [101]. Compliance with GDPR or CCPA can signal readiness for larger markets.

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[95] Parikh, "Artificial Intelligence: ChatGPT to Artificial Intelligence Washing."
[96] Csaszar, Ketkar, and Kim, "Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors."
[97] Alsbou, "No Title."
[98] Linder, Moulick, and Lechner, "Necessary Conditions and Theory-Method Compatibility in Quantitative Entrepreneurship Research."
[99] Petković et al., "The Odyssey of Strategic Investing in Artificial Intelligence (AI) Startups."
[100] Reichenbach and Walther, "Signals in Equity-Based Crowdfunding and Risk of Failure."
[101] Montanaro, Croce, and Ughetto, "Venture Capital Investments in Artificial Intelligence."

- **Market Differentiation:** AI startups need to demonstrate clear value beyond generic automation solutions [102]. Domain-specific AI models provide a competitive advantage.

1.5.3 Growth Stage (Scaling & Expansion)

At the growth stage, startups focus on scaling operations, expanding market reach, and refining AI capabilities. AI's role becomes more strategic, influencing automation, efficiency, and personalization.

Key AI Considerations:

- **AI Scalability & Automation:** AI models need to adapt to increasing demand while maintaining efficiency [103]. Startups must ensure their AI infrastructure is robust enough to handle rapid growth.
- **Infrastructure & Integration:** Cloud-based AI solutions, edge computing, and API integrations become critical for operational efficiency [104]. Leveraging AI as a service (AIaaS) can offer scalability benefits.
- **Personalization & Advanced Analytics:** AI-driven startups leverage predictive modeling, recommendation systems, and process automation to enhance user experience and business intelligence [105]. Personalization increases user retention and revenue.
- **Investor Expectations:** Series A/B investors assess AI's direct impact on revenue generation, operational cost reduction, and customer retention [106]. AI-driven startups with strong data network effects could attract more funding because they have the potential to offer scalable growth, a competitive advantage, enhanced customer experience, predictive analytics for better decision-making, and efficient capital allocation. These factors collectively signal the potential for long-term success and market leadership, making them highly appealing to investors who are looking for stable and growing investment opportunities.

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[102] Csaszar, Ketkar, and Kim, "Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors."
[103] Petković et al., "The Odyssey of Strategic Investing in Artificial Intelligence (AI) Startups."
[104] Alsbou, "No Title."
[105] Csaszar, Ketkar, and Kim, "Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors."
[106] Linder, Moulick, and Lechner, "Necessary Conditions and Theory-Method Compatibility in Quantitative Entrepreneurship Research."

Challenges:

- **Computational Costs:** Scaling AI requires significant investment in computing power and infrastructure [107]. Startups may need partnerships with cloud providers for cost efficiencies.
- **Bias & Compliance Risks:** AI systems must be tested for fairness and ethical concerns as they scale [108]. Transparent AI models and explainability frameworks are crucial for regulatory compliance.
- **Competitive Pressure:** Established players may introduce AI-driven alternatives, challenging startups to maintain innovation momentum [109]. Differentiation through proprietary algorithms and data assets can help to create barriers to entry, reduce the risk of imitation, and enhance long-term scalability.

1.5.4 Late-stage Startup Growth (Scaling Toward Exit or Market Domination)

At the late stage, AI startups either prepare for an exit (IPO, acquisition) or solidify their market dominance. AI shifts from being an innovation driver to an essential component of long-term sustainability and differentiation.

Key AI Considerations:

- **Enterprise & Industry Adoption:** At this stage, start-ups tend to expand their solutions to a larger scale. Incase of AI startups with individual customers, they often expand into B2B partnerships, SaaS models, and large-scale enterprise solutions [110]. AI-powered enterprise solutions provide higher revenue predictability.
- **Strategic AI Moats:** Proprietary algorithms, patent-protected models, and exclusive datasets become critical competitive advantages [111]. AI startups with patented innovations could attract acquisition interest
- **Operational Efficiency & Cost Reduction:** AI-driven automation and predictive analytics optimize business operations, increasing profitability (Abuzaid and Alsbou 2024). AI-enhanced Efficiency increases a startup's readiness and appeal for exit strategies including initial public offering.[112]
- **Investor Expectations:** Late-stage investors focus on financial performance, sustained AI differentiation, and regulatory compliance [113]. Consistent AI-driven revenue growth increases valuation.

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[107] Montanaro, Croce, and Ughetto, “Venture Capital Investments in Artificial Intelligence.”
[108] Jobin, Ienca, and Vayena, “Artificial Intelligence: The Global Landscape of Ethics Guidelines.”
[109] Reichenbach and Walther, “Signals in Equity-Based Crowdfunding and Risk of Failure.”
[110] Montanaro, Croce, and Ughetto, “Venture Capital Investments in Artificial Intelligence.”
[111] Petković et al., “The Odyssey of Strategic Investing in Artificial Intelligence (AI) Startups.”
[112] Montanaro, Croce, and Ughetto, “Venture Capital Investments in Artificial Intelligence.”
[113] Csaszar, Ketkar, and Kim, “Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors.”

Challenges:

- **Monetization pressure and Revenue maturity:** At this stage, startups need to demonstrate steady and predictable revenue streams while transitioning from experimental innovation to operational discipline. Consistently monetizing AI for a variety of clientele grows more difficult.[114]
- **Scaling talent and organization complexity:** Scaling highly specialized technical and operational teams is necessary to manage growth. It gets harder to maintain agility, communication, and innovation speed as the organizational structure grows. [115]
- **Market Saturation and Differentiation:** Startups are under more pressure to exhibit distinct technological or data-driven moats as rivals, including tech behemoths, enter the market with comparable AI products. In crowded markets, they run the risk of becoming indistinguishable without defensible intellectual property [116]

In conclusion, this chapter has established the theoretical framework for comprehending the evaluation of startups by investors, particularly venture capitalists. It emphasizes how conventional investment standards, and the expanding impact of artificial intelligence interact. The debate has made clear AI's dual role in the investment landscape as a technological component and a strategic signal, considering the different expectations across startup growth stages and signaling theory and cognitive heuristics. These conceptual understandings serve as the foundation for this investigation into the practical evaluation of such factors. The research design and methodology used to empirically investigate these dynamics are described in the following chapter. The study utilizes both qualitative and quantitative data sources to systematically examine the role of AI in startup fundraising.

[114] Rohan Sharma, *AI Monetization: Strategies for Profitable Innovation*, 2024.
[115] Francesc Font Cot, Pablo Lara Navarra, and Enric Serradell-lopez, "AI Monetization: Strategies for Profitable Innovation," *SSRN*, 2025.
[116] Shinjinee Chattopadhyay, "Free Range Startups ? Market Scope , Academic Founders , and the Role of General Knowledge in AI," no. November (2024): 1027–79, https://doi.org/10.1002/smj.3685.

Chapter 2 : Research Design and Methodology
2.1 Research Design

This research uses a convergent mixed methods design [117] to investigate whether AI serves as a probability raiser (just a piece of the puzzle that increases the possibility of securing funds) or as a necessary condition for attracting startup investment. To evaluate quantifiable trends and interpretive investor reasoning, the research design is organized around the combination of comparative case studies, quantitative funding data analysis, and semi-structured interviews with venture capital (VC) professionals.

The general reasoning is in line with explanatory sequential [118], in which qualitative techniques are used to contextualize and elaborate quantitative findings. This makes sense considering the theoretical framework of the study, which evaluates AI as a signaling mechanism and strategic narrative in investment contexts rather than just as a technological feature.

Theoretical Framing: The approach is based on necessity logic in comparative social science [119], and on signaling theory [120] which propose that startups may use AI references in their pitches as indicators of technological sophistication and scalability, qualities that lessen information asymmetry for investors.

2.1.1 Hypotheses:

- **H1**: AI is a necessary condition for attracting venture capital investment.
- **H2**: AI increases the probability of securing investment but is not strictly required.
- **H3**: Startups without AI can succeed through other signals such as branding, execution, or founder credibility.

2.2 Data collection Methods
2.2.1 Quantitative Dataset of Startups

A dataset made up of 36 startups was created using publicly accessible investor and funding information. Three groups that are mutually exclusive were created from the startups:

- **AI-Core**: 12 Startups whose primary value proposition is built on AI technologies

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[117] V. L. (2006) Creswell, J. W., & Plano Clark, "Book Review: Creswell, J. W., & Plano Clark, V. L. (2006). Designing and Conducting Mixed Methods Research. Thousand Oaks, CA: Sage," *Research on Social Work Practice* 18, no. 5 (September 27, 2008): 527–30, https://doi.org/10.1177/1049731508318695.
[118] Nataliya V. Ivankova, John W. Creswell, and Sheldon L Stick, "Using Mixed-Methods Sequential Explanatory Design: From Theory to Practice," *Field Methods* 18, no. 1 (2006): 3–20, https://doi.org/10.1177/1525822X05282260.
[119] Charles C. Ragin, "Redesigning Social Inquiry - Presentation," *Redesigning Social Inquiry*, 2008.
[120] Spence, "*The MIT Press, Job Market Signaling*."

- **AI-Pitch**: 12 Startups that incorporate AI into their investor narratives or product descriptions, though not fundamentally AI-driven
- **Non-AI**: 12 Startups with no identifiable AI component in product or pitch

Each startup was coded according to:

- Total capital raised
- Time to first funding (In months)
- Number of funding rounds (1,2,3,4,….etc)
- Investor type (e.g VC, Crop VC…etc)
- Funding stage (e.g; Seed, series A,B,….IPO,…etc)
- Sector/industry classification
- Role of AI (core/pitch/none)

These data were collected from **Crunchbase, Tracxn**, and **Techcrunch** and other validated press releases. They were formatted in structured spreadsheet form for statistical analysis.

2.2.2 Qualitative Case Studies

To provide narrative depth and strategic context, nine startups (3 from each category) were selected for comparative case study analysis. This involved reconstructing their investor-facing narratives using materials such as:

- Pitch decks
- Public interviews
- Blog posts
- Funding announcements

This component provides qualitative insight into how AI framing is deployed strategically, even when not technically essential, and how that framing may affect investor perception.

2.2.3 Expert Interview with Venture Capitalists

To explore investor attitudes toward AI signaling, 6 interviews were conducted with venture capitalists. The interviews covered:

- The perceived necessity of AI in deal evaluation
- How AI influences due diligence and valuation
- Sectoral differences in the relevance of AI
- Cases where AI was over- or under-valued in pitch narratives
- Interviews were semi-structured and coded for thematic analysis.

2.3 Sampling Methods

Every stage of the data collection process was directed by a purposive sampling strategy [121]:

- **Startups**: Selected based on available funding data and clear alignment with one of the three AI typologies.
- **Case Study Selection**: The sampling logic [122], was used to ensure a representative diversity in startup sectors, AI usage, and funding outcomes,
- **Interview Participants**: Based on professional venture capital experience in technology or high-growth industries, they were selected through expert sampling [123]. To reach more valuable respondents, snowballing techniques were employed.

This guaranteed that every sample was rich in information and in line with the main research questions.

2.4 Data Analysis Techniques
2.4.1 Quantitative Analysis: Necessity logic and Testing setting

The purpose of this study's quantitative analysis is to identify trends and variations in funding success among startups that use AI to differing degrees: AI-Core, AI-Pitched, and Non-AI. The research hypotheses are tested using a combination of visual necessity condition assessment, inferential testing, and descriptive statistics. In accordance with the data structure and methodological limitations of the study, the analysis is carried out using Excel and SPSS.

The primary trends in the dataset are first summarized using descriptive statistics. Key variables like the amount of money raised, the number of funding rounds, and the time to first funding are measured using metrics like means, medians, and standard deviations. This helps put later statistical testing in context and offers a baseline understanding of the differences among the three AI categories. The sectoral distribution and preferred investor types of AI and non-AI startups are also investigated using frequency tables and cross-tabulations.

The mean funding levels of AI-Core, AI-Pitched, and Non-AI startups are compared using **One-Way ANOVA** in order to test for statistically significant differences between groups. A Kruskal-Wallis H test is employed as a non-parametric substitute in the event that the assumptions of normality or homogeneity of variance are not satisfied. By examining whether startups that use AI see better average investment outcomes, this analysis directly tests **H2**.

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[121] Lawrence A. Palinkas et al., "Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research," *Administration and Policy in Mental Health and Mental Health Services Research* 42, no. 5 (2015): 533–44, https://doi.org/10.1007/s10488-013-0528-y.
[122] John Wakeford, "Review Reviewed Work (s): The Discovery of Grounded Theory : Strategies for Qualitative Research by Barney Glaser and Anselm L . Strauss Review by : JOHN WAKEFORD Published by : Sage Publications , Ltd . Stable URL : Http://Www.Jstor.Org/Stable/42850772" 3, no. 2 (2016): 269–70.
[123] Martin N Marshall, "Sampling for Qualitative Research.," *AORN Journal* 73, no. 2 (2001): 522–25, https://doi.org/10.1016/S0001-2092(06)61990-X.

The relationship between categorical variables, such as startup type and funding success (e.g., received Series B or above), and AI category vs. investor type, is examined using chi-square tests. This analysis backs up the finding of trends in investor behavior that might work in favor of startups with AI labels.

The study also includes a visual necessity condition analysis based on manual ceiling-line plotting in Excel to investigate whether using AI is not only advantageous but also required to meet high funding thresholds. This plots startups with total funding on the y-axis and AI involvement on the x-axis. To find out if startups without AI fall short of higher funding tiers, a ceiling line is visually examined. (e.g., >$X Millions or >Series X). Then, to support a visual interpretation of necessity, a bottleneck table is made to show threshold cutoffs. This method allows for exploratory validation of **H1** using [124] logic of necessity condition analysis, even though it does not produce formal effect sizes.

By combining these statistical techniques, it is ensured that **H1** is evaluated for necessity, **H2** for probabilistic improvement, and **H3** for counterexamples of non-AI startups that are successful because of other factors like team quality or traction. For a more comprehensive interpretation, this quantitative strand is then triangulated with qualitative findings in subsequent chapters.

2.4.2 Qualitative case Comparison

A structured cross-case synthesis approach was used, based on [125] case study methodology, to investigate how startups strategically integrate Artificial Intelligence (AI) into their funding narratives. To capture variance in AI usage, investor perception, and funding outcomes, nine startups were chosen, three from each of the AI categories (AI-Core, AI-Pitched, and Non-AI). These cases were chosen for their sectoral diversity, theoretical significance, and explanatory power rather than statistical representation.

To compare important narrative and investment characteristics across all cases in a methodical manner, a cross-case matrix was created. Both within-group (such as AI-Core only) and between-group (such as AI vs. Non-AI) comparisons were possible with the matrix. The following variables were compared across each case:

- **Nature of AI Usage**: Whether AI was core to the product offering, lightly integrated, or absent

- **Placement in Pitch**: Whether AI appeared in the product narrative, vision statement, investor materials, or media interviews

[124] Jan Dul, "Necessary Condition Analysis (NCA): Logic and Methodology of 'Necessary but Not Sufficient' Causality," *Organizational Research Methods* 19, no. 1 (2016): 10–52, https://doi.org/10.1177/1094428115584005.
[125] Robert Yin, "Robert_K-_Yin_Case_Study_Research_Design_and_Mebookfi-Org.Pdf," 2018.

- **Funding Outcomes**: Total capital raised, number of funding rounds, and funding stage reached
- **Investor Type Attracted**: Whether investment came from traditional VCs, corporate VCs, or private equity firms

Thematic coding, based on [126] six-step framework, was used to analyze each case. We thoroughly examined the founder statements, press articles, pitch materials, and transcripts. Both inductive (data-driven) and deductive (theory-driven) approaches were used for coding.

Novel themes that weren't previously specified in the coding guide, like "AI used as a market credibility booster" or "superficial AI mention with no technical backing," were able to emerge thanks to inductive coding. Conversely, deductive coding was informed by theoretical frameworks like framing theory [127], signaling theory [128], and earlier research on startup pitch dynamics [129]

Codes were then grouped into higher-order themes such as AI as essential infrastructure, AI as a symbolic signal, or traction over technology. The matrix was used to map thematic clusters across all nine cases, highlighting areas of divergence (such as non-AI startups still obtaining significant funding through team strength or market growth) and convergence (such as investors favoring AI-integrated models in technical sectors).

This analysis lends interpretive weight to **H1–H3**, especially when it comes to determining whether AI serves as a genuine necessity or as a narrative enhancer.

2.4.3 Interview Analysis

A manual thematic coding procedure conducted in Microsoft Excel was used to analyze the interview data. This approach was selected to guarantee that the researcher remained highly involved and acquainted with the data, as well as to offer transparency regarding the development of themes. Although qualitative research frequently uses software tools like NVivo, manual thematic analysis was both methodologically sound and practical due to the small number of interviews and the structured nature of the questions [130].

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[126] Virginia Braun and Victoria Clarke, "Using Thematic Analysis in Psychology," *Qualitative Research in Psychology* 3, no. 2 (2006): 77–101, https://doi.org/10.1191/1478088706qp063oa.
[127] 1974 Goffman, "Reviewed Work (s): Frame Analysis : An Essay on the Organization of Experience . by Erving Goffman Review by : Murray S . Davis Published by : American Sociological Association Stable URL : Http://Www.Jstor.Org/Stable/2064021," *Contemporary Sociology* 4, no. 6 (1975): 599–603.
[128] Spence, "*The MIT Press, Job Market Signaling*."
[129] Martin L. Martens, Jennifer E. Jennings, and P. Devereaux Jennings, "Do the Stories They Tell Get Them the Money They Need? The Role of Entrepreneurial Narratives in Resource Acquisition," *Academy of Management Journal* 50, no. 5 (2007): 1107–32, https://doi.org/10.5465/AMJ.2007.27169488.
[130] Lorelli S. Nowell et al., "Thematic Analysis: Striving to Meet the Trustworthiness Criteria," *International Journal of Qualitative Methods* 16, no. 1 (2017): 1–13, https://doi.org/10.1177/1609406917733847.

Every line of the transcript was examined. Initially, the responses were arranged in columns based on the five predetermined thematic areas specified in the interview guide:

- Investor perceptions of AI in startup pitches
- AI as a necessity vs. enhancer
- Investor sentiment toward AI (enthusiasm or skepticism)
- Sector-specific expectations about AI
- Influence of AI on actual funding outcomes

Responses were coded using a combination of inductive (data-driven) and deductive (theme-based) techniques within each of these themes. Although inductive coding allowed for the emergence of unexpected insights, such as subtle distinctions between superficial vs. technically credible AI claims or shifting investor expectations over time, deductive coding ensured alignment with the study's conceptual framework and research questions. The analysis was conducted in accordance with [131] six-phase framework for thematic analysis:

- **Familiarization** – Transcripts were read and re-read for immersion
- **Generating initial codes** – Descriptive and interpretive codes were assigned to segments of text
- **Searching for themes** – Codes were grouped into broader conceptual categories
- **Reviewing themes** – Coherence and distinction between themes were checked
- **Defining and naming themes** – Each theme was clearly defined and refined
- **Producing the report** – Key excerpts were selected to illustrate each theme

Five overarching themes and numerous sub-themes were found as a result, and these were connected to the study's goals. Visualizing the frequency of specific concepts throughout interviews and their clustering around each theme was made possible by manual Excel-based tracking. Later, quotes were chosen to bolster the findings chapter's thematic categories.

The interviews were interpreted in a transparent, thorough, and theoretically informed manner thanks to this methodical yet adaptable approach, which also helped to clarify how investors view and assess AI in startup pitches. Triangulation with results from the case study and quantitative analyses was also supported.

2.4.4 Triangulation and Integration of Findings

The study uses a triangulation strategy, combining evidence from three different but complementary analytical approaches; qualitative comparative case studies, quantitative statistical analysis, and semi-structured investor interviews to guarantee thorough understanding and boost the validity of findings.

[131] Braun and Clarke, "Using Thematic Analysis in Psychology."

This is consistent with methodological triangulation principles [132]; [133]which combine various data sources and methodologies to investigate a single phenomenon, in this case, the necessity and role of AI in luring startup capital.

Each analytical strand addresses the research problem from a different angle:

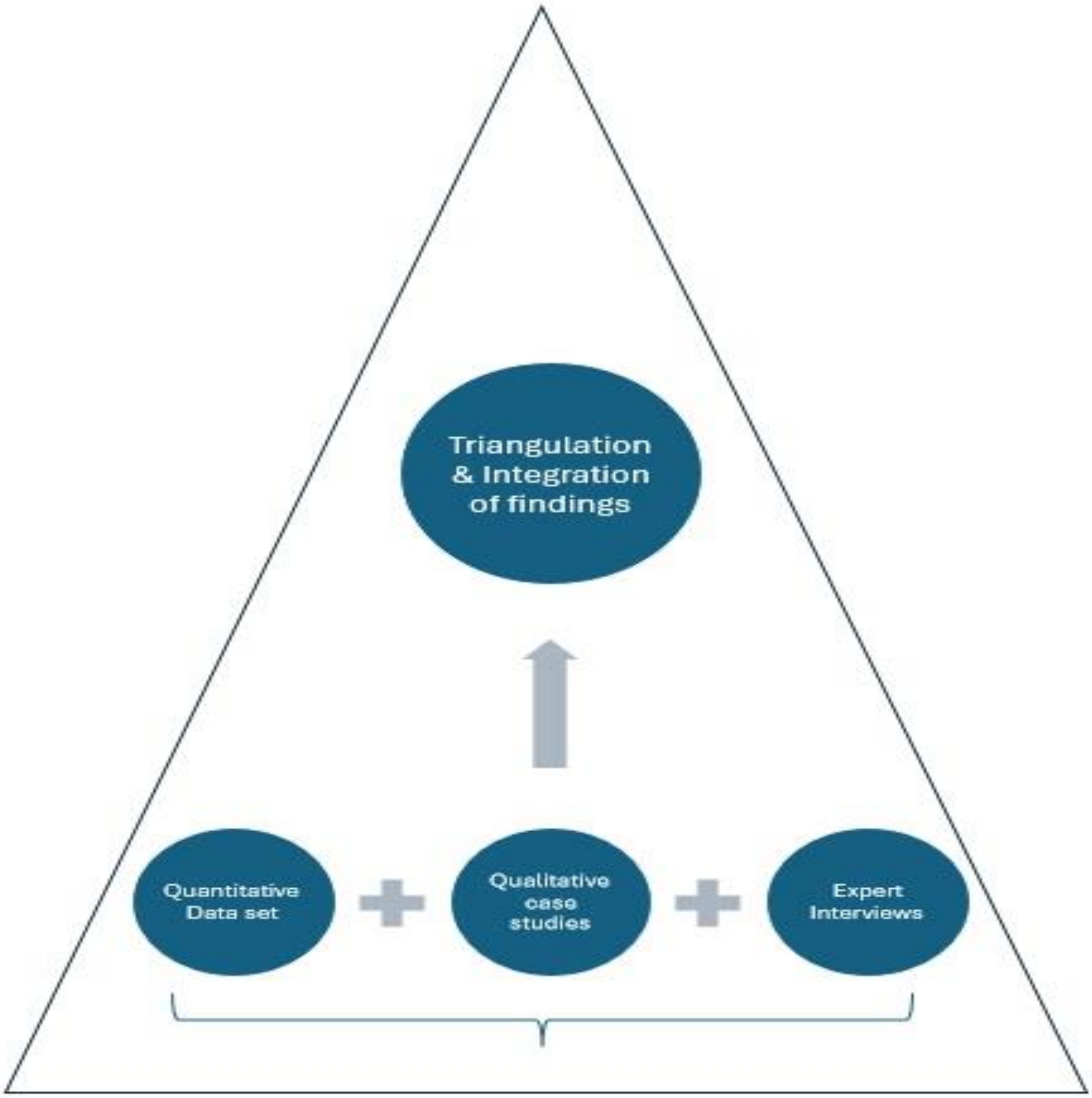
- **Quantitative analysis** looks at quantifiable trends and relationships among 36 startups, such as whether AI is associated with higher stages, more rounds, or more funding.
- **Expert Interviews** provide insight into how investors themselves view, understand, and react to the presence or absence of AI in startup pitches.
- **Case study comparison** scrutinizes the strategic positioning of AI in real-world startup narratives, exposing investor targeting, framing strategies, and sectoral variations in AI use.
- **Convergent triangulation**, which compares results side by side to see where they complement, diverge, or align, then combines these three methods.

Thus, the triangulated interpretation allows for a synthesis of the quantifiable and perceived value of AI in the startup investment landscape, going beyond simple confirmation or contradiction. This increases the research's explanatory power and lends credence to more complex findings regarding whether AI is a strategic enhancer, a necessity, or a symbolic signal in various contexts.

[132] 1978 Denzin, "Review Reviewed Work (s): The Research Act : A Theoretical Introduction to Sociological Methods by N . K . Denzin Review by : Dan Krause Source : Teaching Sociology , Oct ., 1989 , Vol . 17 , No . 4 (Oct ., 1989), Pp . 500-501 Published by : American" 17, no. 4 (1989): 500–501.

[133] U Flick, *Introducing Research Methodology: Thinking Your Way Through Your Research Project* (SAGE Publications, 2025), https://books.google.it/books?id=p8g9EQAAQBAJ.

Figure 2.1: Triangulation approach



Chapter 3 : Results, Discussion, and Implications
3.1 Overview

The study's empirical results are presented in this chapter along with an interpretation of their significance for startup investment decision-making and the strategic application of artificial intelligence (AI) as a signaling mechanism. The findings are organized into three distinct strands, which adhere to the mixed-methods framework described in Chapter 2: expert insights from semi-structured interviews with venture capital experts, qualitative case study comparison, and quantitative analysis of financing data.

This chapter has two goals in mind. It begins by summarizing the data acquired from every methodological element and assessing the relationship between startup financing outcomes and AI narratives and technology integration. Second, it talks about how these findings have wider ramifications for startup strategy, signaling dynamics, and venture capital theory.

The three hypotheses put forward in Chapter 2 are tested with special attention:

- **H1**: AI is a necessary condition for attracting venture capital investment.
- **H2**: AI increases the probability of securing investment but is not strictly required.
- **H3**: Startups without AI can succeed through other signals such as branding, execution, or founder credibility.

Using triangulated information from the three analytical threads, each of these hypotheses is examined again. The following is how the chapter is arranged; The quantitative results are presented in Section 3.2, the case study comparisons are described in Section 3.3, the expert interview insights are summarized in Section 3.4, and the results are synthesized through methodological triangulation in Section 3.5, which provides an integrated interpretation and discusses the theoretical and practical implications for investors, startups, and innovation ecosystems.

3.2 Quantitative analysis: Start-up funding patterns across AI-startup categories
3.2.1 Descriptive statistics

The descriptive statistics of funding-related variables throughout the sample are summarized in Table 3.1. A total of 36 startups were evenly divided into three AI categories: **AI-Core**, **AI-Pitch**, and **Non-AI** (12 startups in each group).

Table 3.1: Descriptive Statistics Across All Startups (N = 36)

Variable	Min.	Max.	Mean	Std.Dev
Total funding raised ($M)	11.4	61,900	3,463.4	10,741.5
Time to first funding (months)	-3	89	14.52	16.53
No. of funding rounds	2	24	8.31	5.12

Note: Negative time-to-funding values reflect fund reception some time before the official startup launch.

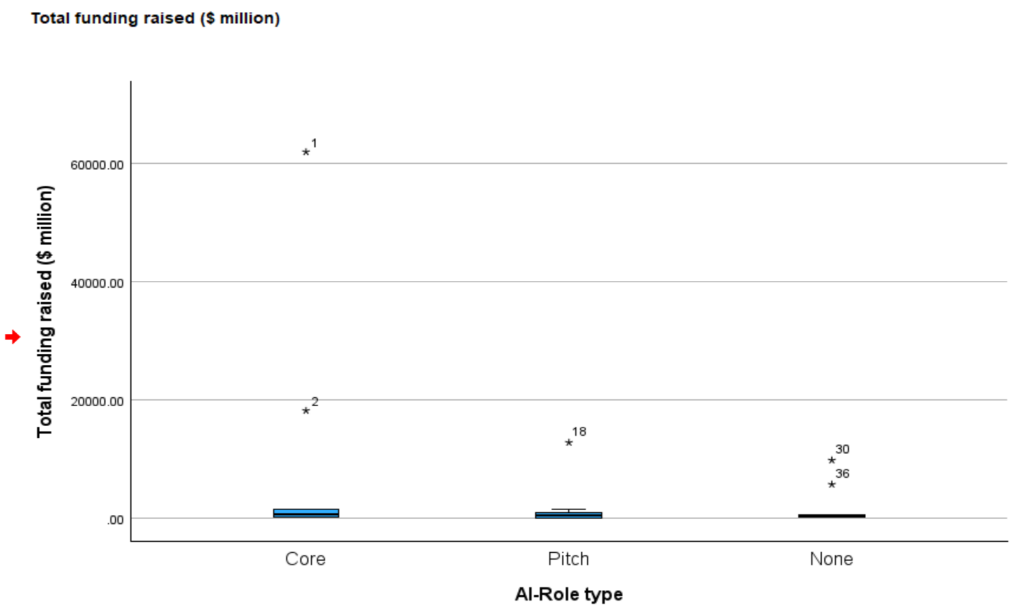
This initial finding offers early descriptive support for Hypothesis 3 (H3), which suggests that different signals can help non-AI firms prosper. High funding is not limited to AI-based storytelling, as seen by the existence of non-AI companies with funding levels in the billions, including one valued at $9.81 billion.

3.3.2 Funding Differences by AI Narrative Role

Table 3.2: Category means overview

AI role	Mean ($M)	Std.Dev	Min.	Max.
AI-Core	7,270.8	17,929.6	181.0	61,900.0
AI-Pitch	1,539.8	3,577.3	11.4	12,800.0
Non-AI	1,581.2	3,021.8	183.0	9,810.0

Figure 3.1: Boxplot of Total Funding by AI Category



Distribution of the total funds raised to startups that are AI-Core, AI-Pitch, and non-AI. Interquartile ranges are shown by boxes, and medians are displayed by horizontal lines. Outliers are indicated by stars, and all categories have noteworthy high-funding cases. Despite not being statistically significant, this graphic supports the practical funding differences found in the ANOVA.

A real disparity in funding between groups is reflected in the statistical and visual spread seen in Figure 3.1 and Table 3.2. The significantly greater average funding in the AI-Core category provides some support for **H2**, which contends AI raises the probability of investment, even though it is not statistically significant. At the same time, the obvious non-AI outliers reinforce **H3**.

ANOVA Test

A one-way ANOVA was used to determine whether these changes are statistically significant.

Table 3.3: Analysis of Variance

Source	SS	df	MS	F	p-value
Between categories	260,878,114	2	130,439,057	1.140	.332
Within categories	3,777,385,277	33	114,466,221		
Total	4,038,263,391	35			

There is no statistically significant difference in mean financing between AI-Core, AI-Pitch, and Non-AI categories ($p = .332$). However, the average for AI-Core startups was noticeably higher, indicating a useful effect that needs further interpretation.

Even though the mean funding difference is not statistically significant ($p = .332$), the effect size ($\eta^2 = 0.065$) and the AI-Core group's large variance suggest a possible useful impact. Although there isn't much statistical evidence to support it, this is consistent with Hypothesis 2 (H2).

Table 3.4: Effect Size Estimates

Metric	Value
Eta-squared (η^2)	0.065
Omega-squared (ω^2)	0.008
Epsilon-squared (ε^2)	0.008

Given AI-Core's high mean budget, the eta-squared number (6.5%), albeit being small, suggests non-trivial practical variance between groups.

Note: These effect sizes were manually determined using the ANOVA sums of squares (SS) that were displayed in the output of SPSS. Although η^2, ω^2, and ε^2 are not calculated by SPSS by default, they are frequently provided in academic research to show the percentage of variance explained by the grouping variable (in this case, AI role type).

While epsilon-squared and omega-squared account for sample size and error variation, eta-squared provides a simple effect size.

Table 3.5: Post Hoc Test: Tukey SD

Group comparison	Mean difference($M)	p-value
Core Vs. Pitch	5,731.1	.399
Core Vs. None	5,689.7	.404
Pitch Vs. None	41.4	1.000

No significant pairwise differences between AI categories were found at the 95% confidence level,

Although there is no statistically significant difference in fundraising between the groups, core (AI-core) firms raised an average of 4.5 times more than other startup groups.

3.2.3 AI Role Vs. Investor Type

The relationship between the type of investors (VC only, VC + corporate, etc.) and the AI narrative role was investigated using a chi-square test.

*Table 3.6: Chi-Square Test – AI Role * Investor Type*

$\chi^2(8) = 9.859$	$p = .275$	Cramer's V = .370

There is no statistically significant correlation between the type of AI role and the makeup of investors. This finding implies that investor type is not independently correlated with AI narrative category, but it does not directly test any of the main hypotheses. This suggests that AI positioning is not the only element influencing investor behavior, which has a tenuous connection to **H2** and **H3** because it suggests non-AI factors also play a role.

3.2.4 Necessity Condition analysis

A ceiling-threshold approach [134] was employed to test necessity logic, defining "success" as any startup that raises more than $11.5 billion in fundraising. Using a common statistical rule, the $11.5 billion budget cap was established:

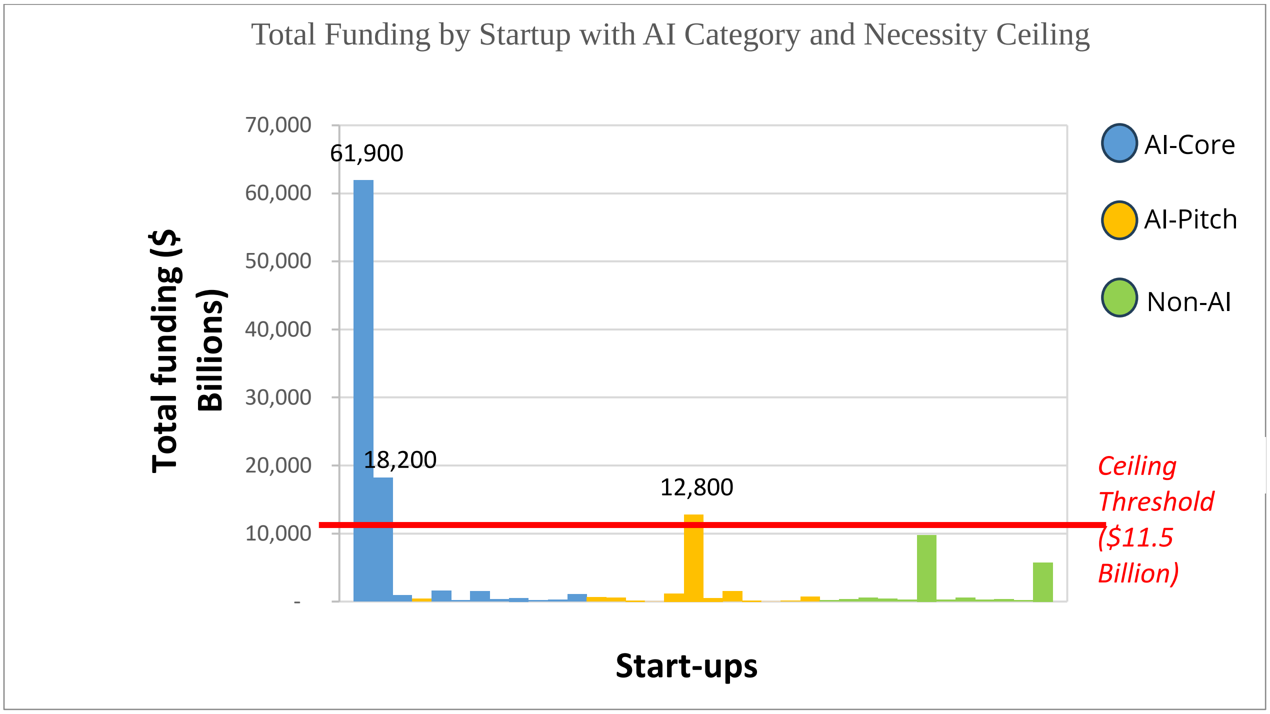
Threshold=Median Total Funding+1 Standard Deviation

The statistics indicated a ceiling of roughly $11.5 billion, with the median funding being $757 million and the standard deviation being $10.74 billion. The purpose of this criterion was to visually evaluate whether being classified as AI-Core was a prerequisite for reaching such extreme levels of money and to define exceptional funding.

[134] Dul, "Necessary Condition Analysis (NCA): Logic and Methodology of 'Necessary but Not Sufficient' Causality."

In terms of the amount of venture capital, startups that surpassed this threshold were regarded as anomalies. To see if any non-AI startups went above the limit, a crucial visual representation was created.

Figure 3.2:Total Funding by Startup with Necessity Ceiling



- Some AI-Core startup surpassed the threshold (up to $61.9 billion)
- One AI-Pitch startup raised $12.8 billion.
- Critically, one non-AI business came in just short of $10 billion, but it was still a significant outlier that was significantly higher than the median.

Table 3.7: Funding distribution Vs $11.5B ceiling by category

AI Role	**Number of startups over $11.5B**	**Max. funding ($B)**	**Ceiling Violator?**
AI-Core	2	61.9	Yes
AI-Pitch	1	12.8	Yes
Non-AI	0	9.81	No (But close)

The primary quantitative data do not completely refute **H1** in a logical sense, but they raise serious questions about its empirical validity. This is the main quantitative test **H1**, which asserts that AI is a prerequisite for high funding success. Although no non-AI firm exceeded the $11.5 billion ceiling, the existence of a non-AI outlier at $9.81 billion challenges the rigidity of this claim.

3.3 Qualitative analysis: Case Study Comparison

3.3.1 Overview and case selection logic

Nine carefully chosen startups are compared in this section, divided into three groups according to how they relate to artificial intelligence (AI):

- **AI-Core** (technically deeply integrated infrastructure)
- **AI-Pitch** (strategic or symbolic use of AI in their narratives).
- **Non-AI** (no AI emphasis at any stage).

Three sample startups from each cohort were chosen based on their stage, visibility, and data availability. The purpose of the analysis is to determine how their funding results and investor alignment were impacted by narrative positioning around AI.

Table 3.8: Startup Case Study Sample by AI Category

Category	Startup	founded	Sector	AI narrative role	Funding Year(s)	Strategic outcome	Narrative Type
AI-Core	OpenAI	2025	AI&RD	Core technical mission (AGI-focused)	2019-2023	$13B+ from Microsoft; key strategic partnership	DeepTech Builder
	Anthropic	2021	AI safety	Core technical (AI alignment/safety)	2022-2024	$14.8B+ from Amazon, Google, top-tier AI firms	DeepTech Builder
	Hugging face	2016	ML DevTools	Core infrastructure (tooling, open-source)	2021-2023	$235M Series D; valued at $4.5B	Infrastructure Enabler
AI-Pitch	Wework	2010	Real estate	Symbolic AI use (AI analytics in decks)	2014-2019	$20B+ raised; failed IPO; reputational fallout	Strategic story telling
	Compass	2012	Proptech	Supportive AI framing (e.g., Video Studio)	2018-2021	$1.5B+ raised; IPO in 2021	Strategic story telling
	ClearCo	2015	Fintech	AI-based growth insights (lightly integrated)	2020-2021	$681M+ raised; backed by Softbank	Tactical Tech Hybrid
Non-AI	Calendly	2013	Saas/prouctivity	No AI narrative	2021	$350M Series B; valued at $3B+	Product-led growth
	Basecamp	1999	Saas/Project management	No AI; deliberately simple	2004-present	Bootstrapped; sustainable revenue model	Independent minimalist
	Spanx	2000	Fashion/consumer	No AI; brand-led model	2000-2021	PE-backed exit in 2021; $1.2B valuation	Brand-led growth

3.3.2 Theme 1: AI as Essential Infrastructure for Strategic Depth

AI is positioned as the technological and strategic foundation of AI-core startups rather than as an add-on feature. AI is portrayed by startups such as Hugging Face, Anthropic, and OpenAI as the primary facilitator of their financing trajectory, products, and mission.

These startups, which mostly emerged between 2019 and 2024, took advantage of a mature stage in the AI sector when alignment frameworks, tooling ecosystems, and foundation models were starting to grow and draw in long-term institutional investment.

Narrative Strategy and Timing

- **OpenAI** was established in 2015 with the goal of creating artificial general intelligence (AGI) for the good of all people. The company, which is renowned for developing groundbreaking models such as GPT-3 and GPT-4, switched to a capped-profit structure in 2019 to draw in long-term investment while maintaining protections for the public interest. The same year, it signed a multibillion-dollar deal with Microsoft, which went on to invest more than $13 billion between 2019 and 2023. Additionally, Microsoft integrated OpenAI's models into its Office and Azure products and became the sole cloud provider for the company.
- **Anthropic** was founded in 2021 by Former OpenAI with a focus on AI alignment and safety. When developing the Claude model family, it prioritized interpretability and moral AI concepts. Between 2022 and 2024, it raised about $14.8 billion from investors, including Google and Amazon, two cloud partners.
- **Hugging Face** was launched in 2016 and has emerged ever since as a major player in open-source machine learning tools. With a valuation of $4.5 billion, it raised $235 million in a 2023 Series D round from investors like Salesforce, Nvidia, and Google. It is well-known for its Transformers collection and model-sharing platform.

Strategic Outcomes

The success of AI-core firms demonstrates that when AI is mission-critical and aligned with market maturity, it becomes both a technological asset and a strategic financial anchor. This theme provides contextual and interpretive insights into dynamics surrounding **H2**, suggesting that deep AI integration may enhance credibility with strategic investors. illustrating how deep AI integration enhances credibility with strategic investors.

The quantitative trend that AI-core companies lead in funding volume is further supported by the timing of these developments. Because their technical focus and investor readiness for infrastructure-grade technologies align, these startups seem to have drawn substantial strategic capital and long-term partnerships.

3.3.3 Theme 2: AI as Strategic Signaling in Competitive Markets

During times of competitive fundraising, startups in this category mainly employed AI as a symbolic storytelling tool to strengthen their innovative credentials. Despite having little operational significance, companies like WeWork, Compass, and Clearco used ambiguous terms like "AI-powered," "smart tech," or "predictive analytics" in their messaging to draw in investors between 2014 and 2021, when artificial intelligence (AI) was still new but not yet fully defined.

Narrative Strategy and Timing

WeWork (2014–2019) positioned itself as a tech company rather than just a real estate company by using analytics and AI claims in pitch decks.

Prior to its 2021 IPO, **Compass** incorporated AI branding (such as Video Studio) into its Protech story.

ClearCo (2020-2021) signaled innovation in fintech by showcasing its proprietary AI underwriting model.

Strategic Outcomes

Despite raising over $20 billion, **WeWork** suffered a reputational fallout after its failed IPO.

Despite investors doubting **Compass**'s true tech worth, the company raised more than $1.5 billion and went public.

Despite drawing $681M, **ClearCo**'s expansion halted after its Series C due to investor scrutiny.

Viewed alongside the funding patterns, these findings demonstrate how symbolic AI-signaling may attract attention in the short-term but may not be stable over time. Investor sentiment seemed to change after 2020 in favor of demanding more observable technical depth. In the short term, AI-based framing might have aided these start-ups in obtaining funding, but later-stage difficulties might have been exacerbated by the lack of a fully integrated technical infrastructure. This interpretation is consistent with lower funding averages found in the quantitative data for the AI-pitch category.

3.3.3 Theme 3: Non-AI Narratives and Alternative Signals of Credibility

These startups relied on strong brand identity, founder credibility, and a clear product value to achieve strategic success without mentioning AI. Their paths show that alternative investor signals are still relevant today, spanning both pre-AI and AI-saturated eras.

Narrative Strategy and Timing

Calendly (2013–2021) raised $350M at a $3B value without mentioning AI, thanks to its viral usage.

After an initial investment, **Basecamp** (formed in 1999) turned down venture capital and instead bootstrapped its way to profitability.

Spanx, which was purchased for $1.2 billion in 2021, relied on customer loyalty and founder storytelling to grow without the need for AI.

Strategic Outcomes

These startups used brand equity, execution, and product-market fit to reach billion-dollar valuations or exits without depending on tech narratives.

Discussion
These illustrations show that success as startup does not necessarily require AI. Throughout market cycles, value clarity and executional credibility continue to be reliable indicators. These examples provide interpretive insights that cast doubt on **H1**'s premise and suggest instances in which **H3**'s assumptions may be applicable, especially in relation to alternative credibility signals in investor decision-making.

3.3.4 Cross-Theme Synthesis

The narrative power of AI seems to be largely dependent on timing. AI-related language provided investor appeal and narrative novelty from 2014 to 2019, but after 2020, as technical scrutiny increased and capital deployment became more selective, its stand-alone signaling power decreased. start-ups in the AI-Core group showed a better strategic fit with long-term investors when they matched deep technical integration with narrative framing.

On the other hand, AI-Pitch companies frequently experienced an increase in visibility early on but lacked narrative stability over time. As investor expectations changed, many found it difficult to remain credible. In the absence of AI, non-AI start-ups emphasized that execution, brand equity, and distinct value propositions can still convey legitimacy. These trends are consistent with findings from various industries and market cycles.

While AI-Pitch firms demonstrated more variance and weaker overall performance compared to AI-Core start-ups, AI-Core firms tended to achieve higher average funding levels. These themes theoretically portray the quantitative findings. Despite being smaller in terms of funding size, non-AI start-ups demonstrated more consistent results. These patterns imply a convergence of narrative substance and capital outcomes; however, they do not constitute evidence.

Taken together, these details raise a question about **H1**'s premise, specifically whether AI is always a necessary condition. According to the patterns seen, this requirement might not always be met, especially in the presence of other credibility signals. Although the data from early-stage examples could be interpreted as giving **H2** some initial interpretive weight, its generalizability is complicated by the long-term instability observed in the use of symbolic AI. In a similar vein, the underlying assumptions of **H3** seem relevant in this situation, inviting further inquiry into how non-AI signals affect investor behavior across startup categories.

3.4 Interview Findings: Expert Perceptions on AI and Startup Investment
3.4.1 Overview

Semi-structured interviews with three expert stakeholders in the European innovation and venture capital ecosystem, including senior professionals with experience in VC fund management, innovation policy, and accelerator leadership were conducted to contextualize and triangulate the findings from quantitative and case-based analyses.

The interviews were then thematically analyzed using [135] six-step approach, which is described in the methodology chapter. The resulting themes provide insight into how AI functions in modern funding narratives, how investors interpret AI claims, and which alternative signals have gained prominence.

3.4.2 Interview Findings: Expert Insights on AI, Narrative, and Startup Investment

Three seasoned experts in startup evaluation, venture capital, and digital innovation; **Michele Costabile** (LUISS, MITO/LINFA Funds), **Paolo Celini** (LUISS, innovation advisor), and **Roberto Magnifico** (Zest Group, formerly LVenture), participated in semi-structured interviews. The interviews helped to clarify how artificial intelligence (AI) functions as a signal in startup investment narratives and how investors evaluate such claims in light of founder capability, market trends, and credibility. The responses were categorized both inductively and deductively across key themes derived from the interview guide and emergent patterns in the expert responses.

3.4.2.1 Theme 1: AI is ubiquitous but not automatically valuable

According to all three experts, artificial intelligence is currently pervasive in startup industries. However, unless it is visibly incorporated into the very foundation of the company model, its existence is no longer seen as intrinsically remarkable or distinctive.

- **Roberto Magnifico** referred to startups as "data factories," highlighting the fact that most digital business activities currently incorporate data and artificial intelligence.
- Similar to fundamental digital infrastructure, **Michele Costabile** observed that AI has evolved into a "hygienic factor": "It's no longer the differentiator, it's expected."
- **Paolo Celini** clarified that although AI is essential in industries with a lot of data, it can be completely irrelevant in others (such as materials or certain hardware kinds).

This highlights the significance of sector-specific expectations it raises interpretive questions about **H1**’s assumption that AI is a universal prerequisite for startup funding.

3.4.2.2 Theme 2: Substance Over Symbolism-AI-Washing Is Penalized

- **Paolo Celini** stated: “If you quote AI generically, like ‘we use AI’, we don’t believe it. It’s like saying Italians eat pasta. What does that mean?”
- **Michele Costabile** emphasized the need for specificity and strategic integration: “It’s not about whether AI is there, it’s about how it’s used.”
- **Roberto Magnifico** pointed out that investors now look past superficial mentions and focus on what the AI enables within the business model.

[135] Braun and Clarke, “Using Thematic Analysis in Psychology.”

These insights closely match the diminishing impact of AI as a symbolic signal assumed in **H2** and highlight the rise in investor scrutiny seen in both case studies and dataset.

3.4.2.3 Theme 3: Founder Capability Is the True Differentiator

Investors now place more importance on the founding team's competence and their ability to use technology effectively rather than just AI.

- **Michele Costabile** stated: "What makes the difference now is the human brain applying the technology."
- **Paolo Celini** clarified that in the current investment climate, founder competence is given more weight than technological buzz.
- **Roberto Magnifico** reaffirmed this, particularly for early-stage decisions, saying: "It's the team's capacity that drives investment."

This strongly resonates with **H3**, which holds that alternative signals can replace AI and drive funding success.

3.4.2.4 Theme 4: AI May Accelerate Interest but Doesn't Guarantee Success

Experts concurred that firms with obvious AI integration might draw investors more quickly, particularly during hype cycles. Such enthusiasm, meanwhile, does not necessarily translate into investment unless the AI is incorporated properly.

- According to **Paolo Celini**, the AI funding boom might soon experience a correction, akin to the dot-com bust: "Valuations are high... though sustainability is another matter."
- **Roberto Magnifico** pointed out that although startups focused on AI might gain traction more quickly, due diligence still weeds out false claims.

This demonstrates the drawbacks of depending solely on AI as a narrative tool, while also partially lending interpretive weight to **H2**.

3.4.2.5 Theme 5: Sector Expectations Still Matter

- **Paolo Celini** and **Michele Costabile** highlighted sector-specific differences,
- **Roberto Magnifico** contended that almost all investable startups eventually use AI in some capacity.
- **Paolo Celini** pointed out that AI is essential in fields like computer vision, pharmaceuticals, or chip processing, but not in materials engineering.
- **Michele Costabile** provided examples from clean tech and agri-tech funds, where AI is helpful but not decisive.

This raises question to **H1**, suggesting that AI may not be a fixed necessity across sectors, and closely align with the findings from necessity ceiling analysis.

3.4.2.6 Theme 6: Investor Maturity Is Increasing

All experts emphasized a developing ability among investors to detect and dismiss overblown AI claims. Dedicated technical staff, customer due diligence, and rising market familiarity with AI have increased the bar.

- **Michele Costabile** stated that his examination teams included "AI specialists" to judge the veracity of statements pertaining to AI.
- **Roberto Magnifico** stated: "We believe we can see through business models, and I haven't been duped (by AI-washing)."
- **Paolo Celini** emphasized that technical clarity, not fad language, is what is expected nowadays.

3.5 Triangulation and Hypothesis Testing

3.5.1 Purpose and Rationale

This section summarizes the results from the three analytical components of the study: expert interviews (investor perceptions and heuristics), comparative case study analysis (narrative-based strategy in nine startups), and quantitative analysis (SPSS-based funding data). The goals were:

1. To evaluate the role that artificial intelligence (AI) plays in startup funding processes as a narrative or strategic tool.
2. To assess how much the empirical data confirms or disproves the three theories presented in Chapter 2.

By pointing out similarities and differences amongst approaches, triangulation strengthens the validity of discoveries and, in the end, offers a stronger basis for theoretical and applied conclusions.

3.5.2 Cross-Method Convergence and Contrast

AI is ubiquitous but not inherently valuable

A recurring feature in all three assessments was that, although AI is now widely used in startup environments, it no longer serves as a universal differentiation. Quantitatively, AI-Core companies showed greater average and maximum financing levels, but there was no statistical significance, and non-AI companies generated significant outliers (such as $9.81 billion in fundraising).

Evidence from case studies demonstrated that while symbolic AI signaling (e.g., Wework, Compass, ClearCo) had limited sustainability, AI-centric businesses prospered when AI was strategically and technically central (e.g., OpenAI, Anthropic). This pattern was echoed by interviewees: AI has evolved into an expected but insufficient "hygienic factor." "Now it's not about AI being there, it's about how it's used," said Michele Costabile.
The role of AI is contextual and situational rather than always decisive.

Superficial AI Narratives Are Penalized

The three methods showed that AI signaling is becoming more and more scrutinized. The performance of AI-Pitch enterprises was inconsistent, according to quantitative data. Narratives from case studies demonstrated that, particularly recently, exaggerated or generalized AI claims backfired. This was further supported by expert interviews, where Roberto Magnifico underlined that "AI must have substance" and Paolo Celini cautioned against "generic AI claims."

Without depth, consistency, and operational integration, narrative inflation surrounding AI becomes less and less effective.

Alternative Signals Drive Success in Non-AI Startups

Calendly, Basecamp, and Spanx are examples of non-AI companies that were shown to rely on alternative signals, such as founder credibility, usability, and brand clarity. Although more erratic, quantitative analysis verified that non-AI companies continued to raise a sizable amount of capital. Strong consensus emerged from the interviews: founder skill and execution quality were cited by all experts as the main factors influencing investment.

These patterns demonstrate that other legitimacy signals are still potent, and that **AI is not a necessity condition.**

3.5.3 Hypothesis-by-Hypothesis Evaluation

1. **Hypothesis 1:** AI is a necessary condition for attracting venture capital investment.

- **Quantitative:** Refuted by the existence of exceptional non-AI outliers.
- **Case Studies:** Explicit instances of counterexamples (Calendly, Basecamp, and Spanx).
- **Interviews:** Every expert categorically disagreed with the necessity argument; AI is "expected" or "infrastructural," but not required.

H1 is not supported. AI as a universal prerequisite for startup funding is rejected.

2. **Hypothesis 2:** AI increases the probability of securing investment but is not strictly required.

- **Quantitative:** AI-Core companies displayed better averages, but there was no statistical significance.
- **Case Studies:** When AI was fully incorporated, AI-Core companies (OpenAI, Anthropic) drew significant, ongoing investment.
- **Interviews:** Conditional support; AI can increase visibility and valuation, but only if it is used in conjunction with timing, execution, and relevance.

H2 is partially supported. AI can increase fundraising possibility even though its impact depends on industry fit, integration, and founder credibility, AI can increase fundraising possibility.

3. **Hypothesis 3:** Startups without AI can succeed through other signals such as branding, execution, or founder credibility.
    - **Quantitatively**, non-AI companies yielded favorable results for individual funding.
    - **Case Studies:** Non-AI companies were valued at billions of dollars due to their constant delivery, storytelling, and usability.
    - **Interviews:** The most compelling theme was that investors value team quality and technology deployment skills more than artificial intelligence (AI) in and of itself.

H3 is strongly supported. The success of funding is still strongly predicted by alternative credibility signals.

3.5.4 Hypothesis Testing output summary

Table 3.9: Summary Table of Hypothesis Testing

Hypotheses	Quantitative evidence	Case study	Interviews	Final Verdict
H1	Refuted (high non-AI outlier)	Contradicted by multiple non-AI successes	Cast into doubt by expert reflections on sector variation	Not Supported
H2	Weakly supported (avg. funding higher)	Illustrates advantages when deeply integrated (AI-core)	Viewed as conditional on timing and technical substance	Partially Supported
H3	Supported (outliers exist)	Suggests strong alternatives (brand, execution, clarity)	Emphasized by all experts	Strongly Supported

3.5.5 Investor Evolution and Future Considerations

A consistent message emerged from all approaches: investor expectations are maturing. What was once a novelty (AI) is now an infrastructure assumption. The role of AI in funding narratives is changing from novelty to necessity, not as a differentiator but as a baseline expectation, much like websites and digital channels were 20 years ago.

As **Paolo Celini** put it, "If you don't have AI, it sounds like you don't have internet." Michele Costabile referred to this as the "end of AI exceptionalism." Going forward, narrative buzzwords won't define fundraising success; instead, strategic clarity, sector logic, and founder capacity will.

3.6 Implications of the study

The findings of this study have several important implications for theory, practice, and future research on how artificial intelligence (AI) affects startup funding dynamics.

3.6.1 Implications for Startup Founders and Entrepreneurs

The findings provide startup founders with tactical guidance on managing investor expectations in an ecosystem that is becoming more and more reliant on artificial intelligence. Even though integrating AI into a startup can make it more appealing, especially if it is central to the business plan, this study shows that its existence by itself does not ensure funding success. According to the findings, investors now distinguish between three types of startups: non-AI startups, which rely on other strengths, AI-core startups, where AI is essential to creating value, and AI-pitch startups, where AI is mentioned in passing.

Most importantly, if AI is signaled superficially without demonstrating technical or operational depth, it may backfire. Building a convincing story around AI capabilities should thus be the founders' top priority. They should also make sure that the technology is in line with team competencies, strategic scalability, and core market needs. The study also reassures non-AI startups that investment is still feasible without embracing AI narratives, especially those with strong market traction, differentiation, or founding teams.

3.6.2 Implications for Investors and Venture Capital Firms

The study shows the evolution of investor discernment regarding AI narratives. According to expert interviews, generic references to artificial intelligence are increasingly viewed with suspicion, and due diligence procedures now place greater emphasis on the founders' capacity to use AI effectively than on its existence alone. This emphasizes for investors the necessity of improving assessment criteria to distinguish between true technological integration and "AI washing."

Sectoral nuance also turned out to be a significant moderating factor. Investors need to think about whether AI is a structural requirement (for example, in data-intensive industries like computer vision, fintech, and health tech) or just an improvement in other areas (for example, consumer goods or basic materials). The typology presented in this study provides a useful framework for differentiating startups based on how well AI fits into their business plans.

3.6.3 Implications for Theory and the Startup Funding Literature

The theoretical discussion on signaling in entrepreneurial finance is expanding, and this thesis adds to it. It adds nuance to current signaling theory by demonstrating how, although AI was once a potent indicator of innovation, its power has diminished as the signal has grown more "noisy" and pervasive. The empirical study offers a unique mixed-methods viewpoint on how investors react to AI narratives by fusing statistical performance analysis, necessity logic modelling, and expert triangulation.

Given this, the study gives credence to the idea that the signaling environment is dynamic and that investors' perceptions of signals change over time, particularly in reaction to hype cycles and the spread of new technologies. In line with a contingent view of venture evaluation, the data also supports the idea that other signals, like team quality, traction, and execution clarity, can be used in place of AI to draw funding.

3.6.4 Implications for Policy and Ecosystem Development

The study presents important considerations at the ecosystem level for incubators and policymakers looking to promote innovation. While encouraging the use of AI is beneficial, support initiatives should also promote openness, moral communication, and the growth of fundamental business principles that go beyond fads. Critical thinking and market alignment ought to be given the same weight in entrepreneurial education as technical skills. Additionally, by emphasizing the dangers of over-incentivizing AI adoption without taking sectoral appropriateness or business logic into account, the findings could help shape public and private funding frameworks. This is especially significant for emerging markets like Rwanda or developing innovation economies like Italy, where AI integration must be based on needs and capabilities that are pertinent to the local context.

3.6.5 Recommendations for future research

Although this study provides insightful information about the perceived role of AI in startup funding, it also highlights several significant research directions. The following suggestions are organized to promote methodological improvement, scholarly continuity, and wider applicability of the results.

- **Expand Sample Size and Geographic Scope**
  The quantitative and case-based elements of this thesis cover a wider international landscape, while the interview insights are mainly from Italian venture capitalists and innovation leaders. Future studies should build on this by comparing and contrasting various geographical areas, particularly by taking into account the viewpoints of investors from Asia, Africa, and North America. Such research could reveal regional heuristics or biases in funding decisions by exposing culturally and institutionally specific variations in the way AI is perceived and valued in startup narratives.

- **Investigate Investor Signal Interpretation Mechanisms**
  This study used a startup-centric approach, concentrating on the correlation between funding outcomes and the signals that founders give off about AI. Future studies might take an investor-centric approach, looking at how various investor types, such as impact investors, corporate venture capitalists, and seed funds, decipher startup narratives. Interviews with a wider range of investors or ethnographic research may reveal internal biases and heuristics in decision-making concerning innovation signals and technology hype.

- **Deconstruct Artificial intelligence into More Granular Technological Signals**
  Future studies could break down this label into distinct sub-technologies, like computer vision, natural language processing, predictive analytics, or generative AI, as this thesis treated AI as a single, broad category. This would assist in determining whether certain types of AI are thought to be more reliable or deserving of funding than others.

The impact of various AI subfields on investor perceptions and startup valuations could be examined using quantitative models.

- **Integrate Ethical and Social Considerations**
  Concerns regarding algorithmic fairness, data privacy, and ethical use are also intensifying as AI is incorporated more deeply into startup ecosystems. Future research could examine how funding outcomes and investor trust are impacted by responsible AI narratives as opposed to purely functional ones. For startups working in delicate industries like health tech, edtech, or surveillance technologies, this would be particularly useful.

Conclusion

The purpose of this study was to examine how artificial intelligence (AI) is portrayed in startup investment narratives, specifically examining whether AI serves as a prerequisite for a start-up to obtain capital. The thesis assessed the signaling power of AI in modern European startup ecosystems using a mixed-methods approach that included expert interviews, qualitative case studies, and quantitative statistical analysis of startup funding data.

The results clearly reject that AI is a universal requirement for financing (H1). Rather, they indicate a more complex environment where AI is neither sufficient nor required on its own but can increase the likelihood of funding (H2) in certain circumstances. The data specifically shows that the inclusion of AI in a startup's story only results in funding success when it is viewed as being implemented in a meaningful way rather than being invoked symbolically. This is particularly true in industries where AI is anticipated to provide competitive or functional benefits.

More importantly, the study supports (H3) the idea that other signals, like sector fit, team strength, and the clarity of the business model among many more, can make up for or even outweigh AI's contribution to investor decision-making. Investor respondents highlighted founder competence and domain-specific execution as key selection criteria, a finding that was consistent across the case study analysis and interview themes.

The Study bridges the gap between investor-centric evaluation logic and founder-centric signaling theory through triangulation. By demonstrating the growing significance of signal credibility and empirically testing the declining symbolic value of "AI" as a buzzword, it adds to the body of research on entrepreneurial signaling, narrative framing, and technology hype.

The term "AI-enabled" might carry as little persuasive weight in the near future as "internet-connected" is now. This necessitates narrative authenticity and strategic clarity from founders. It indicates that due diligence needs to be recalculated for investors beyond mere platitudes. This study provides a starting point for both parties to interact more critically with the changing innovation language.

This thesis documents a pivotal point in the development of startups: the shift of AI from an innovation differentiator to an infrastructure baseline. It draws attention to the founders' strategic actions, investors' flexible reactions, and the limitations of symbolic signaling in a developing tech environment. The study is a reminder that substance eventually prevails over style in narrative-driven capital markets. The evaluation focus will continue to move from what startups claim to use to how and why they use AI as it becomes more widely available and integrated.

Limitations of the Study

This study has certain limitations despite its depth. Despite its robustness, the dataset was primarily geographically concentrated in the European and American contexts, specifically within innovation ecosystems that were impacted by market dynamics and EU policy. Although insightful, the case study and expert interview sample cannot be statistically generalized. Additionally, subjective interpretation played a role in the coding of AI signaling categories (AI-core, AI-pitch, and non-AI), which may introduce bias among coders even though it was triangulated. Finally, because AI adoption is dynamic, some results might become outdated as investor and market heuristics change quickly.

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Appendices

Appendix A: Raw Data used for quantitative Analysis

Startup	AI_Category	category	Total_Funding	Time_First_Fund	Funding_Rounds	Stage_Code	Investor_Type	AI_In_Pitch	Industry
OpenAI	1	AI-Core	61,900	1.00	11	7	VC, Corp VC	Yes	GenAI / ML infra
Anthropic	1	AI-Core	18,200	3.00	14	6	VC, Corp VC	Yes	GenAI
Cohere	1	AI-Core	970	17.00	5	5	VC, Corp VC, VC, GOC	Yes	NLP / Enterprise
Adept AI	1	AI-Core	415	4.75	2	3	VC, Corp VC	Yes	ML Agents
Scale AI, inc	1	AI-Core	1,600	2.00	8	7	VC	Yes	Gen AI/ML
Stability AI	1	AI-Core	181	30.00	3	1	VC	Yes	GenAI / Imaging/ saas
Inflection AI	1	AI-Core	1,500	4.50	2	14	VC, Corp VC	Yes	Gen AI/ML
Synthesia	1	AI-Core	337	2.00	6	5	VC	Yes	Video AI
Runway	1	AI-Core	545	12.00	9	5	VC	Yes	Creative AI
Replit	1	AI-Core	222	23.00	6	3	VC, Corp VC	Yes	Dev tools AI
Eleven Labs	1	AI-Core	281	13.00	5	4	VC	Yes	Gen AI
Mistral AI	1	AI-Core	1,100	1.50	7	3	VC	Yes	NLP/ML/ Gen AI
Lemonade	2	AI-Pitch	619	8.00	9	12	VC, PE	Yes	Insurtech
Gong.io	2	AI-Pitch	583	9.00	8	15	VC	Yes	Sales AI
Eight Sleep	2	AI-Pitch	162	16.00	12	4	VC	Yes	Sleeptech

Clara Labs	2	AI-Pitch	11	36.00	4	2	VC	Yes	Virtual Assistants
Babylon Health	2	AI-Pitch	1,200	39.00	9	13	VC	Yes	Healthtech
Wework	2	AI-Pitch	12,800	18.00	22	14	Corp VC	Yes	Real estate tech
Grammarly	2	AI-Pitch	545	89.00	4	3	Corp VC	Yes	Edtech , MarTech
Compass	2	AI-Pitch	1,520	8.00	9	16	VC	Yes	Proptech
Upstart	2	AI-Pitch	129	4.00	8	11	VC	Yes	Fintech
Fathom Health	2	AI-Pitch	61	6.00	3	3	VC	Yes	Medical Coding
Drift	2	AI-Pitch	107	9.00	3	14	VC, Corp VC	Yes	SalesTech
Hopper	2	AI-Pitch	740	12.00	12	8	VC	Yes	Traveltech
Duolingo	3	Non-AI	183	3.00	9	11	VC	No	Edtech
Notion	3	Non-AI	353	10.00	6	5	VC	No	Productivity SaaS
Warby Parker	3	Non-AI	573	15.00	9	13	VC	No	E-commerce
Asana	3	Non-AI	453	22.00	5	6	VC, Corp VC	No	Productivity Saas
Glossier	3	Non-AI	266	36.00	6	6	VC	No	DTC Beauty
Stripe	3	Non-AI	9,810	16.00	24	10	VC, Corp VC	No	Fintech
Calm	3	Non-AI	225	9.00	9	4	VC	No	Wellness
Canva	3	Non-AI	589	14.00	18	7	VC	No	Design SaaS
Allbirds	3	Non-AI	255	23.00	9	6	VC	No	Eco Footwear

Casper	3	Non-AI	340	-3.00	5	14	Corp VC	No	DTC Sleep
Hims & Hers	3	Non-AI	197	2.00	4	11	VC	No	Telehealth
Robinhood	3	Non-AI	5,730	8.00	14	11	VC	No	Fintech

Appendix B: SPSS Output

Paragraph

Warning # 67. Command name: GET FILE

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Descriptives

[DataSet1] C:\Users\HP\OneDrive\Desktop\Thesis\Startups dataset-Thesis.sav

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
Total funding raised ($ million)	36	61888.60	11.40	61900.00	3463.9194	1790.24326
Time to first funding (months)	36	92.00	-3.00	89.00	14.5208	2.75455

Number of funding rounds	36	22	2	24	8.31	.853
Valid N (listwise)	36					

Descriptive Statistics

	Std. Deviation
	Statistic
Total funding raised ($ million)	10741.45959
Time to first funding (months)	16.52729
Number of funding rounds	5.120
Valid N (listwise)	

Paragraph

Oneway

Descriptives

Total funding raised ($ million)

					95% Confidence Interval for Mean	
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound
Core	12	7270.8417	17929.59019	5175.82686	-4121.0764	18662.7598
Pitch	12	1539.7500	3577.27312	1032.66980	-733.1409	3812.6409
None	12	1581.1667	3021.84946	872.33280	-338.8249	3501.1582
Total	36	3463.9194	10741.45959	1790.24326	-170.4676	7098.3065

Descriptives

Total funding raised ($ million)

	Minimum	Maximum
Core	181.00	61900.00
Pitch	11.40	12800.00
None	183.00	9810.00
Total	11.40	61900.00

ANOVA

Total funding raised ($ million)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	260878114.551	2	130439057.275	1.140	.332
Within Groups	3777385276.846	33	114466220.510		
Total	4038263391.396	35			

ANOVA Effect Sizes[a,b]

			95% Confidence Interval	
		Point Estimate	Lower	Upper
Total funding raised ($ million)	Eta-squared	.065	.000	.229
	Epsilon-squared	.008	-.061	.182
	Omega-squared Fixed-effect	.008	-.059	.178
	Omega-squared Random-effect	.004	-.029	.098

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: Total funding raised ($ million)

Tukey HSD

(I) AI-Role type	(J) AI-Role type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Core	Pitch	5731.09167	4367.80304	.399	-4986.5995	16448.7828
	None	5689.67500	4367.80304	.404	-5028.0162	16407.3662
Pitch	Core	-5731.09167	4367.80304	.399	-16448.7828	4986.5995
	None	-41.41667	4367.80304	1.000	-10759.1078	10676.2745
None	Core	-5689.67500	4367.80304	.404	-16407.3662	5028.0162
	Pitch	41.41667	4367.80304	1.000	-10676.2745	10759.1078

Homogeneous Subsets

Total funding raised ($ million)

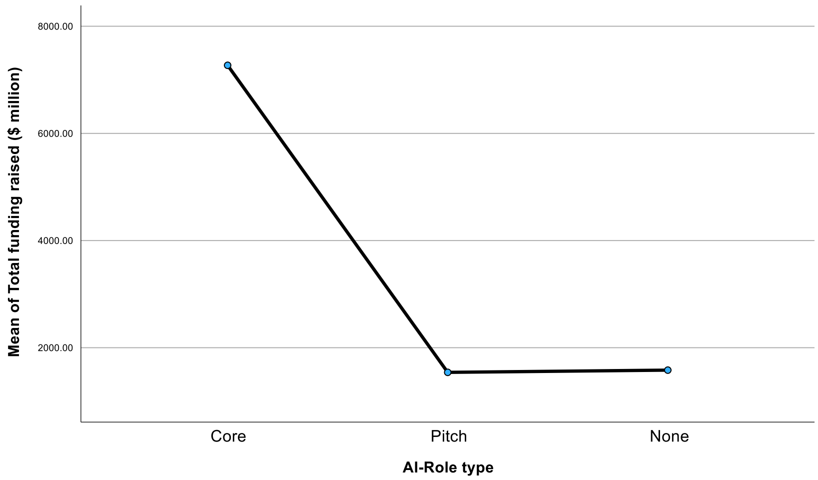
Tukey HSD[a]

AI-Role type	N	Subset for alpha = 0.05
		1
Pitch	12	1539.7500
None	12	1581.1667
Core	12	7270.8417
Sig.		.399

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 12.000.

Means Plots



Paragraph

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AI-Role type * Type of investor(s)	36	73.5%	13	26.5%	49	100.0%

AI-Role type * Type of investor(s) Crosstabulation

	Type of investor(s)			
	Corp VC	VC	VC, Corp VC	VC, Corp VC, GOC

AI-Role type	Core	Count	0	6	5	1
		% within AI-Role type	0.0%	50.0%	41.7%	8.3%
		% within Type of investor(s)	0.0%	26.1%	62.5%	100.0%
	Pitch	Count	2	8	1	0
		% within AI-Role type	16.7%	66.7%	8.3%	0.0%
		% within Type of investor(s)	66.7%	34.8%	12.5%	0.0%
	None	Count	1	9	2	0
		% within AI-Role type	8.3%	75.0%	16.7%	0.0%
		% within Type of investor(s)	33.3%	39.1%	25.0%	0.0%
Total		Count	3	23	8	1
		% within AI-Role type	8.3%	63.9%	22.2%	2.8%
		% within Type of investor(s)	100.0%	100.0%	100.0%	100.0%

AI-Role type * Type of investor(s) Crosstabulation

			Type of investor(s)	
			VC, PE	Total
AI-Role type	Core	Count	0	12
		% within AI-Role type	0.0%	100.0%
		% within Type of investor(s)	0.0%	33.3%
	Pitch	Count	1	12
		% within AI-Role type	8.3%	100.0%
		% within Type of investor(s)	100.0%	33.3%
	None	Count	0	12

	% within AI-Role type	0.0%	100.0%
	% within Type of investor(s)	0.0%	33.3%
Total	Count	1	36
	% within AI-Role type	2.8%	100.0%
	% within Type of investor(s)	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	9.859[a]	8	.275
Likelihood Ratio	10.966	8	.204
N of Valid Cases	36		

a. 12 cells (80.0%) have expected count less than 5. The minimum expected count is .33.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.523	.275
	Cramer's V	.370	.275
N of Valid Cases		36	

Paragraph

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AI-Role type * AI Pitched	36	73.5%	13	26.5%	49	100.0%

AI-Role type * AI Pitched Crosstabulation

			AI Pitched		
			No	Yes	Total
AI-Role type	Core	Count	0	12	12
		% within AI-Role type	0.0%	100.0%	100.0%
		% within AI Pitched	0.0%	50.0%	33.3%
	Pitch	Count	0	12	12
		% within AI-Role type	0.0%	100.0%	100.0%
		% within AI Pitched	0.0%	50.0%	33.3%
	None	Count	12	0	12
		% within AI-Role type	100.0%	0.0%	100.0%
		% within AI Pitched	100.0%	0.0%	33.3%
Total		Count	12	24	36
		% within AI-Role type	33.3%	66.7%	100.0%
		% within AI Pitched	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)

Pearson Chi-Square	36.000[a]	2	<.001
Likelihood Ratio	45.829	2	<.001
Linear-by-Linear Association	26.250	1	<.001
N of Valid Cases	36		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 4.00.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	1.000	<.001
	Cramer's V	1.000	<.001
N of Valid Cases		36	