AI as Co-Founder? Examining the Role of AI in New Venture Teams

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Abstract

Artificial intelligence (AI) is rapidly transforming entrepreneurship, not only by optimizing workflows but also by reshaping how startups are founded and managed. This study explores how AI influences early venture processes, the extent to which it can be conceptualized as a co-founder rather than a tool, and the risks and challenges that accompany this integration. A qualitative approach was adopted to investigate these dynamics. Semi-structured interviews were conducted with 17 founders of early-stage ventures across diverse industries, primarily in Lisbon and Milan. The data were analyzed using the Gioia Methodology, enabling the inductive development of themes that capture how entrepreneurs perceive and implement AI within their ventures.

The empirical findings reveal three major patterns. First, AI acts as an operational catalyst, accelerating development, experimentation, and productivity, and enabling compressed timelines. Second, the technology drives a reconfiguration of team structures and dynamics, allowing ventures to remain lean; hybrid decision-making processes emerge, where human judgment is combined with AI-supported reasoning, creating new forms of cognitive collaboration. Third, significant barriers and risks were identified, including technical implementation challenges, concentration of AI expertise in large corporations, and limited engagement with complex regulatory frameworks such as the EU AI Act. These findings point to a dual reality: while AI lowers traditional entry barriers, it also creates new dependencies and systemic vulnerabilities.

Theoretically, the study extends entrepreneurship scholarship by challenging anthropocentric assumptions about founding teams. The findings suggest a need to conceptualize entrepreneurial agency as hybrid, distributed between humans and machines.

Title: AI as Co-Founder? Examining the Role of AI in New Venture Teams

Keywords: Artificial Intelligence, Entrepreneurship, Venture Teams, Scaling, Startups, Startup Ecosystem, Digital Entrepreneurship

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Resumo

A inteligência artificial (IA) está a transformar rapidamente o empreendedorismo, não apenas ao otimizar fluxos de trabalho, mas também ao redefinir a forma como startups são fundadas e geridas. Este estudo explora como a IA influencia os processos iniciais de criação de empresas, até que ponto pode ser conceptualizada como cofundadora em vez de mera ferramenta, e os riscos e desafios que acompanham essa integração. Para investigar essas dinâmicas, adotou-se uma abordagem qualitativa. Foram realizadas entrevistas semiestruturadas com 17 fundadores de startups em fase inicial, de diferentes setores, principalmente em Lisboa e Milão. Os dados foram analisados através da Metodologia Gioia, permitindo o desenvolvimento indutivo de temas que captam como os empreendedores percebem e implementam a IA nos seus projetos.

Os resultados empíricos revelam três padrões principais. Primeiro, a IA atua como catalisador operacional, acelerando o desenvolvimento, a experimentação e a produtividade, e possibilitando cronogramas mais curtos. Segundo, a tecnologia impulsiona uma reconfiguração das estruturas e dinâmicas das equipas, permitindo que as startups permaneçam enxutas; emergem processos de decisão híbridos, nos quais o julgamento humano se combina com o raciocínio suportado por IA, criando novas formas de colaboração cognitiva. Terceiro, foram identificadas barreiras e riscos significativos, incluindo desafios de implementação técnica, concentração de competências em grandes corporações e envolvimento limitado com enquadramentos regulatórios complexos, como o AI Act da UE. Esses resultados apontam para uma dupla realidade: embora a IA reduza barreiras tradicionais de entrada, cria também novas dependências e vulnerabilidades sistémicas.

Teoricamente, o estudo expande a investigação em empreendedorismo ao desafiar pressupostos antropocêntricos sobre equipas fundadoras. Os resultados sugerem a necessidade de conceptualizar a agência empreendedora como híbrida, distribuída entre humanos e máquinas.

Título: Inteligência Artificial (IA) como Co-Fundadora? Examinando o Papel da IA em Novas Equipas Empreendedoras

Palavras-chave: Inteligência Artificial, Empreendedorismo, Equipas Empreendedoras, Escala, Startups, Ecossistema Empreendedor, Empreendedorismo Digital

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Introduction

Problem Statement

The rapid advancement of artificial intelligence (AI) has significantly impacted various sectors, including entrepreneurship (Shepherd et al., 2022). New ventures - firms in their early stages of development and growth, in the process of bringing their initial products/services to market, forming a customer base, and putting into place organizational processes and procedures (Klotz et al., 2014), often face challenges such as resource scarcity, limited expertise, and constraints in decision-making processes (Knight et al., 2020); this limitations become particularly apparent in ventures founded by solo entrepreneurs or small teams. AI, with its capacity to augment human capabilities, offers a promising solution to these challenges (Chalmers et al., 2021). However, the conceptualization of AI as a co-founder in startups remains largely unexplored. Existing models, which emphasize human ownership and strategic autonomy, inadequately capture the role of AI as an increasingly active collaborator in venture creation. This research aims to address this gap by investigating how AI tools and agents can be integrated as a co-founder to enhance entrepreneurship in small teams and solo ventures, helping founders automate workflows, bootstrap and reduce the need for additional hires. We examinate the associated opportunities and risks.

Research Question

- How does AI transform the early processes of startups, particularly in terms of process optimization, decision-making, and resource orchestration?
- To what extent can AI systems be conceptualized as co-founders rather than tools in new venture teams?
- What are the risks associated with AI integration in startup founding, especially for small teams managing potentially very large AI startups?

Significance and Contribution

This research makes substantial contributions to both entrepreneurship theory and practice. Theoretically, it extends founding team literature by reconceptualizing what constitutes a "founder" in the age of artificial intelligence, challenging traditional anthropocentric definitions while proposing new frameworks for understanding human-AI collaboration in venture creation. From a practical perspective, the research provides entrepreneurs with evidence-based guidance for effectively integrating AI systems into founding processes, helping them identify appropriate applications, implement effective governance mechanisms, and anticipate potential challenges. Furthermore, the findings inform policy development regarding AI regulation in entrepreneurial contexts, particularly addressing concerns about concentration of control and ethical implementation in rapidly scaling ventures.

Literature Review

2.1 Artificial intelligence and its role in business and entrepreneurship

Generative Artificial Intelligence (AI) represents one of the most significant technological revolutions of recent decades. The advent of ChatGPT, a platform developed by OpenAI, has profoundly transformed how we create and engage with content, making interactions with the digital world increasingly intuitive and natural. Launched in November 2022, the Large Language Models (LLMs) based platform allows users to engage in conversational exchanges with an algorithm capable of generating responses that closely mimic human communication, demonstrating capabilities that challenge the Turing Test. The impact of this technology was immediate: within just two months, ChatGPT reached 100 million monthly users globally, becoming the fastest-growing platform in history.

The widespread adoption of AI has opened up unprecedented business opportunities. Entrepreneurs now have easier access to AI solutions, which are no longer seen as futuristic or exclusive innovations but are instead available at a relatively affordable cost. This democratization of AI means that it is no longer limited to large corporations (Iansiti and Lakhani, 2020) and could be leveraged by new venture teams, the group of individuals that is chiefly responsible for the strategic decision making and ongoing operations of a new venture (Klotz et al., 2014). AI changes how entrepreneurs develop, design, and scale their companies throughout the entrepreneurial process (Chalmers et al., 2021). As with any disruptive innovation, AI can empower entrepreneurs, enabling the creation of new opportunities and the introduction of novel products and services (Obschonka and Audretsch, 2020). Additionally, AI techniques can enhance decision-making systems within entrepreneurial ventures, improving the quality, effectiveness, and efficiency of decisions, ultimately boosting operational performance (Kraus et al., 2020).

Entrepreneurship literature is increasingly recognizing AI as an external enabler for entrepreneurship, impacting economic transformation by facilitating new business opportunities through data-driven innovation (Obschonka et al., 2020). The integration of AI into entrepreneurship has implications for venture creation, influencing both the decision to

start a business and the operational dynamics of scaling it (Chalmers et al., 2021). Entrepreneurs must now navigate an evolving landscape where AI not only optimizes processes but also plays a role in shaping the quality of life for those engaging in new venture creation. A particularly comprehensive framework for examining the intersection of AI and entrepreneurship is the model developed by Chalmers et al., (2021), which categorizes key touchpoints into five domains. These include (a) the antecedents of venture creation, examining AI's influence on entrepreneurial triggers; prospecting, addressing AI-driven information search and value creation; (b) organizational design, exploring AI's impact on venture structures and decision-making; exploiting, focusing on AI-driven commercialization and scaling strategies; and (c) venture outcomes, assessing AI's broader effects on success, well-being, and economic impact.

To fully understand AI's effects on entrepreneurship Chalmers' framework benefits from integration with Nambisan et al., (2017) foundational work on digital entrepreneurship theory. Nambisan argues that digital technologies create less bounded entrepreneurial processes and outcomes, challenging traditional conceptions of entrepreneurial agency by distributing it across human and technological actors. This theoretical lens is essential for examining the spectrum between AI, a complex digital artifact, as enabler versus co-founder, as it helps explain how agency shifts when AI systems demonstrate increasing autonomy in activities traditionally performed by human entrepreneurs. The blurring boundaries between human and technological agency that Nambisan et al., (2017) identifies directly inform our understanding of how AI might function not merely as a tool but as an agent with co-founder-like capabilities in entrepreneurial ventures.

Building upon these theoretical foundations, Giuggioli et al., (2022) provides a systematic analysis of the AI-entrepreneurship relationship through a comprehensive literature review, identifiying a sequential process model for AI-enabled entrepreneurship consisting of four interconnected clusters: (1) opportunity recognition, (2) decision-making, (3) performance enhancement, and (4) education and research. This process model offers a structured approach to understanding how AI transforms each stage of entrepreneurial activity.

It is therefore crucial to understand the ways in which AI is influencing entrepreneurship, the opportunities and risks it presents, and how it is reshaping the entrepreneurial process. To explore this, I begin by examining the evolution of the technology.

2.1.1 Definition of AI and Key Technologies

The success of ChatGPT didn't happen overnight; this transformative moment is the result of AI's evolution from an academic field into a force shaping industries, businesses, and daily life. AI formally emerged as a research field in the 1950s. Alan Turing's seminal paper, Computing Machinery and Intelligence, explored the possibility of intelligent machines and introduced the Turing Test as a benchmark for evaluating machine intelligence. The discipline was then officially established in 1956 at the Dartmouth Summer Research Project on Artificial Intelligence, an event that set the stage for modern AI applications (Ertel & Black, 2018).

For much of its history, AI remained a theoretical field with limited real-world applications. Progress was marked by alternating cycles of enthusiasm and stagnation, commonly referred to as AI "winters" (Haenlein & Kaplan, 2019). However, since the early 2010s, AI has undergone a resurgence, driven by advancements in statistical machine learning, deep learning, and computing power (Dunjko & Briegel, 2018). These breakthroughs have enabled AI applications in industries ranging from financial services and pharmaceutical research to automotive manufacturing. Deep learning, in particular, has revolutionized AI by leveraging artificial neural networks inspired by human biology. Through hierarchical layers, each identifying distinct features, these networks recognize patterns in vast pools of unstructured data, enhancing technologies such as facial recognition, natural language processing, and autonomous systems (LeCun et al., 2015).

The diffusion of AI (Taddy, 2018) is central in the Fourth Industrial Revolution (4IR), or Industry 4.0. These systems integrate a range of emerging general-purpose technologies, artificial intelligence, blockchain, genomics, and the Internet of Things (IoT), and are being applied across multiple industries. What sets Industry 4.0 apart from previous industrial revolutions is the unprecedented speed of change. The speed of AI diffusion, in particular, is driven by advancements in the AI technology stack, including a new generation of intelligent processors and quantum computing (Dunjko et al., 2018). Another key distinction of Industry 4.0 is the decoupling of labor costs from economic outputs (Chalmers et al., 2021). Unlike previous industrial eras, wealth creation is now increasingly independent of human labor, owing to the near-zero marginal costs associated with nonrival and nonexcludable digital goods

(Goldfarb et al., 2019; Schwab et al., 2017). Striking examples are WhatsApp, which had only 55 employees but over 450 million users when it was acquired by Facebook in 2014 for $19 billion, and Midjourney which reached $200 millions in annual recurring revenues in 2 years with 10 people.

AI's role in these transformations extends beyond automation; it influences decision-making, optimizes business processes, and redefines interactions between firms and stakeholders (Giuggioli et al., 2022). It's disruptional power is being recognized by the market: venture capital investment in AI has surged (Su, 2019), marking a shift from past AI "winters" to sustained commercial traction (Furman & Seamans, 2019).

When analyzing the impacts of AI on new ventures, it becomes crucial to understand its various forms and capabilities. AI can be classified in multiple ways. One approach distinguishes between analytical AI, human-inspired AI, and humanized AI based on the type of intelligence exhibited (Kaplan et al., 2019). Another framework categorizes AI's evolutionary trajectory into Artificial Narrow Intelligence (ANI), which specializes in specific tasks, Artificial General Intelligence (AGI), which aspires to human-like cognitive abilities, and Artificial Super Intelligence (ASI), a theoretical stage surpassing human intelligence (Kaplan et al., 2019). Despite these classifications, what AI systems have in common, is the ability to interpret data, learn from it, and adapt their behavior to achieve specific goals. AI refers to a range of advanced technologies including machine learning, autonomous robotics, vehicles and computer vision; in this paper I focus on AI tools used by new venture teams, that can "ingest human-level knowledge, and use this information to automate and accelerate tasks that were previously only performed by humans" (Taddy, 2018, p.62).

While existing research acknowledges AI's potential to democratize entrepreneurship by lowering resource barriers (Iansiti et al., 2020), it inadequately addresses the unique implications for solo entrepreneurs and small teams. The distinction between AI as an enabling technology versus AI as a semi-atonomous team member has implications for entrepreneurial processes. This conceptual distinction is not merely semantic but affects how we understand agency, decision-making authority, and accountability in new venture creation. Additionally, as AI-enabled ventures operated by small teams can rapidly scale to serve massive user bases (as exemplified by WhatsApp's 450 million users with just 55 employees), the literature has not sufficiently examined the associated systemic risks.

2.2 Founding new ventures with AI

The conceptualization of new venture founding has evolved substantially from early views centered on the "lone entrepreneur" to more sophisticated team-based models. Timmons et al. (1978) was among the first to identify the role of founding teams rather than individual entrepreneurs in venture creation, suggesting that entrepreneurship is a team activity. This perspective has been reinforced through decades of research showing that team-based ventures consistently outperform those led by solo entrepreneurs in terms of survival rates, growth, and value creation (Timmons et al., 1994). Traditional entrepreneurship theories have also focused primarily on human agency, cognitive processes, and social dynamics (Timmons et al., 1978; Klotz et al., 2014; Knight et al., 2020). However, the advent of AI necessitates a reconceptualization of these foundational elements to accommodate technological agency and human-machine collaboration in venture creation. The shifting paradigms in founding processes reflect broader changes in how entrepreneurs conceptualize and execute new venture creation. Von Briel et al. (2018) highlight how digital technologies have altered the temporal dynamics of entrepreneurship, enabling faster iteration, more rapid scaling, and non-linear growth trajectories. This chapter explores how AI technologies are reshaping the theoretical foundations, practical processes, and organizational dynamics of startup founding. As AI becomes increasingly integrated into entrepreneurial activities, scholars and practitioners must reconsider traditional frameworks of new venture formation and examine the implications of this technological shift.

While AI offers transformative potential for startup founding, it also introduces significant challenges. In their paper, Chalmers et al. (2021) indicate that technical expertise in AI remains concentrated, creating a potential misalignment between what nascent entrepreneurs believe they can accomplish with the technology and what ultimately proves possible. Furthermore, there exists a substantial skills gap in key roles required to implement complex AI systems (Chalmers et al., 2021), with high salaries at leading technology companies making it difficult for early-stage ventures to build teams with requisite skills. The integration of AI into founding processes must therefore be understood as both enabling and constraining, introducing new dependencies and resource requirements that entrepreneurs must navigate during early venture development.

2.2.1 Elements of Founding Startups

The founding process of new ventures includes several elements that together determine a new venture's ability to establish itself and grow successfully. These elements include founding team formation and organizational design, opportunity identification and evaluation, resource acquisition and allocation. Each of these elements faces unique challenges that AI technologies can potentially address, transforming the nature of early-stage venture creation (see Fig.1).

Knight et al. (2020) provide a framework for understanding startup teams through three key dimensions: ownership of equity, autonomy of strategic decision-making, and the degree to which a group is perceived as a cohesive. The ownership dimension captures the financial stake that team members hold in the venture. While earlier definitions often insisted that all team members must hold equity (Ensley et al., 1999), contemporary research recognizes variations in equity distribution. The autonomy dimension reflects the team's authority in strategic decision-making. As Knight et al. (2020) note, this dimension distinguishes new venture teams from other organizational entities, as new venture teams are typically described as having a "greater managerial discretion in shaping the venture's direction and wider latitude of action than most teams." (Klotz et al., 2014, page 228). This autonomy allows the team to create initial policies and procedures (Lin et al., 2017), recruit employees, and set the vision of the venture (Klotz et al., 2014). The cohesion dimension refers to the degree to which the team is perceived as a coherent social entity, both by team members themselves and by external observers.

Lazar et al. (2020) identify three primary strategies through which founding teams form, each with distinct implications for team composition and dynamics. The interpersonal attraction strategy drives team formation based on social and psychological factors, including shared values, mutual trust, and personal compatibility. The resource seeking strategy focuses on assembling complementary skills and capabilities. The hybrid approach balances relational factors with instrumental considerations. As Lazar et al. (2020) note, these hybrid approaches may yield the most effective teams, combining the social cohesion of interpersonal attraction with the functional diversity of resource seeking.

The identification and evaluation of entrepreneurial opportunities represents another foundational element of venture creation. Traditional models emphasize human insight and intuition in recognizing potential opportunities. The nature of opportunity identification reflects broader debates between discovery and creation views (Alvarez and Barney, 2007). While

discovery perspectives assume opportunities exist objectively and await identification, creation perspectives emphasize the active role of entrepreneurs in constructing opportunities through their actions. AI introduces new dimensions to this debate, as algorithmic systems can both enhance discovery processes (Chalmers et al., 2021) and enable new forms of opportunity creation introducing new products or services via entrepreneurial means (Obshonka et al., 2020)

Resource acquisition is a critical aspect of venture creation too, encompassing financial capital, human capital, and knowledge resources. As Knight et al. (2020) note, new ventures face significant resource constraints that shape their development trajectories. Financial capital acquisition follows several pathways, including self-funding, angel investment, venture capital, and alternative funding mechanisms such as crowdfunding. The choice among these pathways has implications not only for resource availability but also for venture governance and strategic autonomy (Bernstein et al., 2017).

2.2.2 AI Disrupting the Founding of Startups

Opportunity Recognition and Market Analysis

AI systems are transforming how entrepreneurs identify and evaluate opportunities by enabling the analysis of vast, unstructured datasets to identify patterns imperceptible to humans. As Chalmers et al. (2021) note, AI offers "superhuman information search and prediction" capabilities that enhance the opportunity recognition process. AI is significantly transforming idea production and validation during the founding phase. As Chalmers et al. (2021) observe, AI offers three distinct approaches to enhancing entrepreneurial search and idea production. First, science and technology-focused new ventures can leverage AI to search for technical solutions across complex combinatorial problem spaces dramatically accelerating experimentation that would traditionally require vast resources. Second, entrepreneurs can utilize social sentiment analysis and natural language processing to analyze social media and other online content to identify customer needs, uncovering market insights at unprecedented scale and speed. Third, entrepreneurs can test business assumptions with greater confidence using AI systems that predict customer reactions to features, pricing, or marketing approaches.

Gaspar et al. (2016) explore how AI can be deployed for analyzing social sentiment and identifying customer needs. Their research demonstrates how natural language processing and

sentiment analysis can extract valuable insights from social media, reviews, and other unstructured data sources. These insights enable entrepreneurs to identify latent customer needs, anticipate market trends, and develop solutions that address emerging problems before they become widely recognized. Machine learning techniques offer powerful capabilities for predicting market trends and assessing business potential. By analyzing historical data and identifying patterns that may not be apparent to human observers, these techniques can help entrepreneurs evaluate opportunity attractiveness with greater precision. Agrawal et al. (2019) examine how AI techniques enable searching of complex problem spaces, allowing entrepreneurs to explore solution landscapes more efficiently and identify promising opportunities that might otherwise remain undiscovered. Ramesh et al. (2018) and Suguna et al. (2019) explore machine learning applications for market analysis and customer segmentation, highlighting how AI can enhance entrepreneurs' understanding of market dynamics and customer preferences. These technologies enable more granular segmentation, more precise targeting, and more personalized customer engagement than traditional analytical approaches. For resource-constrained new ventures, these capabilities create opportunities to identify and serve niche markets more effectively, potentially offsetting competitive disadvantages relative to established incumbents.

Resource Orchestration and Optimization

AI is transforming how founding teams acquire, allocate, and optimize resources by enabling more precise matching between resources and needs. This capability is particularly valuable for new ventures, which typically face significant resource constraints that limit their strategic options. Duan et al. (2020) investigate the application of deep learning for predicting crowdfunding outcomes based on facial features of the founders, demonstrating how AI can enhance resource acquisition strategies to such a specific level. Their findings suggest that machine learning algorithms can identify patterns in successful funding campaigns that may not be apparent to human observers, enabling entrepreneurs to optimize campaign design and increase funding probability. AI tools support the screening of candidates (Shepherd et al., 2022), helping to set up a strong early team; automation enabled by AI technologies, not only reduces operational costs but also minimizes errors and improves the overall reliability of processes (Dash, et al., 2019). Entrepreneurs adopting AI-driven operational strategies gain a competitive edge by ensuring resource allocation is optimized, and workflows are streamlined;

by automating routine tasks and optimizing processes, entrepreneurs can allocate resources towards innovation and business growth (Eyo-udo et al., 2024). However, the literature also sheds light on the challenges entrepreneurs face in adopting AI technologies. High implementation costs emerge as a recurrent theme, as noted by Brynjolfsson and McAfee (2017), who argue that the initial investment required for AI integration can be a barrier for resource-constrained startups

New Organizational Designs Enabled by AI Integration

The integration of AI is driving changes in the organizational structure of founding teams. While Chalmers et al. (2021) note that AI's impact on venture structures has so far been moderate, emerging evidence points to a shift in labor division. Huang and Rust (2018) propose that tasks within new ventures will be distributed based on four distinct types of intelligence: mechanical, analytical, intuitive, and emotional. Initially, AI will enhance tasks requiring mechanical and analytical intelligence, gradually expanding its role to more complex intuitive and emotional functions. As a result, certain job categories will shrink or disappear, compelling entrepreneurial organizations to restructure around AI systems. This transformation will generate new tasks and job roles, often leading to higher-paid positions that are increasingly outsourced to skilled self-employed professionals (Aghion et al., 2017). However, as Davenport and Ronanki (2018) highlight, simply inserting AI into existing processes, an approach many firms currently take while experimenting with the technology (Brock et al., 2019), will not unlock its full potential. Instead, we can expect the emergence of novel organizational structures as AI deployment scales, particularly in ventures designed around AI as a core driver rather than a supplementary tool.

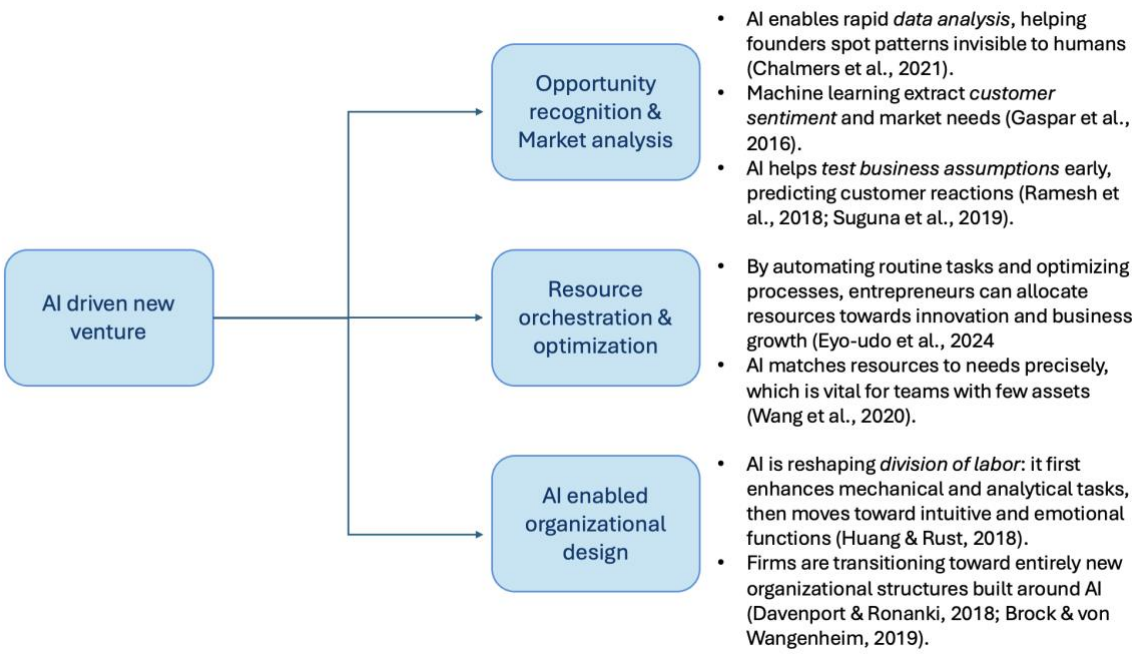

Figure 1: AI disrupting the founding of new ventures

2.3 AI's impact on entrepreneurial decision-making

Decision-making processes represent a core element of entrepreneurial activity, particularly in the context of the fundamental uncertainty that characterizes new venture creation (Knight, 1921). Traditional decision-making processes in new ventures have emphasized the entrepreneur's judgement (Foss and Klein, 2012), heuristic reasoning (Busenitz et al., 1997), and experiential learning (Politis et al., 2009). These approaches acknowledge the inherent limitations of rational decision models in contexts characterized by novelty and ambiguity. The tension between entrepreneurial intuition and data-driven approaches represents a central dynamic in contemporary venture founding. While intuition has traditionally played a prominent role in entrepreneurial decision-making, the availability of sophisticated analytical tools creates opportunities for more systematic approaches. Kraus et al. (2020) observe that AI techniques can enhance decision-making systems within entrepreneurial ventures, improving quality, effectiveness, and efficiency while ultimately boosting operational performance. This enhancement stems from AI's capacity to process vast quantities of data and identify patterns that might elude human perception. AI is hence transforming strategic decision-making in founding teams by augmenting cognitive capabilities and reducing decision biases. As Agrawal

et al. (2018) observe, AI-driven prediction serves as a critical input to decision processes, complementing human judgment in ways that enhance overall decision quality. Dellermann et al. (2019) examine hybrid intelligence decision support systems for business model validation, integrating human and artificial intelligence to evaluate proposed business models more effectively than either could achieve independently. Their research demonstrates how complementary capabilities, AI's analytical power and humans' contextual understanding, can be synergistically combined to enhance decision quality in conditions of uncertainty. This hybrid approach represents a promising direction for integrating AI into critical founding decisions while maintaining appropriate human oversight.

2.4 AI's broader influence on entrepreneurial activity

AI is found to influence individual-level desirability of pursuing the entrepreneurial route as it is undeniably one of the most fashionable and dynamic fields in the startup ecosystem. As a general-purpose technology, AI-driven entrepreneurial opportunities are emerging across a wide range of industries, attracting significant venture capital investment (Tricot et al., 2021). However, the increasing consolidation of "large tech" has already been associated with a long-term decline in business dynamism (Shapiro et al., 2019). Since these dominant technology firms lead AI investment, hold the majority of patents (Hartmann et al., 2020), and are well-positioned to sustain their market dominance, there is a risk of prolonged stagnation in entrepreneurial activity. Without effective antitrust legislation to enhance allocative efficiency and productivity, this concentration of power could further hinder innovation and competition within the economy (Decker et al., 2017). AI is also able to enhance the selling activity (Chalmers et al., 2021), which holds fundamental importance for the growth and sustainability of new ventures (Gimmon et al., 2020), by agumenting or replacing salespeople. By offering valuable support to new venture employees, for instance, a startup can leverage the technology to assess customer reactions to product features or pricing, enabling real-time adjustments to their value proposition based on the needs of diverse customer segments. Additionaly, AI as a general purpose technology, is found to compress the times related to multiple venture activities (Von Briel et al., 2018) where speed is a fundamental factor for venture success (Heirman et al, 2007). Finally, as Chalmers (2021) analyzes, the integration of AI technologies in new ventures enables cost savings in scaling activities; a future Industry 4.0-native organization could in fact utilize an AI-blockchain platform to streamline financial management, legal operations, and compliance processes (Susskind & Susskind, 2015). Customer service could be almost entirely managed by advanced conversational AI bots (Ghazvininejad et al., 2018). Additionally, sales,

marketing, and pricing tasks could be fully or partially automated and dynamically adjusted (Ghazvininejad et al., 2018), reducing commission fees and shifting customer acquisition costs toward data collection, maintenance, and analysis.

2.5 Risks of AI as a startup co-founder

The integration of artificial intelligence into venture creation represents a paradigmatic shift in entrepreneurial practice, redefining traditional notions of entrepreneurial opportunity recognition, strategic decision-making and organizational scaling. While Chapter 2.3 outlined AI's transformative potential, this chapter gives an overview to the technological liabilities inherent in human-AI founding teams, risks that remain critically understudied despite their profound implications for venture survival and societal welfare (Shepherd et al., 2022). AI systems that enhance operational efficiency simultaneously introduce risk exposures not fully captured by conventional entrepreneurship frameworks. Chalmers (2021) demonstrate how AI's capacity for exponential scaling amplifies the consequences of decision errors, transforming localized mistakes into systemic failures. For example, in 2014 Amazon developed a machine learning-based hiring tool that exhibited gender bias. The bias stemmed from training the AI system on predominantly male employees' CVs which the algorithm perceived as an indicator of success (Beneduce, 2020). This necessitates a reevaluation of governance models predicated on human-centric notions of responsibility.

Regulatory frameworks like the EU AI Act attempt to mitigate these risks through stringent compliance requirements, yet their implementation creates new barriers for resource-constrained ventures. Moreover, as Montes et al. (2019) caution, the centralization of AI infrastructure under tech oligopolies risks replicating power imbalances from the platform economy era, potentially stifling innovation while concentrating systemic risk.

2.5.1 Regulation and EU AI Act

The EU AI Act (European Union, 2024) establishes a risk-based regulatory framework that categorizes AI systems into four tiers: unacceptable risk (prohibited), high-risk (strict compliance), limited risk (transparency obligations), and minimal risk (self-regulation). High-risk AI applications in entrepreneurship, such as recruitment tools, credit scoring systems, and

biometric identification, require pre-market conformity assessments, including dataset validation and human oversight mechanisms. This creates a complex compliance environment for AI-driven ventures, particularly those operating in sensitive sectors like fintech or HR tech. Kop's analysis (2021) highlights that while legal sandboxes, regulatory tools allowing businesses to test and experiment with new and innovative products, services or businesses under supervision of a regulator for a limited period of time, aim to foster innovation, they fail to offset the structural advantages of large tech firms that dominate AI infrastructure (e.g., cloud platforms like AWS). This regulatory asymmetry risks stifling competition, as startups face compliance burdens that scale nonlinearly with customer growth, a phenomenon termed regulatory diseconomies of scale (Wiseman et al., 2014).

High-risk AI systems must undergo third-party audits and obtain CE certification to access EU markets, ensuring alignment with technical standards for robustness, transparency, and non-discrimination. Furthermore, article 10 mandates that training datasets for high-risk AI must be "representative, error-free, and adequately labeled" to mitigate algorithmic bias, imposing significant costs on new ventures collecting or curating proprietary data. Finally, AI systems interacting with humans (e.g., chatbots) must disclose their artificial nature, potentially reducing customer trust in AI-driven ventures.

The EU's strict "trustworthy AI" paradigm conflicts with the U.S.'s laissez-faire approach, forcing globally oriented ventures to maintain parallel compliance frameworks. This risks fragmenting innovation ecosystems, as seen in the GDPR's extraterritorial effects.

2.5.2 Accountability and Ethical Risks

AI's role in strategic decisions (e.g., pricing, hiring) creates ambiguity in assigning liability when outcomes harm stakeholders. Shepherd et al. (2022) identify "moral disengagement" risks, where founders attribute poor decisions to algorithmic errors rather than human oversight. Deep learning systems often produce unexplainable outputs, complicating business' ability to justify decisions to investors or regulators (Ras, 2022). This undermines traditional notions of entrepreneurial judgment, particularly in high-stakes scenarios like crisis management.

Futhermore, AI enables ventures to scale customer bases exponentially with minimal human labor, but increased delegation of decision-making from human employees to AI algorithms, amplifies systemic risks (Chalmers et al., 2021). For example, algorithmic errors in AI-driven

platforms can cascade globally within hours, as seen in fintech flash crashes. Additionaly, biases in training data (e.g., historical hiring patterns) can lead to discriminatory outcomes and poor operational decisions, exposing ventures to litigation under the EU AI Act's non-discrimination clauses.

Moreover, Gasser et al. (2017) highlight that the "black box" nature of many AI algorithms makes it challenging to understand and explain how decisions are made and complicates compliance with Article 13's transparency requirements. For new ventures managing large customer bases, ensuring transparency and providing clear explanations for AI-driven decisions becomes crucial. A World Economic Forum (Kumar et al., 2024) report indicate that AI and agentic AI are bringing corporate might to small teams and paving the way for solopreneur unicorns, fundamentally transforming how ventures can scale with limited human resources. However as Bain & Company (2025) observes, AI increases the operational, model, and ethical risks that organizations already manage. This increase is driven by several factors: unclear accountability, as AI-related risks are often missing from existing frameworks and lack a defined owner; lack of resources for validation processes, which rely on pre-generative-AI practices and require ongoing monitoring rather than one-time approval; vendor and third-party exposure, as embedded generative AI features demand more rigorous assessment to avoid unintended use; and a rapidly changing regulatory environment, which requires AI operating models to align continuously with evolving laws and industry standards.

Finally, AI-enabled ventures achieve faster scaling than traditional startups, employing fewer resources, exacerbating wealth concentration (Giuggioli et al., 2022). This risks political backlash, as seen in gig economy regulations targeting algorithmic management.

3 Methodology

To ensure the transparency and reliability of the study's findings, this chapter outlines the research design, data collection procedures, and analysis approach. A qualitative research methodology enables an in-depth and contextually rich exploration of how AI technologies enable founding teams in early-stage ventures.

3.1 Reasearch Design

The aim of this study was to identify how AI transforms the founding process of startups, particularly exploring the extent to which AI systems can be conceptualized as co-founders rather than tools in new venture teams; a research endeavor deemed best undertaken by a qualitative, inductive research design. According to Corley (2015), the objective of qualitative research is to provide "local (i.e. realistic and precise) interpretations of a phenomenon". Complementing this perspective, Lim et al. (2025) establish that qualitative approaches are especially valuable for comprehensive description and explanation of complex phenomena. This methodological foundation is particularly useful in our case, to uncover the context and experiences of entrepreneurs integrating AI into their founding processes as well as the lenghts to which AI supports them, similar or less to the enabling role of a co-founder.

3.2 Data Collection

Sample selection was an iterative process of criteria setting, drawing on the aims of our methodology, as well as interactions with nascent entrepreneurs engaging with AI-enabled startups, mostly in the Milan and Lisbon entrepreneurial ecosystems. I selected Portugal for its growing and dynamic ecosystem in AI solutions that are transforming many domestic sectors (Parracho et al., 2017). As for Milan, the city's startup ecosystem has seen 15-fold growth in the last decade, with AI and Machine learning as leading areas of startup investments (Milan ecosystem report 2024, Startup Reporter). Through collaboration with innovation hubs, incubators and acceleration programs in both cities, I was able to identify, from an array of industry sectors, 17 AI-driven ventures whose entrepreneurs confirmed that they were at a critical stage in their process of emergence. The selected startups are all early-stage ventures, spanning a variety of sectors and business models, and were chosen based on their proximity to the Catòlica Lisbon Entrepreneurship center (CLEC) , Bocconi for innovation (B4i) pre-accelerator and acceleration program or through direct outreach when their activities closely aligned with the research objectives. I used purposive sampling procedures where sample

members were handpicked to meet specific criteria (Campbell 2020), including being less than two years old, actively integrating AI technologies into core processes or embedding AI technologies into their offerings, and operating within the Euopean startup ecosystems (Table 1). Unlike random sampling, this approach involves selecting participants based on their alignment with the research objectives, thereby maximizing the relevance and depth of the insights gathered (Hamilton et al., 2019). Similar to previous studies, our sample was drawn from a variety of industries (Gemmell et al.). Industry and business model heterogeneity in the sample broadens the understanding of how different types of ventures conceptualize and implement AI in founding processes.

Nr.	Industry	Position	Ecosystem	Reference code
1	FinTech	Founder CEO	Zurich	AK
2	FinTech	Co-founder CTO	Lisbon	IM
3	FinTech	Founder CEO	Lisbon	SI
4	ClimateTech	Founder CEO	Lisbon	EM
5	PropTech	Co-founder COO	Milan	BS
6	Consumer	Co-founder CEO	Milan	KD
7	Consumer	Founder CEO	Milan	HM
8	SaaS	Co-Founder CMO	Lisbon	VA
9	SaaS	Founder CEO	Milan	DI
10	SaaS	Founder CTO	Milan	SS
11	SaaS	Founder CEO	Milan	SP
12	SaaS	Co-founder CEO	Lisbon	LA
13	SaaS	Co-founder CTO	Milan	AY
14	SaaS	Co-Founder CTO	Lisbon	CF
15	SaaS	Co-Founder	Lisbon	C2
16	Agentic AI	Founder CEO	Lisbon	DM
17	Agentic AI	AI Architect	Lisbon	MS

Table 1. Overview of interview partners

Multiple data sources were utilized to develop a comprehensive understanding of each case; in qualitative research, different data collection techniques can be applied, such as interviews,

focus groups and observations (Hamilton et al., 2019). Interviews were deemed as the most insightful data source for this study, employing a crucial assumption: the people constructing their organizational realities are “knowledgeable agents”, namely we assume that people in organizations know what they are trying to do and can explain their thoughts, intentions, and actions (Gioia et al., 2012). Furthermore, the flexibility of interview formats, such as semi-structured interviews, applied in this research, allows to address pre-defined topics as well as emerging, unexpected topics (Adhabi et al., 2017). Semi-structured interviews follow a predefined set of questions organized around key themes, providing a structured framework for the conversation. However, the interviewer retains the flexibility to introduce follow-up questions as needed to delve deeper into specific topics as the discussion evolves (Qu et al., 2011). While interviews served as the primary data collection method, these were supplemented with additional sources to enable triangulation. This approach also reduced the potential for researcher, source and respondent bias (Jick et al., 1979).

The core data collection involved semi-structured in-depth interviews with founders and key decision-makers, conducted online between March-August 2025, in English or Italian, typically lasting approximately 40 minutes per session. The interview protocol focused on four main areas aligned with our research questions: (1) the founder and venture’s background and business context, (2) how AI is integrated in the venture’s processes, (3) instances where AI functioned beyond a tool to influence strategic direction, and (4) perceived risks, governance and regulatory challenges of AI integration.

3.3 Data analysis

This study employs the Gioia Method (GM) as its analytical framework, which provides a structured yet flexible approach to interpreting qualitative data. The GM is particularly well-suited for inductive research, facilitating rigorous analysis while allowing for the emergence of novel insights (Magnani et al., 2023). Rooted in grounded theory, the GM emphasizes systematic data collection and analysis to enhance the trustworthiness and validity of the study’s findings (Gioia et al., 2013).

The methodological process within the GM consists of several key phases, including data gathering, three core stages of coding using the Nvivo software, and the final visualization of the data structure. The first stage involves identifying 1st-order concepts, which reflect the informants' own language and viewpoints, capturing their experiences without researcher

interpretation. This phase is considered *informant-centric* (Magnani et al., 2023). The second stage transitions into the formulation of 2nd-order themes, described as *researcher-centric*, in which the raw concepts are abstracted into broader thematic categories. Here, theoretical framing begins to shape the interpretation. The final stage focuses on consolidating these themes into aggregate dimensions, higher-level constructs that synthesize the data into a coherent theoretical structure (Magnani et al., 2023). By the 15th interview, participants' responses showed a clear repetition of key themes, with the final two interviews primarily confirming existing patterns rather than introducing new concepts, generating less than three percent of new codes.

Figure 2: Data Analysis Process based on Gioia incl. the achieved quantities

4 Results

This chapter presents the findings of the qualitative data analysis conducted interviewing 17 early-stage ventures integrating artificial intelligence into their processes. Following the Gioia method, four aggregate dimensions were derived from the interviews, capturing AI's role in entrepreneurial processes, agency and team dynamics, as well as the enabling effects and systematic risks related to its integration.

4.1 AI as an operational catalyst

Synthesizing the second-order themes, we derive the aggregated dimension "AI as an operational accelerator", which advances our answer to the research question concerning AI's impact on early-stage venture processes. This first aggregated dimension explores how AI technologies function as accelerators within new venture operations. Across the sample, founders described AI not merely as a support tool, but as a central driver of productivity gains, rapid experimentation, and speed in development processes. As their ventures matured,

entrepreneurs adopted increasingly sophisticated applications of AI, suggesting an evolutionary pattern in how the technology is integrated.

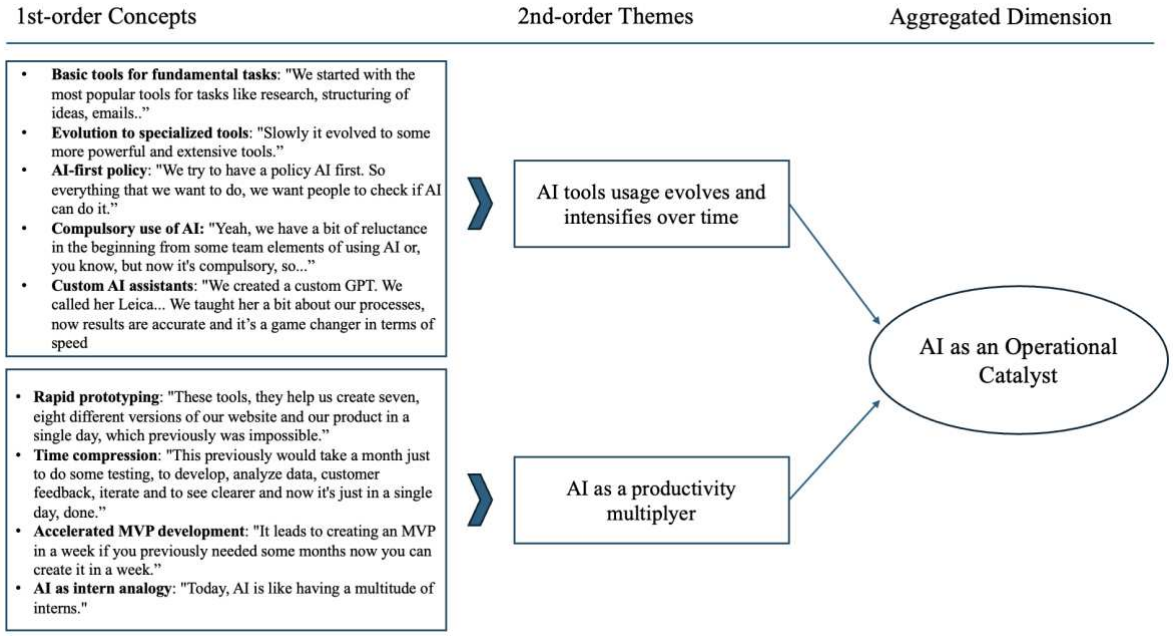

Figure 3: Data structure first aggregate dimension

4.1.1 Evolution of AI tools adoption

Results show an experimental approach carried on by founders, generally characterized by an initial use of LLMs (e.g., ChatGPT, Gemini, Claude), followed by an exploration of specialized ones (e.g., Cursor for coding, Bolt.new for prototyping). As venture matures and founders move up on the technology learning curve, usage also intensifies, shifting from initial reluctance to an AI-first culture. One ClimateTech founder notes:

"*We had a bit of reluctance in the beginning by certain team elements on AI use, but now it's cumpolsory to do so".(EM)* And another one*: "We try to have a policy AI-first. So everything that we want to do, we want people to check if AI can do it." (KD)*

Finally, more than 75% of the startups interviewed developed or is planning to develop their proprietary AI model, trained on domain-specifc data. Custom GPTs allow founders to enhance the quality of their AI's outputs, which are perceived as more accurate and less subject to hallucinations.

4.1.2 AI as a productivity multiplier

In addition to evolving use patterns, founders consistently emphasized AI's role in accelerating operational tasks. Rapid prototyping emerged as a prominent example, with one founder noting: *"These tools, they help us create seven, eight different versions of our website and our product in a single day, which previously was impossible."* (AK). Another founder highlighted the collapse of timelines across multiple processes: *"This previously would take a month… just to do some testing, to develop, analyze data, customer feedback, iterate […]. Now it's just in a single day, done."(CF).* Such compression not only increases speed but also allows teams to iterate more frequently, potentially improving product-market fit in shorter cycles. Furthermore, through the automation of administrative tasks, encountered in 88% of the interviews, times are compressed even further, empowering founders to focus on higher-value activities.

At this stage, several interviewees used the analogy of AI as an extension of the workforce, often characterizing it as an intern in the team:*"Today, AI is like having a multitude of interns."* (AI, DI, C2, SS, SP). These findings demonstrate how AI acts as a force multiplier within early-stage ventures. By enabling faster testing, reducing development bottlenecks, and lowering the cost of iteration.

Moreover, 82% of founders expressed a forward-looking view on the integration of agentic AI systems into their ventures. Rather than limiting AI to isolated support tasks or productivity enhancements, interviewees described ambitions to embed Agentic AI into product offerings and process workflows, describing a shared view that tool-based use of AI will shift into a more integrated and autonomous application. Several startups already implemented or were planning for agentic AI systems for customer-facing functions such as automated support. As one founder noted: "We want to deploy agentic AI, chatbots or copilots that can handle customer queries and even basic support." (AK) and "The most established agentic process we integrated in our startup is probably the chatbots." (DI) pointing towards a model where AI handles not only repetitive internal tasks but also dynamic interactions with end users.

4.2 Reconfiguration of venture teams structure and dynamics

AI's integration led to fundamental shifts in team composition, role definitions, and decision-making dynamics, enabling leaner teams and expanding venture teams' operational scope.

4.2.1 AI enables reduced teams structure

All cases ventures operated with teams ≤ 5 members leveraging AI to eliminate tradtional time-consuming tasks, *"For a startup it's normal to have a really small team and scale, but in the age of AI this goes even further" (AK).* Acting a s a productivity multipliyer for venture teams, AI enables founders to maintain larger control over their startup and give up less equity to business partners as noted by a FinTech CEO *"I am sure I would need more partners and I would need to give away more equity to my team" (IM).* Mantaining a leaner team helps early-stage ventures cut personell costs, reducing the startup burn rate and hence reshaping its financial planning activities, return on investment and probability of succes, ultimately making it more likely to attract external funds: *"Five years ago, I would have needed $1 million because I needed 10 people. But now, since I know that in two years, for example, I won't need junior devs anymore, I plan completely differently."(AY).* A sentiment shared by the majority of the founders interviewed. When addressing this category of questions, founders commonly described AI as akin to a highly productive and well-informed intern, used primarily for support tasks that enhance efficiency, as reported by a SaaS startup founder: "*An excellent intern who works 24/7 and doesn't complain (AI)".* Beyond internal implementation, founders reflected on how AI is altering the overall dynamics of the entrepreneurial landscape. The technology is widely perceived as lowering traditional entry barriers, suggesting that AI is contributing to a more accessible entrepreneurial environment, where smaller teams can undertake initiatives that previously required substantial human and financial capital: "On the one hand I see that it could lead to democratization because you don't need that much technical talent... you can basically create and scale one idea with a two-person team." (AK).

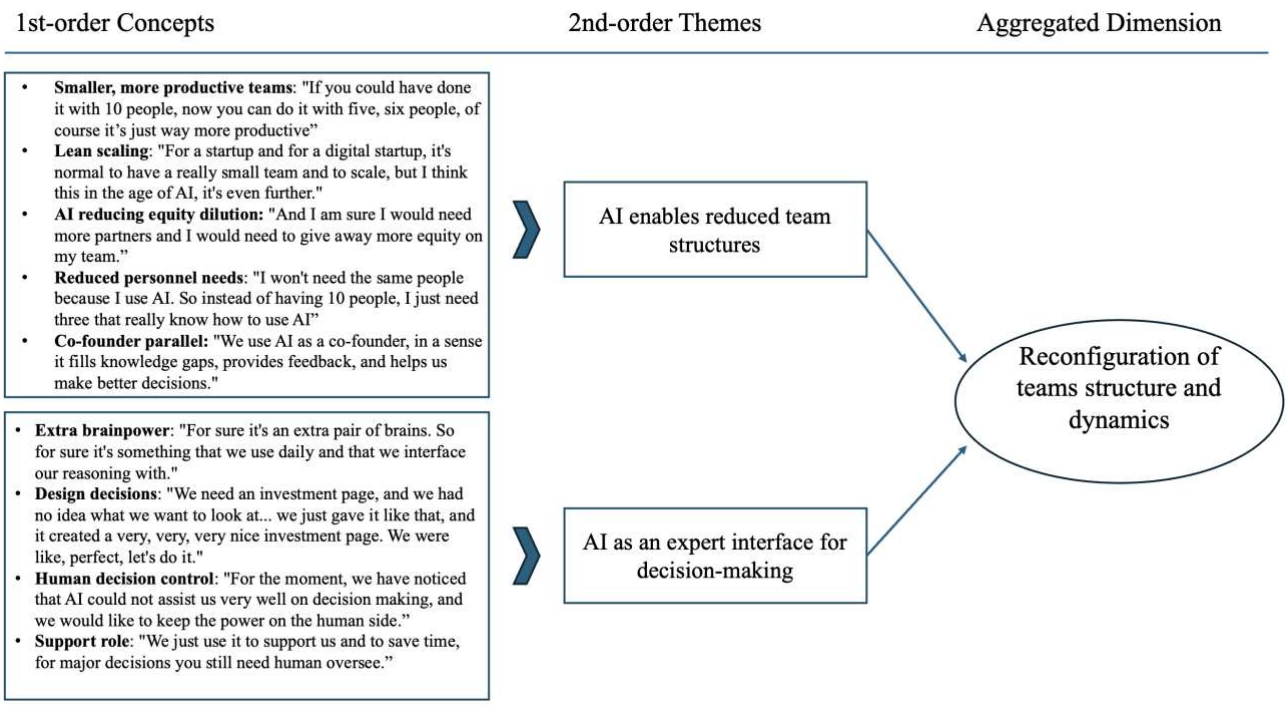

Figure 4: Data structure second aggregate dimension

4.2.2 AI as an expert interface for decision making

AI enables founders to perform tasks in domains beyond their expertise, lowering the barrier for non-experts to engage in tasks that previously required specialized knowledge. In particular, for founders that don't posses technical knowledge, AI tools act as accelerators, enabling them to perform tasks such as, among others, back-end and front-end app development, web design and prototyping. As a PropTech founder states: "*Even for me, as someone who barely codes, these tools let me bring my ideas to life."(BS).* While AI co-pilots coding tools Cursor and Bolt.new, have shown the greatest impact in expanding non-technical founders' ability to engage with software development tasks: *"90% of our mvp was made by bolt.new" (SI)*, large language models are also widely used as interfaces for rapid learning, helping founders build confidence and competence in unfamiliar domains. As reported by 59% founders in the sample, AI tools were frequently used to better prepare for meetings with co-founders or external stakeholders, such as investors or clients, as well as to address operational challenges in areas where they lacked prior knowledge. When adressing this topic, the dominant feeling towards AI, characterize it as a senior employee, with an expertise which brings utility beyond the knowledge domain of the venture team: "*It's like having a senior developer always available to try your ideas" (EM).*

4.2.3 Hybrid decision-making

Founders reported routinely engaging with LLMs to support their reasoning processes. Specifically, they described using AI tools to gain clarity on complex topics, deconstruct problems into manageable components, and fill knowledge gaps, often leading to more informed decisions: *"for sure it's an extra pair of brains. So for sure it's something that we use daily and that we interface our reasoning with."* (EM) and *"We use AI as a co-founder, in a sense it fills knowledge gaps, provides feedback, and helps us make better decisions"* (HM). However, while LLMs serve as valuable cognitive assistants, their role in strategic decision-making remains limited. As expressed by 65% of participants, there is a shared perception that AI is currently inadequate for core decisions. Participants cited concerns such as lack of domain-specific accuracy, generalist outputs, occasional hallucinations, and insufficient creativity. As such, major decisions remain predominantly human-driven, with AI occupying a complementary, support-oriented function: *"We just use it to support us and to save time, for major decisions you still need human oversee" (DI)*

4.3 Implementation barriers and capability gaps

This aggregate dimension explores the challenges organizations face when implementing AI technologies in their operations as well as the underlying skills gap that slows successful adoption. The findings reveal that technical implementation challenges and human capital limitations collectively create barriers to effective AI integration.

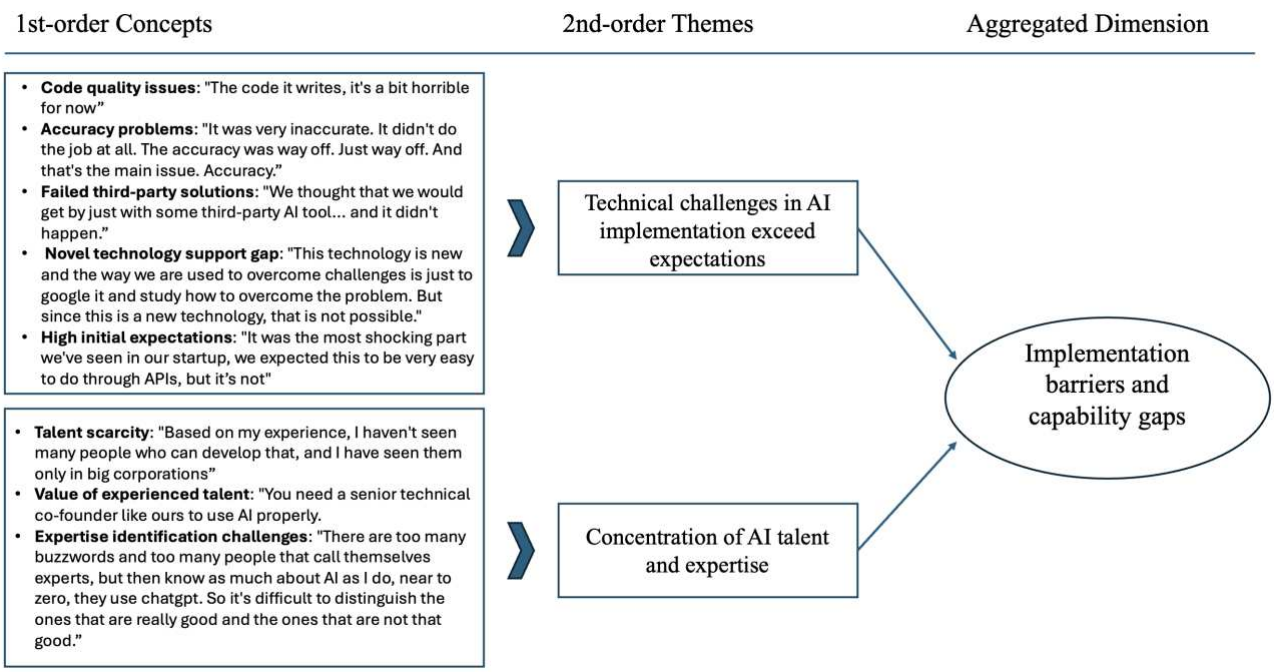

Figure 5: Data structure third aggregate dimension

4.3.1 Technical challenges in AI implementation

Across several cases, founders reported a significant disparity between the perceived ease of AI integration and the practical difficulties encountered during implementation. Despite early-stage optimism, ventures frequently struggled with issues of output quality, reliability, and the limited adaptability of third-party AI tools. Several founders entered the AI integration process under the assumption that readily available APIs would suffice, only to encounter unexpected complexity. One interviewee described this as *"the most shocking part we've seen in our startup,"(AK)* explaining that what was expected to be a plug-and-play solution revealed itself to require significant backend engineering. These limitations are especially relevant for startups without robust technical teams, where dependency on automated code generation leads to inefficiencies, refactoring delays, and potentially flawed product development: "*There is a risk of having many code stability and scalability problems and also new developers who don't understand how something was conceived" (LA).*

A consistent theme was the inaccuracy of AI-generated outputs, as one SaaS founder recounted, "*It didn't do the job at all. The accuracy was way off. Just way off. And that's the main issue."* (DI). This sentiment reflects a broader concern, mentioned by 53% of founders, that current generative models, while performing well in generalist tasks, fall short when applied to nuanced, domain-specific use cases without significant customization.

Compounding these challenges is the lack of established best practices or community-driven problem-solving pathways. As a AI market research startup founder noted, *"This technology is new, and the way we are used to overcome challenges is just to Google it and study how to overcome the problem. But since this is a new technology, that is not possible."* (VA). The novelty of AI tools, and the fast-paced evolution of the underlying models, means that implementation hurdles often lack standardized solutions, forcing entrepreneurs into inefficient trial-and-error cycles*: "We are still exploring them, we don't know which is the best for what, and which at the most favorable price, or is more tailored to us, and there is so many of them right now, so it's hard to decide" (VA),* also mentioned by AK and IM.

4.3.2 Concentration of AI Talent and Expertise

A second structural barrier to effective AI integration in new ventures lies in the concentration of relevant talent and technical knowledge. As one founder explained, *"I haven't seen many people who can develop that, and I have seen them only in big corporations, or they have done, or they're doing their own startups."(SS)*. This talent bottleneck, where individuals with advanced machine learning skills are employed in established tech giants, creates a scarcity effect that disadvantages smaller startups.

Several interviewees highlighted the critical role played by experienced technical co-founders. One SaaS founder stated bluntly, *"You need a senior technical co-founder like ours to use AI properly."* (LA). In contrast, ventures without such profiles frequently found themselves unable to exploit AI beyond basic functionalities, despite strong strategic intent.

Another layer of complexity is added by the difficulty of identifying qualified experts. Founders consistently lamented the noise in the AI talent market, where inflated claims and buzzwords mask actual skill levels. One founder observed: *"There are too many buzzwords and too many people that call themselves experts, but then know as much about AI as I do, near to zero." (HM)*. This challenge reflects not just an issue of supply but also one of signal distortion in emerging technical labor markets. In practice, these barriers slow down AI integration processes in early-stage ventures that might otherwise benefit the most from AI's cost-reduction and efficiency-enhancement potential.

4.4 Risk Management and Regulatory Considerations

While the integration of AI into new ventures offers substantial benefits in speed, efficiency, and scalability, it also introduces significant risks. These include both operational

vulnerabilities and emerging regulatory challenges. This aggregated dimension captures the concerns voiced by founders around reliability, compliance, and the human oversight required when deploying AI across critical functions.

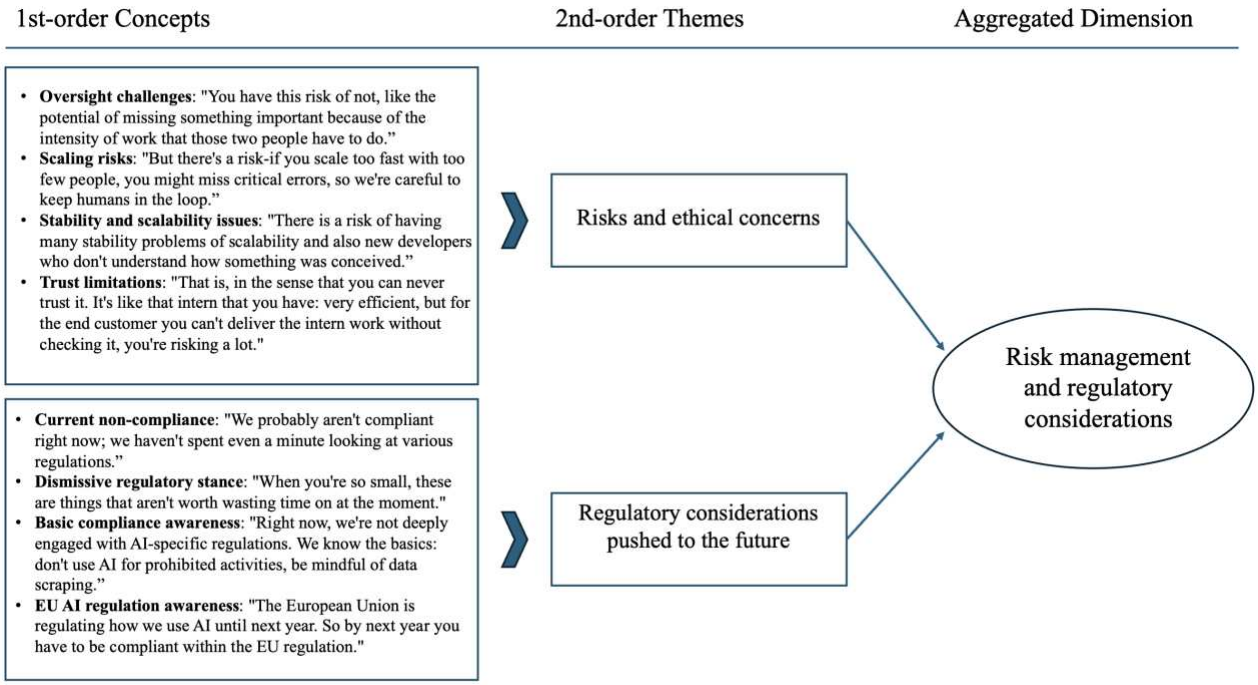

Figure 6: Data structure fourth aggregate dimension

4.4.1 Risks and ethical concerns

Multiple founders highlighted the risks associated with overreliance on AI, particularly in lean teams. One ConsumerTech founder noted the challenge of maintaining vigilance over automated processes, warning that *"you have this potential of missing something important because of the intensity of work that those two people enabled by AI have to do."(KD)* The concern is not simply about AI malfunctioning, but about human oversight being spread too thin in small teams where responsibilities are already stretched.

This risk is compounded during periods of rapid growth. Several interviewees pointed out that while AI enables faster scaling, it can simultaneously increase the likelihood of errors being overlooked. A SaaS founder reflected: *"If you scale too fast with too few people, you might miss critical errors, so we're careful to keep humans in the loop."* (SS). This cautious approach reveals a growing recognition that AI, despite its advantages, requires human-in-the-loop mechanisms to ensure quality and safety.

Trust also emerged as a major theme. Founders repeatedly described AI as a powerful assistant that still requires constant human supervision, as highlighted by this parallel built by a founder: *"You can never trust it. It's like that intern that you have, super good, super efficient, but for the end customer, you can't deliver the intern's work without checking it. You're risking a lot."* (SI).

These concerns reveal a cautious approach to AI deployment among founders. Despite the enthusiasm for its productivity gains, there is widespread awareness that AI's current limitations require not only technical checks but also ethical responsibility and human intervention.

4.4.2 Regulatory Considerations

In contrast to the detailed operational concerns expressed around risk, regulatory issues were largely acknowledged but deferred. Founders consistently admitted that they were not actively engaging with AI-specific regulations, often due to time and resource constraints. One founder stated plainly: *"We probably aren't compliant right now; we haven't spent even a minute looking at various regulations." (EM).*

This sentiment was shared by others who viewed regulatory compliance as a secondary priority during the early stages of their venture. A SaaS founder observed: *"When you're so small, these are things that aren't worth wasting time on at the moment."* (AY). Rather than a rejection of regulation, this stance reflects a calculated trade-off typical of startups, : in the critical phases of product development and market fit, legal concerns are often postponed in favor of operational execution.

A minority of participants displayed more proactive awareness, particularly in relation to the upcoming EU AI regulation. Only one founder mentioned it before being adressed by the questions: *"The European Union is regulating how we use AI until next year. So by next year you have to be compliant within the EU regulation."* (DM).

Together, these insights suggest a gap between the pace of AI integration and the preparedness of early-stage ventures to navigate the regulatory landscape. Founders are aware that the environment is changing but actively decide not to address compliance at this stage. This lag raises important questions about how startups can be supported to engage with regulation before enforcement becomes a risk factor for their growth and legitimacy.

Discussion

This research investigated the role of AI in new venture creation, examining how AI systems are evolving from their traditional function as tools, to operate as co-founders within entrepreneurial teams. Through qualitative analysis of 17 early-stage AI-enabled ventures, this study provides empirical insights into how AI technologies are reshaping the processes of startup founding. The findings reveal how AI demonstrates capability enhancement effects while simultaneously introducing novel challenges and dependencies that entrepreneurs must navigate.

The first research question explored how AI transforms new ventures, particularly regarding process optimization, decision-making, and resource orchestration. The findings demonstrate that AI impacts each of these entrepreneurial activities, with generalized benefits perceived by founders in terms of both effectiveness (e.g. reduced biases in decisions) and efficiency (e.g. increase in speed) of the business.

Decision-making processes represent a recurring topic emerged from the interviews, and a core element of entrepreneurial activity. Prior research emphasizes the entrepreneur's judgement (Foss & Klein, 2012), heuristic reasoning (Busenitz et al., 1997), and experiential learning (Politis et al., 2009) as key to effective decision-making. These approaches acknowledge the inherent limitations of purely rational models in contexts marked by novelty and ambiguity. Recent literature highlights a central tension in contemporary venture founding: intuition against data-driven approaches. While intuition remains essential, the increasing availability of sophisticated analytical tools enables more systematic, pattern-based decision-making. Kraus et al. (2020) find that AI techniques can enhance decision-making systems within entrepreneurial ventures, improving quality, effectiveness, and efficiency and ultimately boosting operational performance. AI strengthens decision-making because it can process vast quantities of data and spot patterns human perception misses (Agrawal et al., 2018).

Our findings directly support and extend this literature by documenting how hybrid intelligence models, blending human judgment and AI capabilities, operate in resource-constrained startup contexts. Founders reported that effective AI use requires what might be termed "technological literacy": the ability to critically evaluate AI outputs and maintain human oversight (SI, EM, VA). The AI-human sequential decision-making model proposed by Shrestha et al., (2019), that shifts problem-solving focus from generating solutions to evaluating and selecting solutions, is

particularly coherent with this study's empirical evidence, describing a hybrid approach where AI augments rather than replaces human judgment. This is also in accordance with Agrawal et al. (2018) assertion that human judgment becomes more valuable as prediction costs fall. However, eleven out of thirteen participants explicitly stated that AI remains inadequate for core strategic decisions, citing concerns about domain-specific accuracy and creativity limitations.

Resource orchestration emerges as perhaps one of the most transformed aspect of the founding process. The study indeed reveals how AI enables operating with leaner teams, shifting from traditional structures. All case ventures operated with teams of five members or fewer, highlighting their use of AI to complete time-consuming tasks and reduce the need for hires. For the interviewees the use of Artificial Intelligence is also a fundamental element in today's funding landscape, leading to a higher probability of gathering investments (EM, DI, VA, LA, AY). This phenomenon, together with lower personnel costs and compressed timelines, is disrupting the resource allocation in new ventures, letting founding teams focus their spending on for example, product improvements and commercial activities.

On the other hand, opportunity recognition did not emerge as a recurring theme across interviews, though founders occasionally referenced using AI to evaluate the quality of business ideas and streamline market research and early validation efforts (AK, BS, HM). This suggests that while AI supports some aspects of the opportunity identification process, it has not yet become a dominant factor in how startup founders systematically recognize and assess new venture opportunities.

Finally, founders commonly framed agentic AI as a key element of their long-term vision and hold an optimist view of AI evolution, perceived to be on the path of becoming more accurate as foundational models evolve and as vertical specialized tools proliferate: "In the next three months, there will be like very concrete tasks that will be autonomously handled by AI in our company." (VA, SI, C2). Together, these accounts signal growing confidence among entrepreneurs in AI's potential to act as a persistent, semi-autonomous presence within ventures.

The second research question examined the extent to which AI systems can be conceptualized as autonomous systems acting as co-founders rather than tools. The research identifies four distinct levels of AI engagement (see Fig. 7) that align with, yet extend, existing theoretical frameworks.

At the basic level, AI functions as what participants consistently described as an excellent intern supporting routine tasks and administrative functions (AI, DI, C2, SS, SP). This operational

level confirms Chalmers et al. (2021) observations about AI's role in process optimization. However, the study reveals a more sophisticated level where AI serves as an expert interface, enabling non-technical founders to engage in complex tasks beyond their expertise. This finding extends the literature by demonstrating how AI democratizes technical capabilities, allowing entrepreneurs to perform software development or web design, as well as to gather knowledge and perform specialized functions without possessing the traditional skill requirements.

This level approaches what might be considered co-founder-like functionality, where AI systems participate in reasoning processes and strategic discussions. Participants described using AI for deconstructing complex problems and filling knowledge gaps, eventually crediting artificial intelligence as the reason they were able to retain a larger portion of the equity, which would otherwise be granted to co-founders possessing that missing expertise (AK, VA, SI). Between these levels, the research identifies AI as a strategic consultant, where systems provide structured advice and alternative solutions for complex problems without taking autonomous action. Founders relied on AI to analyze data, generate scenarios, and evaluate A/B tests.

In addition, the study highlights AI as a process enabler, where AI autonomously manages low-complexity but complete operational workflows, such as scheduling, monitoring, and note taking. In this role, AI moves beyond basic assistance by taking ownership of routine processes, freeing founders to focus on higher-level activities.

This discussion extends existing founding team literature by challenging anthropocentric definitions of team composition. Traditional frameworks such as Knight et al. (2020) emphasize human agency, equity ownership, and strategic autonomy as defining characteristics of founding teams. The empirical evidence suggests these frameworks require modification to accommodate technological agency. While AI systems do not possess equity ownership, they demonstrate increasing autonomy in operational decision-making and contribute to strategic reasoning processes in ways that parallel some co-founder functions (VA, EM, SI). Nonetheless, our findings still suggest this distribution remains limited. Despite AI's cognitive assistance capabilities, strategic decision-making authority remained usually with human founders. Indeed, while AI appears as an accessible solution on the surface, the underlying implementation often demands more technical expertise, time, and iterative debugging than founders initially anticipate. The early-stage promise of AI as a scalable co-founder becomes tempered by the technical realities that constrain its immediate utility

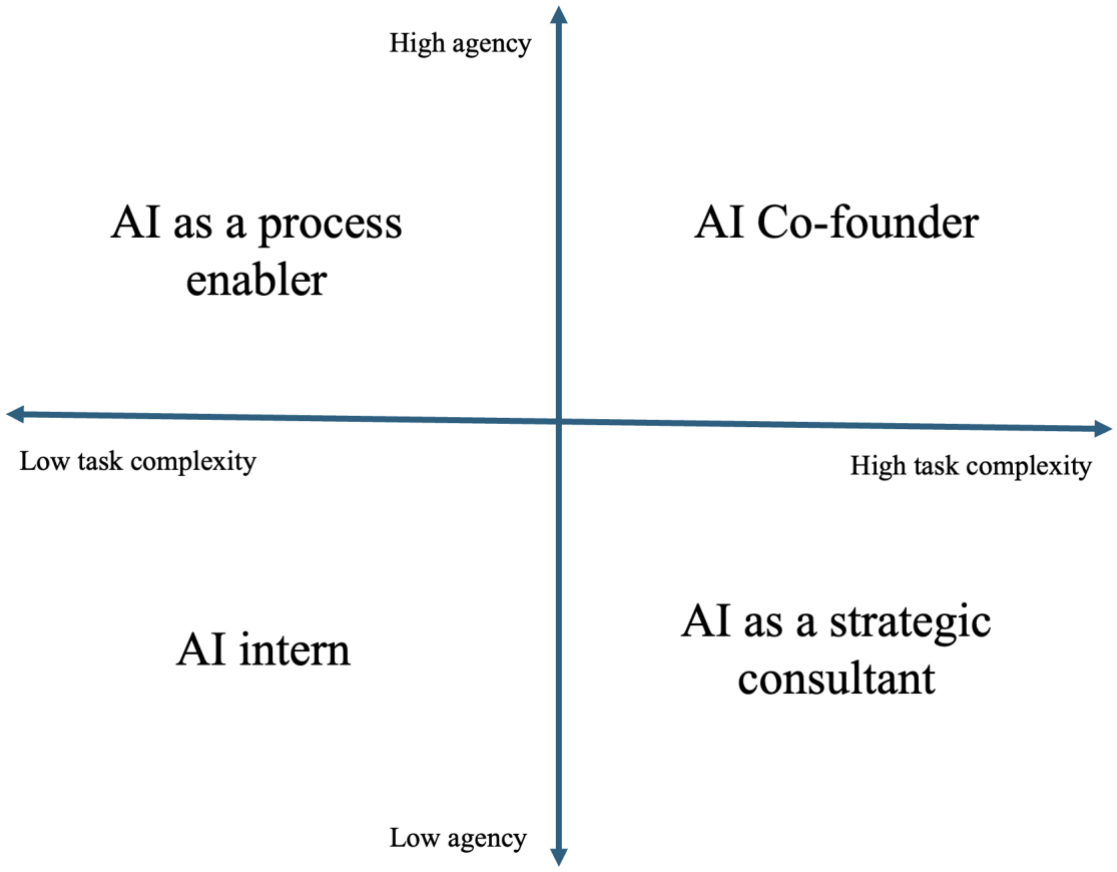

Figure 7: The two levels of AI engagement

The third research question addressed risks associated with AI integration, particularly for small teams managing potentially large ventures. The findings reveal risk profiles that differ substantially from traditional entrepreneurship literature. While conventional risk frameworks emphasize market uncertainty and resource constraints (Knight, 1921; Busenitz et al., 1997), AI-enabled ventures face distinctive technological liabilities that amplify systemic risks. Founders repetitively mentioned oversight challenges as a recurring concern, highlighting human vigilance as the bottleneck in AI-enabled operations (AK, IM, BS, HM, CF, DM).

The research also confirms Chalmers et al. (2021) concerns about the concentration of AI expertise. As his research observes, ventures face particular challenges in acquiring specialized human capital, especially in technical domains with high demand for talent. The global competition for AI talent creates specific challenges for new ventures, as high salaries paid by leading technology companies mean it is often challenging for many nascent entrepreneurs to build a team with requisite skills" (Verdegem et al., 2024). Moreover, many nascent

entrepreneurs lack the expertise required to build and sustain complex AI systems, exacerbating the capabilities gap. In our study, founders consistently reported difficulty in identifying qualified technical talent (DI, AK, VA, SP). This talent bottleneck creates implementation barriers that contradict narratives about AI democratization, suggesting that effective AI integration requires specialized knowledge that remains scarce. Moreover it creates a paradoxical situation where ventures that could benefit most from AI's cost-reduction potential face the highest barriers to safe implementation.

Regulatory risks emerge as a particularly underexplored area in the existing literature. Perhaps the most striking finding regarding AI integration risks (Fig. 8) is the systematic neglect of regulatory considerations among early-stage ventures. Despite the impending EU AI Act and its compliance requirements, the vast majority of founders admitted to deferring regulatory engagement due to resource constraints. This regulatory compliance gap reveals a fundamental mismatch between regulatory development timelines and entrepreneurial resource allocation priorities. Early-stage ventures typically operate under extreme resource constraints where immediate operational concerns take precedence over potential future compliance requirements (Bradley et al., 2011). However, the complexity and scope of AI regulation create compliance burdens that may be disproportionately challenging for small teams to navigate. The empirical evidence suggests that current regulatory frameworks may inadequately address the needs of early-stage AI ventures, creating what can be characterized as a "compliance impossibility" scenario where adherence to regulations requires resources that early-stage ventures cannot allocate without compromising survival prospects. Moreover, this could constitute a dynamic where regulatory complexity may inadvertently favor larger organizations with dedicated compliance resources, potentially creating barriers to entry that contradict innovation policy objectives.

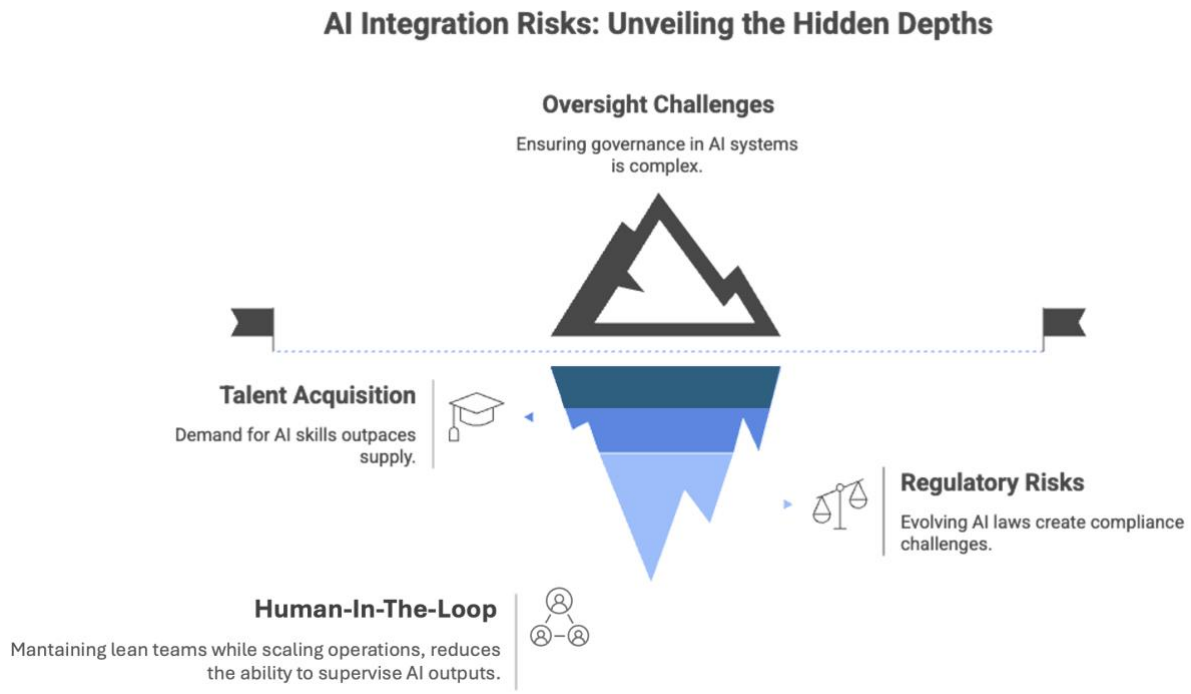

Figure 8: AI integration risks

AI's broader impact on entrepreunership

The findings reveal that AI has two closely linked effects on entrepreneurship: while AI democratizes access to sophisticated capabilities previously available only to well-resourced organizations, it simultaneously commoditizes these capabilities across the competitive landscape. Our findings suggest that this democratization-commoditization tension represents a central dynamic in AI-enabled entrepreneurship.

The democratization effect manifests in AI's capacity to provide small teams with capabilities that traditionally required substantial human capital investment. Founders described using AI to fill knowledge gaps and be able to perform or automate complex tasks, effectively expanding their operational scope without proportional increases in team size (SI, VA, MS, AY, LA, BS). This capability expansion enables solo entrepreneurs and small teams to compete in domains previously dominated by larger organizations with extensive human resources. In line with this, several interviewees (AY, SS, SI, HM) predicted that the availability of AI would lead to a surge in startup activity, at least in terms of initial exploration of the entrepreneurial idea: "It will definitely lead to some entrepreneurial explosion because it leads to creating an MVP in a week if you previously needed some months." (HM).

However, this acceleration led by a compression in development timelines, is also deemed to raise the baseline quality of early-stage projects, which will need to carry extensive validation and go-to-market activities in order to attract funds: “A few years ago, you could raise money with just a PowerPoint and Excel... now you need lots of traction to be able to raise money.”(EM).

Similarly, the commoditization effect emerges from AI's broad accessibility, which means that competitive advantages derived from AI adoption tend to be temporary. As one ClimateTech founder observed: "It will become simple to found a startup while distribution will become much more important". (EM). This insight captures the core tension: while AI lowers the technical barriers to venture creation, it also reduces the sustainability of technology-based differentiation.

The commoditization dynamic is further amplified by AI's standardization across vendors and applications. Unlike proprietary technologies that can provide sustained competitive advantages, AI tools are increasingly available through standardized platforms and APIs, making them accessible to all market participants simultaneously. This creates what economists term "Red Queen" dynamics (Barnett et al., 1996), where continuous innovation is required merely to maintain competitive parity rather than achieve advantage.

Nevertheless, our findings suggest that both the democratization and commoditization effects are tempered by feasibility constraints, particularly those linked to entrepreneurial self-efficacy. Given AI's highly technical nature, there is often a disconnect between what many aspiring entrepreneurs believe they can achieve with the technology and what is realistically possible. (AK, SI, HM)

Theoretical Contribution

This study extends and refines existing theory on AI in entrepreneurship by showing how AI shifts venture creation from an exclusively human-centred process toward a hybrid human–machine collaboration. Prior work by Chalmers et al. (2021) frames AI as an external enabler of new ventures, enhancing efficiency and optimizing processes. In our study, founders confirmed that AI does boost efficiency (acting like a diligent “intern” handling routine tasks), but we also found it becoming embedded in core venture activities. For example, AI tools took on specialized functions, like software development, creative tasks or data analysis, typically carried on by technical co-founder. This means AI not only automates existing tasks but

democratizes expertise, allowing non-technical founders to perform high-skill work without a human partner. In this way, AI surpasses a mere "external" role and starts to influence venture strategy and organization from within. Our findings complicate Chalmers et al.'s framework: they anticipated that AI-driven automation will change organizational design and decision-making systems, and indeed we observed that teams reorganize around AI capabilities. At the same time, we note limits to AI's agency. Consistent with Chalmers et al.'s caution about AI's "liabilities of leverage", our participants reported that complex AI systems still require significant human oversight, and strategic authority remained with human founders.

Our findings likewise nuance Nambisan et al.'s (2017) theory of digital entrepreneurship, which argues that digital technologies make entrepreneurial processes more fluid and distribute agency beyond individual founders. We confirm that AI contributes to this fluidity: entrepreneurial tasks became "less bounded" (e.g. non-technical founders leveraged AI to move rapidly from idea to prototype). Crucially, we show that agency itself becomes hybrid. In interviews, founders often described decision-making as a human–AI partnership: AI systems would analyse data or suggest ideas, while humans made final strategic calls. In Nambisan's terms, startups increasingly resemble "continuously evolving collectives" that now include AI as a member. For instance, several entrepreneurs likened AI to a junior partner who never sleeps, always available to work through problems, indicating that AI has become part of the organizational design. Notably, many founders reported that AI allowed them to shrink their teams: with AI handling specialized work, ventures required fewer human hires. This outcome suggests that digital entrepreneurship theory should account for AI-induced compression of team size and changing skill boundaries, aspects underemphasized in the original framework.

Finally, the evidence challenges traditional models of founding-team structure that assume teams consist only of human members defined by equity stakes, autonomy, and cohesion. In Knight et al. (2020) multidimensional model, for example, a founding team is characterized by human owners with equity and strategic autonomy. Our findings complicate this picture: AI contributes to teamwork without fitting those dimensions. AI systems participated in strategic discussions and problem solving, but of course they held no equity and lacked formal membership. This calls for a reconceptualization of the "team" to include non-human agents. In fact, interviewees sometimes spoke of AI as if it were a co-founder or team member and, by crediting AI with enabling them to keep more equity or handle core tasks, founders implicitly treat AI as a kind of partner. Yet our study also reinforces that human founders retain ultimate authority as they also remain legally accountable. In other words, AI becomes a quasi-member of the founding team: it flattens the traditional hierarchy of skills and knowledge (making

founders more generalist) but does not itself claim autonomy. In sum, our theoretical contribution lies in conceptualizing AI not just as a smart tool, but as an active collaborator in venture creation. We show that AI's presence creates a tension between democratization and commoditization: it empowers solo founders by supplying expertise yet also raises the bar for entry (since competitors gain the same capabilities). By mapping these dynamics onto existing frameworks, we highlight new assumptions: AI enables hybrid human–machine teams, redefines founder roles, and redistributes entrepreneurial agency. These insights invite scholars to update entrepreneurship theory so that it recognizes AI's dual role as both an enabler and a stake holding partner in startups.

Managerial Implications

This research suggests several actionable guidelines for founders operating AI-enabled ventures. Early-stage experimentation with general-purpose AI tools can provide a low-cost learning environment before transitioning to more specialized solutions. From inception, founders that want to build an AI-enabled startup, should design workflows that integrate AI into processes such as market research, business validation, business writing, and prototyping. On this side, among the sample ventures, AI proved to be an operational catalyst able to cut costs and enable automation. AI should also serve as an expert interface for structured problem-solving and decision support, filling knowledge gaps and enabling a data-driven approach in decision-making.

When deploying agentic AI systems (e.g. chatbots), founders should implement monitoring protocols for AI-generated outputs and define clear accountability structures. Adopting what has been coined in the startup ecosystem as "AI-native" approach can enable leaner organizational structures, compressed development timelines, and reduced operating costs. However, this requires an assessment of third-party dependencies created by AI model usage, alongside proactive management of the associated risk profiles.

Most founders reported no engagement with AI regulations such as the EU AI Act, citing resource limits, complexity, and slow policy cycles that risk making rules obsolete.

To address these barriers, regulators should consider more agile regulatory mechanisms, with shorter iteration cycles, tiered compliance requirements proportional to organizational maturity, and simplified guidance for early-stage ventures. Such measures could increase regulatory

engagement, improve compliance rates, and better align innovation policy with the dynamics of rapidly evolving AI markets.

Research limitations & Future directions

The findings of this study should be interpreted with caution due to both methodological and contextual limitations. As in most qualitative research, the small, purposively selected sample of 17 early-stage founders mainly based in Lisbon and Milan, provided rich, in-depth insights but does not fully represent the diversity of startup experiences across industries, regions, and venture stages. The focus on AI-driven, tech-oriented startups means the results may not generalize to non-tech sectors, where AI may be adopted differently or play a less central role in venture creation. The geographic scope also limits applicability, as entrepreneurial ecosystems, regulatory contexts, and cultural norms vary widely across regions, potentially shaping how AI integration unfolds. Furthermore, the research employed a cross-sectional design, capturing a single moment in time, which cannot account for how AI's role and perceived value may evolve as ventures grow, technologies mature, and market conditions shift.

Future research on agentic entrepreneurial teams could address these constraints by adopting larger and more diverse samples, including ventures from multiple industries, geographic regions, and business models. Longitudinal designs would allow for tracking changes in human–AI collaboration over time, providing a deeper understanding of how team composition, decision-making, and business processes adapt during growth and scaling. Comparative studies could examine differences between tech and non-tech sectors, as well as across startup and regulatory environments, to identify contextual factors influencing AI's role. Mixed methods approaches, combining qualitative insights with quantitative measures of performance and adoption patterns, would strengthen the external validity of findings and enable broader generalization. By broadening scope, extending timeframes, and diversifying methodological approaches, future studies can deepen our understanding of the evolving role of AI in venture founding and refine theory on agentic entrepreneurial teams.

Conclusion

This study set out to address a growing question in entrepreneurship: how is the emergence of advanced AI tools reshaping the founding of startups, and to what extent can AI be considered a co-founder in new ventures? As AI becomes more capable and accessible, it is not only changing how ventures operate but also prompting a rethinking of team composition, expertise, and decision-making. Entrepreneurs increasingly adopt AI tools that can automate tasks such as market analysis, or software engineering, shifting the blend of human and machine in ventures. Understanding these shifts is crucial for both scholars and practitioners, as they affect the skills entrepreneurs need, the resources they mobilize, and the way the competitive landscape reshapes. Many venture creation processes rely on human capital and personal know-how; AI may alter what resources are needed, making certain skill sets more or less vital for success.

The aim of this research was to explore how AI is integrated into early-stage startups, identify the roles it takes on within founding teams, and assess its influence on venture creation and early business processes. To achieve this, we conducted semi-structured interviews with 17 startup founders, primarily based in Lisbon and Milan, whose ventures actively used AI in product development, operations, or strategy. These founders came from diverse tech-oriented industries (such as fintech, climate-tech, and SaaS) and were in various stages of early growth. The interviews provided rich qualitative insights into lived entrepreneurial experiences with AI, which we analysed systematically using the Gioia Methodology. This approach allowed us to code the data iteratively, identifying first-order concepts and then aggregating them into broader dimensions.

The analysis revealed four aggregated dimensions. The first, AI as an operational catalyst, captures how AI accelerates development, experimentation, and productivity, enabling faster iteration and output. Founders highlighted that AI tools dramatically reduced manual work (for example, automating coding tasks or synthetizing information from a meeting), leading to faster prototyping and innovation cycles. By automating routine activities and generating quick insights (for instance, AI-driven data analytics or automated design mock-ups), teams could focus their human effort on higher-level strategy and creative problem solving. This capacity for rapid iteration compressed development cycles allowing small teams to attempt more ideas and test new markets quickly. Several founders noted that this operational speed-up encouraged

a culture of experimentation: they could try out features or products without the usual resource bottlenecks, thereby learning and pivoting much faster than before.

The second dimension, reconfiguration of team structure and dynamics, reflects AI's influence on reducing venture team size, reshaping roles, and fostering hybrid human–AI decision-making processes. Across the sample, AI operated primarily as a team member that enabled founders to retain tighter control, cut personnel costs, and remodel financial planning, effects that founders linked directly to different equity and fundraising choices. At an operational level AI function like an "always-on" intern that automates routine work and enables to operate at higher speed; at a more advanced level it serves as an expert interface, allowing non-technical founders to perform tasks (from prototyping to parts of software development) that previously required specialist teammates. These shifts have consequential downstream effects: leaner teams reduce burn rate and can change projected capital needs, while access to AI-enabled capabilities can substitute for co-founder expertise and reshape equity allocations. Founders reported continuously integrating AI into their decision-making processes, noting that it enabled more data-driven judgments, improved the quality of strategic choices, and, by extension, enhanced business outcomes. However, they ultimately expressed to reserve core strategic decisions for humans because of concerns about domain accuracy, hallucinations, and the technical effort required to operationalize AI reliably.

The third dimension, implementation barriers and capability gaps, highlights substantial obstacles to AI adoption. Many founders entered integration projects expecting plug-and-play solutions yet, possessing limited domain expertise, they encountered unanticipated engineering complexity that turned implementation into prolonged trial-and-error cycles. In practice, these exploratory efforts often prove more time-consuming and financially burdensome than the operational efficiencies AI promises, eroding the net gains for resource-constrained ventures. Smaller startups in particular, lack the in-house expertise required to deploy and maintain proprietary AI systems effectively; advanced AI talent is disproportionately concentrated in large technology firms and commands premium compensation, creating a scarcity that constrains hiring and could hinder innovation. The technical complexity and AI talent concentration raise the cost of adoption but also reshapes the risk profile of early ventures, suggesting that democratization narratives must be tempered by structural and human-capital considerations.

The fourth dimension, risk management and regulatory considerations, points to a critical situation. Several founders emphasised the dangers of relying too much on AI, especially in lean teams. Human oversight is being spread too thin in small teams where responsibilities are already stretched, and this danger is exacerbated during times of rapid expansion. Several interviewees noted that although AI facilitates faster scaling, it can also make it more likely that hallucinations will go unnoticed. When taken as a whole, these findings highlight the necessity of clearer role assignments, specific monitoring procedures, and governance methods that grow with the business.

Despite extensive policy development around AI regulation, including the EU AI Act, the vast majority of founders reported complete non-engagement with regulatory requirements due to resource constraints and complexity barriers. Temporally, regulatory development cycles measured in years create lag effects that render regulations partially obsolete by the time they are implemented. Resource-wise, compliance requirements assume organizational capabilities that early-stage ventures lack, creating disproportionate burden effects. Complexity-wise, regulatory frameworks designed for established organizations with dedicated compliance functions may be systematically inaccessible to small entrepreneurial teams.

Compared to previous studies, several findings stand out. While existing research has often framed AI merely as an external enabler of efficiency, our study shows that it can become an integrated, ongoing participant in venture-building. The evidence points to a hybrid form of human–AI agency, where on one side AI is used to automate repetitive tasks, while on the other it provides strategic inputs, domain expertise and creative ideation, now shared between founders and intelligent systems. This completes prior literature by demonstrating that AI's role goes beyond simply speeding up time consuming duties but is frequently metaphorically described as a team member. Another notable finding is the consistent pattern of founders bypassing regulatory requirements, such as those in the EU AI Act, due to complexity and resource constraints. This behaviour of skipping formal compliance is rarely addressed in earlier literature, so our study highlights a practical gap between policy assumptions and entrepreneurial reality.

Theoretically, this study extends established frameworks of entrepreneurial and digital innovation. For example, models by Chalmers et al. 2020; Nambisan et al. 2017; and Knight et al. 2020 generally assume that agency in venture creation is human driven. By positioning AI as a quasi-member of the founding team, blurring boundaries between tool and teammate, the

findings challenge strictly anthropocentric accounts of founding teams (which privilege human agency, equity, and strategic autonomy) and suggest that models of team composition and decision rights need to accommodate technological agency as a functional, though non-proprietary, contributor.

For practice, these insights imply that founding teams need to adapt their strategies. Entrepreneurs should evaluate their technological capabilities and build new competencies to effectively manage the risk profiles and dependencies introduced by AI. Organizational design needs to account for Human-AI hybrid processes from its inception, allowing for the establishment of oversight procedures. In resource orchestration, startups may allocate funds for AI talent or tools and rethink which human roles are essential. Introducing LLMs as expert interfaces will enable founders to maintain a data-driven approach and fill knowledge gaps, but experimentation with vertical, specialized tool (even though costly), has shown to provide the greatest business outcomes for founders as well as a solid learning base to start developing their proprietary model. In short, as AI becomes part of the team, entrepreneurs must plan for both the opportunities and the dependencies it creates.

This study does not come without limitations. The sample was small and geographically concentrated in two European tech hubs (Lisbon and Milan), and it focused on technology-oriented ventures, which may limit the generalizability of the findings. The cross-sectional design captured only a single moment in time, so it may not fully reflect how AI's role in a startup evolves as the venture grows or as technology changes. Future research could broaden the scope by including a wider range of industries and regions, perhaps through larger-scale surveys or additional case studies in different contexts. Longitudinal approaches would also help track how entrepreneurial teams incorporate AI over time and how regulatory engagement might change, providing a fuller picture of AI's impact on entrepreneurship as ventures mature.

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