Faculty of Behavioural, Management and Social Sciences (BMS)

"The Role of Artificial Intelligence In New Venture Creation: A qualitative examination"

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And as always: “If it were easy, everyone would do it.”

Always for the better, always with me.

Abstract

This study explores the strategic role of generative AI in new venture creation, examining its impact on different entrepreneurial phases through semi-structured interviews with 20 AI start-up founders and key industry figures. Using a three-step qualitative approach, the research identifies AI's role in ideation and prototyping while highlighting challenges such as limited automation, venture capital evaluation issues, a lack of educational support for AI applications, and public scepticism due to unclear regulations. It underscores the trade-off between fostering innovation with minimal regulation and addressing societal challenges through a more structured framework supported by clearer regulatory guidelines. This study contributes to the literature on AI and entrepreneurship and offers practical insights for entrepreneurs, investors, and policymakers. Future research should explore sector-specific AI applications and regulatory scenarios to deepen understanding and keep pace with AI developments and updates.

Keywords: Artificial Intelligence, AI, AI Entrepreneurship, New Venture Creation, AI in Start-ups, Technology Entrepreneurship, Regulations and AI, Qualitative Research in AI

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List of Abbreviations

AI	Artificial Intelligence
IoT	Internet of Things
R&D	Research and Development
LLMs	Large Language Models
RBV	Resource-Based View
WEF	World Economic Forum
MIT	Massachusetts Institute of Technology
GANs	Generative Adversarial Networks
AIGC	AI-Generated Content
AGI	Artificial General Intelligence

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1. Introduction

Currently, 5.18 billion people are connected to the World Wide Web, with Northern Europe having the highest internet penetration rate at 97.3% (Petrosyan, 2024). This growth stems from the increasing need for connectivity and data transfer among countless internet-enabled devices, leading to the emergence of the Internet of Things (IoT), which envisions a world of interconnected smart technologies; here, AI plays a crucial role by enabling machines and systems to learn and make autonomous decisions to achieve specific goals (Leiner, 2009), and its adoption is expected to drive an annual growth rate of 15.93% in Europe, reaching a market volume of €185.70bn by 2030 (Statista, 2024).

Today, AI applications span multiple industries, including manufacturing, healthcare, communication, transport, banking, and commerce, with different uses such as visual recognition, autonomous robots and vehicles, virtual assistants, and predictive analysis (Vaia et al., 2023). Between 2021 and 2024, AI maturity has increased by nearly 20%, reaching an average of 52% across industries, driven by its expanding role in entrepreneurship (Accenture, 2022). This shift has transformed the nature of entrepreneurship, influenced by evolving external enablers, institutions (Davidsson, 2016; Eesley et al., 2016), and a new generation of digital-native entrepreneurs (OECD, 2024) leveraging AI in new venture creation have recognised its benefits in reducing costs and enhancing idea generation (Schiavone et al., 2023; Chalmers et al., 2020).

In this study, the terminology of new venture creation will be considered as the process of identifying, developing, and launching a new business, influenced by various factors such as resource availability, supportive policies, entrepreneurial culture, and market conditions. Together with the main key stages, such as idea generation, opportunity detection, business model development, organisational structuring, and initial growth, ultimately aiming to establish a sustainable and innovative enterprise (Kirklev, 2016).

While AI has been considered from a practical point of view as an advantageous element, authors tried to reflect this phenomenon in academia, attempting to keep pace with the evolution of this technology and its application in entrepreneurship (Von Briel et al., 2017; Elia et al., 2019) with growing academic attention. However, maintaining an up-to-date level of research publication in an AI-related environment challenges authors since the AI sector has been considered a swift mover with a “danger” that whatever can be written or hypothesised can become incomplete or quickly obsolete (Lévesque et al., 2020).

Giuggioli & Pellegrini (2022) carried out research by scanning articles linking entrepreneurship and artificial intelligence as fields of study, representing one of the most recent literature review stressing the field of AI and entrepreneurship, and highlights an evident shortage of qualitative research addressing the intersection of these two fields of study (Haleem et al., 2022). Current academic literature largely examines AI and entrepreneurship as separate fields, overlooking their intersection and the role of AI in the new venture creation process (Schiavone et al., 2022). One of the closest and quite recent stand-alone studies following the route of this work can be attributed to Schiavone et al. (2023), which based their work on the venturing processes elaborated by Bakker & Shepherd (2015), composed of a three-step system named prospecting (early-stage exploration), development (later-stage exploration) and exploitation.

The rationale behind those processes demonstrates that the birth of a firm occurs during the identification of an opportunity, the establishment of a business model and the creation of an organisational structure. Subsequently, the prototyping and expansion or business development phases follow (Gruber, 2002).

Although several theoretical and practical contributions are concluded, the study methodology is based on four cases of study, and even if this approach is considered practical to facilitate the inductive gathering of new insights originally unknown to researchers (Sutton, 1997), it does not take into consideration primary data collection or any qualitative study approach, and this lag in the literature stresses the need for research to continually update and address the evolving implications and application of AI in the field of entrepreneurship (Kraus et al., 2019). Despite the few articles published addressing AI as an overall functional key driver for entrepreneurs, very little has been discussed about in which new venture creation phase AI is supporting the most young entrepreneurs, and for this reason, founders and co-founders of AI start-ups will serve as the main data source to get insights regarding the application of AI since they are the actors knowing the exact processes needed to put together the company. Additionally, individuals playing a pivotal role in the development and establishment of the latter, such as CSO and CTO, will be considered.

The research objectives will focus on identifying and categorising the various AI applications used in new ventures, evaluating the effectiveness of AI tools in improving decision-making processes within start-up environments, assessing the challenges and barriers faced by entrepreneurs in integrating AI technologies and determining the impact of AI on the scalability and growth potential of newly founded enterprises.

The main research question of this study can be defined as:

"In which phases of new venture creation is generative AI more impactful?".

The latter aims to provide a deeper understanding of the strategic value of AI in new ventures and visualise in which company's new venture creation phase AI can be considered an essential implementation together with offering a foundation for future research and practical applications in the dynamic landscape of start-up development which might support the already studies addressing the positive connection between AI and new venture creation (Chalmers et al., 2020; Lie et al., 2023; Schiavone et al., 2022; Lee et al., 2022), especially when combined with complementary technologies and internal R&D strategies.

From a research point of view, the literature can be expanded by addressing the subject of AI, helping entrepreneurs understand where this technology can bring crucial benefits and at the same time bring a shift from a firm-level analytical focus to a more macro-level perspective (Chalmers et al., 2020), having a more critical consideration of the ethical and moral aspects that this technology has, rather than focusing only on the economic side (Obreja et al., 2024).

Also, since the AI usage increased even beyond large firms (Iansiti & Lakhani, 2020), a dominance of conceptual and quantitative studies is noted (Füller et al., 2022; Obreja et al., 2024), leaving a gap in qualitative research on AI impact in entrepreneurship. For this reason, this study addresses where AI is most effective in venture creation while mitigating ethical, legal, and operational concerns, even if AI adoption remains complex, with challenges in data access, liability, and transparency (Elsayed & Erol-Kantarci, 2019), alongside the shortage of skilled professionals (Füller et al., 2022).

By analysing entrepreneurs' direct experiences, this research fills an academic gap, offering insights to refine AI implementation in start-ups while contributing to AI-entrepreneurship literature while also providing practical guidance for entrepreneurs, particularly young founders, as they navigate today’s competitive market.

2. Literature Review and Theoretical Framework

This paragraph will analyse the historical context of AI and its impact on the entrepreneurial ecosystem to provide a clear understanding of how AI's evolution has shaped entrepreneurship, fostering technological advancements that influence market dynamics (Chalmers et al., 2020).

2.1 Historical Context of AI

Alan Turing's pivotal contributions to artificial intelligence, particularly his 1950 proposal of the "Turing Test," established a foundational method for evaluating whether a machine could imitate human responses indistinguishably (Oliveira & Figueiredo, 2023). His groundbreaking idea suggested that machines could learn from experience rather than relying solely on prewritten programs, anticipating modern machine learning approaches by several decades and marking a critical milestone in the evolution of intelligent systems.

Straight after, the term artificial intelligence (AI) started appearing in literature, around the mid-1950s (Grudin, 2012), yet with some confusion concerning its exact definition and context: artificial intelligence is smart software and hardware capable of performing tasks that typically require human intelligence.

Another AI's roots can be traced back to 1956, when John McCarthy and Marvin Minsky defined this subject area as "the construction of computer programs that engage in tasks that are currently more satisfactorily performed by human beings because they require high-level mental processes such as perceptual learning, memory organisation and critical reasoning" (Minsky, 1961). Subsequently, the AI definitions evolution has broadened to encompass systems capable of autonomously improving from data, considering this technology as a simulation of human intelligence processes by machines such as reasoning, learning and self-correction (Russel & Norvig, 2010). K.-F. Lee & Quifan (2021), defined AI as the elucidation of the human learning process, the explication of human behaviour and the understanding of what makes intelligence possible. Further, this technology was categorised as narrow AI (weak AI) or general AI (strong AI) (Russel & Norvig, 2010), considering narrow AI, with its specific applications, such as voice assistants, autonomous vehicles and reclamation systems, as a technology able to perform tasks efficiently but without any general cognitive abilities. On the other hand, general AI represents an AI that possesses cognitive abilities like those of humans, allowing this technology to apply knowledge and skills in different contexts.

Over time, AI, once confined to the distinct research areas of computer science and mathematics, evolved into a powerful and widely used industrial tool, gaining prominence across various sectors due to its ability to tackle problems beyond the capabilities of humans or traditional computing systems. As a result, its continuous advancement and expanding range of applications have further driven its integration into numerous industries.

One of the first industries that started implementing AI in its product system was the automotive one, which used this technology to seek both realistic and sophisticated AI techniques so that the vehicles could self-drive in a human-like manner (J. Li et al., 2018). Afterwards, the robotic industry also grew exponentially, providing many prospects for simulation activities in numerous application fields such as household utilities, aerospace expeditions, diagnostic interventions, and combat activities (Alsamhi et al., 2019; Bassil, 2012) together with the healthcare environment, leading this sector to consistent innovations in personalised medicine and diagnostics, improving accuracy and efficiency (Esteva et al., 2017). At this stage, the usability rate of AI tools grows exponentially, and as shown in Figure n.1, it will reach exponential applications by 2030.

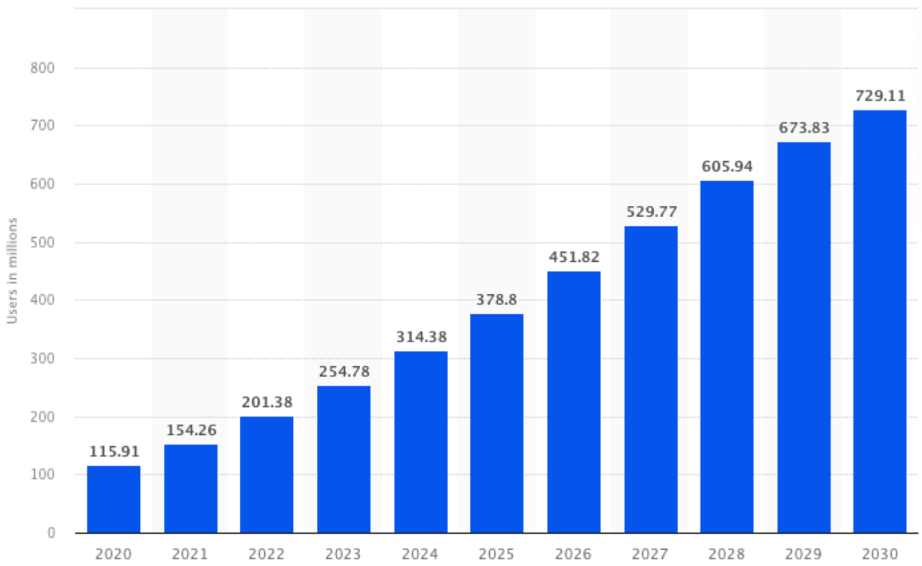

Figure 1. Number of AI Tools Globally Used (Statista, 2024)

On the other hand, while the implementation of AI kept spreading around, ethical implications related to employment, data bias and transparency started to play a crucial role in the public acceptance of this technology (Friedler & Wilson, 2018).

Different studies carried out at MIT by Professor Acemoglu on the impact of technology on the labour market and economic inequality have noted concerns about the potential outcomes coming from the company's application of AI for automation purposes supporting the fact that this technology, if this implementation pace is kept, consequences like labour decline share and a rise in income inequality will drastically challenge current employees (Krishna, 2024).

Alongside the research made by the McKinsey Global Institute, based on a study involving 46 countries, it was reported that up to 800 million global workers might lose their jobs by 2030 due to the increasing implementation of AI in firms (Manyika et al., 2017). Thus, if not supervised, this technology could impact the white-collar labour process where AI large language models (LLMs) might substitute around 40% of all employees' working hours (Accenture, 2023).

Other concerns regarding AI implementation fall into the accuracy and privacy of the data used, where data can be manipulated and used unethically for data collection and analysis, especially in "critical" sectors like health care and transportation, since data quality has to respect a certain level of robustness alongside human oversight and documentation (Lu, 2022). Also, algorithms can be defined as "discriminatory" due to the data based on historical inequalities or societal stereotypes, which can reinforce and amplify the existing societal inequalities and a potential under-representation of specific groups in the training data set. For instance, datasets coming from specific locations can not be applied everywhere universally (Du & Xie, 2020).

Thus, the inherent opacity of AI models poses challenges in explaining certain applications, making it difficult to understand how they process inputs and reach decisions, which in turn exacerbates transparency issues, fuels biases and assumptions among the public, and ultimately reduces trust in the technology (Lipton, 2018). For instance, accountability – whether it lies with users, AI companies or developers – is not easy to define when the outcomes are made by algorithms. Examples can be found in self-driving cars in life-threatening scenarios and the "trolley problem", which was tried to be addressed by Alan Turing. Here, the lack of a regulatory and cybersecurity framework enlarges this issue, since the rapid pace of AI development is outstripping existing legal and regulatory frameworks, leaving critical gaps in how accountability should be better enforced (Du & Xie, 2020).

However, it is worth noting that global initiatives, such as the European Union's AI strategy, aim to ensure responsible AI development (European Commission, 2020), while AI's impact on education and the workforce is significant, enhancing productivity and learning outcomes yet also raising concerns about workforce displacement (Berain, 2014).

The evolution of historical AI, from its early formulation to its widespread implementation across industries, illustrates continuous innovation, with key milestones not only marking the field's origins but also showcasing its potential as a foundation for technological advancement. As AI transitioned from a theoretical concept to practical applications, it became a driving force for innovation that extended beyond its initial scope, emerging as a critical element in transformative technologies and laying the foundation for its role today as a pivotal support system for technological innovation across various domains.

2.2 Artificial Intelligence Support in Technology Innovation

The term "innovation" has been considered a representation of a change in the production function, highlighting its role as a driving force of economic development (Schumpeter & Backhaus, 2006). Rather than emerging in isolation, innovations build upon existing capabilities and technologies, where the continuous exchange of information and the refinement of previous building blocks drive the creation of new value (Arthur & Polak, 2006), as evinced in patent data, where patents are more likely to cite (and therefore involve) recent patents rather than old ones (Valverde et al., 2007). Another example can be seen from the first joint occurrence in a patent of previously unrelated technology areas, which signals the emergence of technological innovation, detected to be more common if the key technology areas were already considered close enough to each other and often result from a collaboration between different firms (Curran & Leker, 2010; Kim et al., 2014; Caviggioli, 2016). Subsequently, this term was linked with the technology one, proposing that technological innovation refers to the results of solving specific issues in research areas and the technological development process having a primary purpose focused on securing a competitive market advantage (Coccia 2014a; 2014b; 2015a; 2015b; 2016a; 2016b).

Technological innovation is essential for enterprises to maintain stability and progress across products, services, managerial operations, and production processes (Marzi et al., 2017; Forrest et al., 2019), relying not on a single ecosystem but on continuous advancements and co-evolving through interactions with other activities (Coccia, 2017).

Studies on technological innovation can be traced back to the 1960s when various models were developed to understand the driving forces behind this phenomenon, displayed in five generations: science push (1st generation), demand-pull (2nd generation), the coupling model (3rd generation), the integrated model (4th generation), and the system model (5th generation) (A. Andersen & P. Anderson, 2014; Barbieri & Alvares, 2016). While there is no direct hierarchy among these models, adjacent models influenced one another, and different generations continue to be applied in today's firms (A. Andersen & P. Anderson, 2014).

Furthermore, the ongoing development of technologies that address human and technical needs more effectively or economically than before continues to drive innovation, accelerating technological advancement (Arthur & Polak, 2006); as a result, the current high-tech innovation cycle is recognised as distinctly different from past cycles (Grottke, 2018). In this context, AI has played a crucial role in overall technological innovation, particularly by accelerating knowledge creation, facilitating technology spillover, improving learning-absorbing capacities, and increasing investments in R&D and talent (Liu et al., 2020).

This technology played a pivotal role in most of Industry 4.0, a term defined as a combination of the virtual and real worlds with an emphasis on engineering applications such as automation, robotics, and digitalisation (Kagermann & Wahlster, 2022).

Industry 4.0, commonly associated with the fourth industrial revolution, represents the ongoing phase of technological advancement built upon the foundation of previous industrial revolutions (Wang et al., 2016), fostering the development of various innovative technologies, with AI serving as a crucial support in their implementation, including augmented reality, blockchain, and the Internet of Things (IoT) (Azuma et al., 2001; Treiblmaier, 2018). Examples can be found in industries ranging from healthcare to manufacturing and finance, with companies like IBM and its AI-driven healthcare tool Watson assisting professionals in analysing vast datasets to provide personalised treatment recommendations (Ferrucci et al., 2010). Similarly, in the automotive field, Tesla company highlights technology innovation with its AI-powered autonomous driving systems, which combine machine learning and real-time data analysis to revolutionise transportation (Shladover, 2017). Also firms like ABB, which integrates robotics for flexible manufacturing solutions, as well as the General Electric Predix platform that uses AI to monitor and optimise industrial operations in real-time (Porter et al., 2015). For instance, Amazon manages to leverage AI for its recommendation system, driving 35% of its revenue through personalised shopping experiences based on user behaviour (Smith & Linden, 2017).

Further, technological innovation involves activities that lead to the creation of novel technologies that enhance productivity and generate added value (Coccia, 2018), particularly evident in renewable energy firms, where Siemens utilises AI to optimise wind turbine performance, ensuring both energy efficiency and sustainability (Sovacool et al., 2018). Similarly, in e-commerce, platforms like Alibaba deploy AI for dynamic pricing and supply chain optimisation, resulting in cost reductions and customer satisfaction.

In recent years, the application of AI has spread across various markets, closely correlating with technology and innovation. However, research specifically addressing the impact of AI on technological innovation remains relatively rare, with only a few scholars exploring this topic in their works (Liu et al., 2020). A few authors have tried to list the true gains coming from the close relationship between AI and technological innovation, and then one common broad point of view arose: AI is considered a universal technology that can support other innovations (Vocke et al., 2019).

There have been noted a few impacts brought by AI to the technology innovation (Liu et al., 2020):

- Accelerating the spillover of knowledge and technology:

  Due to its universal application, AI can be easily applied in different departments of a business firm, leading to the development of inter-departmental technological innovation. Eventually, applying this technology drives substantial business value by streamlining operations and enabling a more informed decision-making process, boosting overall company profitability.

  Therefore, with increasing profits, beneficiary departments will bump up their demands for additional intelligent technologies and subsequently, the R&D department can continue enhancing the firm's technical sophistication and developing new smart technologies to match emerging market demands.

  The authors view the increasing spillover of knowledge and technology coming from AI implementation as a cycle that repeats itself, stimulating a cumulative cycle of growth of AI and technological innovation.

- Increasing investment in R&D and talents:

  Building an in-house R&D department can help firms to generate, exploit and convert knowledge and discover new technologies, entice cooperative partners and construct new technology settings which, in most cases, are very costly or difficult to obtain from competitors or partners (Keizer et al. 2002; Debackere et al. 1996; Lee, 1995).

  In-house R&D has been widely considered a crucial determinant of innovation (Hall & Bagchi-Sen 2002; Parthasrthy & Hammond, 2002); therefore, investments and developments in this department could eventually be seen as a guarantee for technological innovation.

  Investment in R&D plays a crucial role in every aspect of the R&D process. It covers laboratory costs and helps provide test equipment and devices. Other than that, another important component of technological innovation is direct investments in scientific and technological talents.

  Effective organisation of quality scientific and technological talent, along with other essential factors, significantly enhances the capabilities and efficiency of technological innovation. In firms, AI development can lead to intelligent industrial robots, automated production processes, and advanced equipment, which have the potential to replace human labour, reduce costs, and increase productivity, thereby allowing more resources to be allocated to R&D.

- Quickening knowledge creation:

  Effective creation of new knowledge has been noted as the core element of technological innovation (Chen, 2004). Each technological innovation involves the creation of new knowledge and the blending of new and existing information.

  The resulting technology from these innovations emerges from generating new insights, creatively interpreting existing knowledge, or producing entirely original ideas, with knowledge creation further enhanced through the effective development of AI, particularly in data collection, which unlocks new perspectives on existing knowledge and provides fast-paced support for exploring multiple ways to integrate that knowledge.

  The aspect of data collection has received many benefits from AI implementation, due to its ability to manage large datasets by creating and using intelligent algorithms, such as machine and deep learning, to enable more efficient knowledge retrieval and data processing (Vocke et al., 2019).

- Improving the capability of learning and absorption:

  Apart from understanding the market where a company operates, the authors believe that learning and absorption abilities are also directly related to the entry efficiency of external knowledge in a firm. As a definition, absorptive capacity is recognised as an effective means of obtaining and sustaining a competitive advantage (Vlačić et al., 2018).

  Here the development of AI can help directly both employees and enterprises. Employees can support their daily activities by using tools that help them make more effective decisions due to the AI's capabilities of reasoning, learning, association and problem-solving based on known knowledge.

  On the other hand, technologies like deep learning and intelligent image recognition can support enterprises in training systems to form independent judgements and to take responsible actions.

In summary, AI plays a vital role in driving technological innovation across multiple dimensions by accelerating knowledge spillover, increasing investment in R&D and talent, and enhancing the speed of knowledge creation, ultimately fostering cumulative and continuous innovation within firms (Liu et al., 2020).

As already mentioned, AI innovation has supported overall technological advancement by providing critical tools to accelerate idea development and techniques for performing tasks once considered challenging, while also evolving across different fields with applications tailored to specific outcomes (Figure n.2).

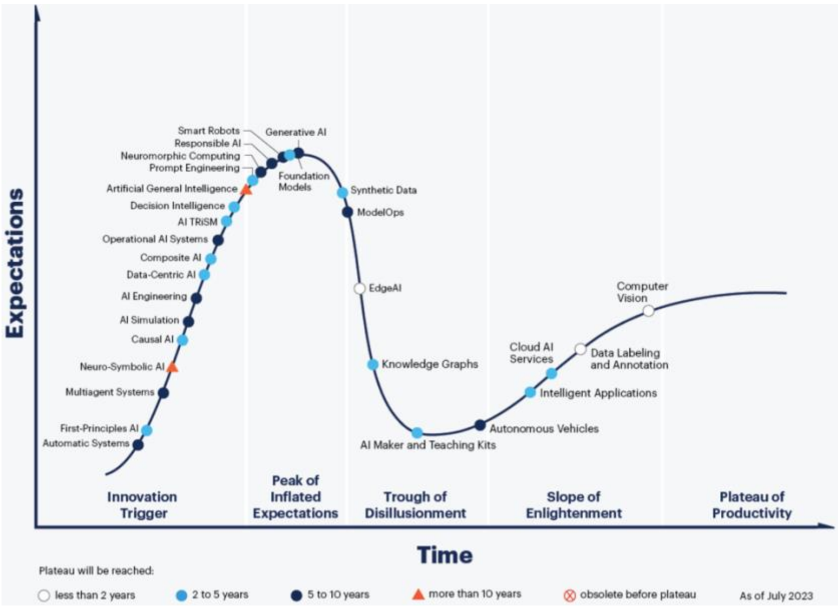

Figure 2. Hype Cycle for Artificial Intelligence (Perri, 2024)

One of the most renowned AI evolutions with the highest peak of inflated user expectations is the well-known platform "Chat Generative Pre-Trained Transformer" (ChatGPT), which uses generative AI, which refers to a type of AI that can generate human-like text and creative content as well as consolidate data from different sources for analysis (Cascella et al., 2023).

Although AI-driven innovations provide several benefits to companies, they hinge on significant investment in research and development (R&D), encompassing financial resources, time and expertise, especially when developing, training and deploying those systems, many high costs have to be faced, starting from hardware costs (GPU and TPU), cloud computing, storage costs and development costs. Proof could be seen from the training of OpenAI's GPT-3, which reportedly cost millions of dollars in computing resources alone, demonstrating that only organisations with a significant budget can afford to undertake such projects (Strubell et al., 2019). These key figures, like data scientists, machine learning engineers and domain experts, represent a critical talent shortage issue together with time-investment development, which becomes a critical resource constraint for the R&D department (Chui et al., 2018). Thus,

AI innovations often involve iterative processes that require significant time before delivering tangible results due to model training and testing, data collection and preprocessing and regularity approval. Let's just think about self-driving vehicle technology, which companies like Tesla spent over a decade redesigning this technology (Rajabli et al., 2020).
However, even if AI's advancements seem to take a little time to be developed, this technology has provided critical tools for startups to spur their innovation pace, reshaping the entrepreneurial ecosystem by creating opportunities for efficiency, new business models and market expansion.

2.3 Technology Entrepreneurship and AI

A few authors have highlighted the close connection between the intention to start a company and the field of entrepreneurship, demonstrating that, in general, people with more flexible cognitive abilities have higher adaptability to a new situation (Martin & Rubin, 1995).
In the context of start-up intention, this cognitive flexibility represents the necessary motivation to enable people to show diverse behaviours to solve a problem in a new way to find the best solution possible (Lee et al., 2019). Consequently, this persona is open to change, has less fear of embracing new experiences, has higher preferences for new tools and applications and tries to seek more innovative solutions without restrictions when facing an issue (Georgsdottir & Getz, 2004). The final outcome of this innovative entrepreneurial mindset is the creation of a startup, defined as a young firm, often less than five years old, characterised by high innovation and strong growth potential. Many other definitions can be drawn from an academic perspective considering start-ups from different standpoints: from a more general and problem-solving viewpoint, start-ups can be considered a company working to solve a problem where the solution is not obvious and success is not guaranteed (Shepherd & Majcharzak, 2022); from a risk-oriented viewpoint these companies are seen as a human institution designed to create a new product or service under conditions of extreme uncertainty (Ries, 2011); from a competitive positioning angle, start-ups are considered a temporary organization structured to search for a scalable business model (Blank & Dorf, 2012) aiming to create high-tech innovative products and grow by aggressively expanding their business in highly scalable markets (Paternoster et al., 2014).
Although start-ups seek to introduce innovative elements to the market, driven by the entrepreneurial motivation of young founders to shape and enhance industries, internal instability—rather than external competition—frequently serves as the primary cause of business failure. Despite numerous success stories, this internal turmoil remains a common

factor contributing to bankruptcy, with the majority of start-ups failing within two years of their inception (Crowne, 2002). Several causes can be listed and considered, but commonly the reason comes from a combination of factors listed as follows: organisational (e.g., lack of strategy), human (e.g., lack of commitment), financial (e.g., lack of cash and financing possibilities), ecosystem (e.g., legal challenges), product (e.g., user-unfriendly product) and market (e.g., strong competition) (Szathmári, 2024).

However, start-ups are also identified as agents of disruption, which can be considered a pivotal characteristic of this company's typologies since producing disruptive innovation is often seen as the only way to successfully compete in a globalised economy, and for this reason, corporations nowadays consider start-ups as an innovation engine in their production due to their important role in technology innovation, which increases companies' overall innovation level by combining information exchange and capabilities (Weiblen & Chesbrough, 2015).

The meeting point between the two fields, such as entrepreneurship and technological innovation, takes the name of technology entrepreneurship, an area focused on how opportunities are advanced through innovation in science and engineering (Zupic, 2014) (Figure n.3).

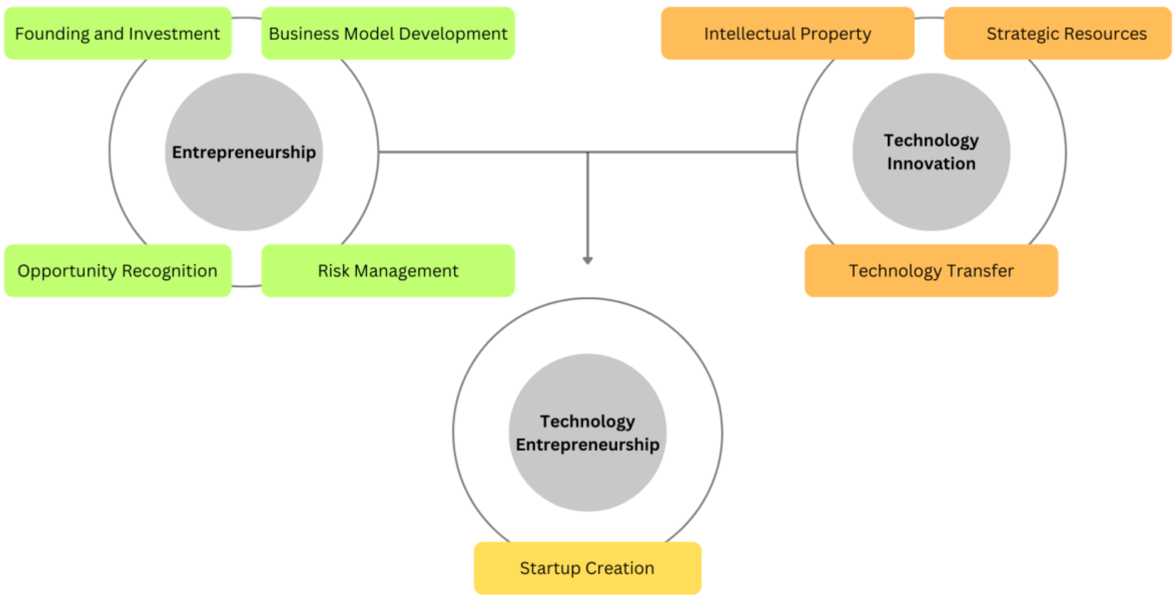

Figure 3. Ecosystems Interaction (Own illustration based on Zupic, 2014)

Technology entrepreneurship operates at the intersection of scientific development and technological innovation, bridging these elements to create and exploit new opportunities by recognising and leveraging technological advancements to generate value through individuals, teams, and firms (Walicka et al., 2015; Shane & Venkataraman, 2000; Beckman et al., 2012).

The ultimate product coming from technology entrepreneurship is the creation of a start-up, defined as a new venture emerging in an innovation ecosystem, focusing on innovative products and services while playing a crucial role in technological development (Reisdorfer-Leite et al., 2020).

As shown in Figure n.3, the desired result cannot be achieved without the interaction between technological innovation and entrepreneurship, as both areas must be paired to navigate market dynamics and business complexities (Nathan, 2022), and among the technologies foundational to technology entrepreneurship, AI plays a crucial role in how young entrepreneurs develop, design, and scale their companies throughout the entrepreneurial process (Chalmers et al., 2020).

Even though the application of this technology can be seen in various sectors and aspects, in the process of new venture creation, AI integration can be detected from two perspectives, such as a process enabler or as a company's core final product. When considered a process enabler, this technology integrates AI into existing workflows to optimise, enhance, or automate operations, particularly in industries where it supports predictive analysis, decision-making, and efficiency improvements (Stige et al., 2023). On the other hand, the use of AI for a company's final purpose refers to applications where AI technologies are directly offered to end-users, with products designed around AI as a central component or by providing specific functionalities (Quan et al., 2023).

A recent survey by Quan et al. (2023) provides comprehensive insights into the application of AI as a final company product, highlighting the development of AI-generated content (AIGC) as a major advancement. AIGC leverages generative AI models to produce large amounts of high-quality data based on user-provided prompts, representing a significant step in the use of AI as a product (Xu et al., 2024; Wang et al., 2023).

The overall implementation of AI, whether as a process or a product, has shown positive outcomes, with 40% of business leaders reporting increased productivity through AI automation and 25% of companies adopting AI to address labour shortages, highlighting its overall impact on entrepreneurship, which can be categorised into two key areas (Salminen, 2024; Shepherd & Majcharzak, 2022). The first one digs into the specific ways in which AI can enhance the capabilities of individual entrepreneurs, and the second one refers to the opportunities that AI brings to the entrepreneurial landscape. AI supports individual entrepreneurs by processing vast amounts of data quickly and accurately, providing valuable insights for decision-making and generating personalised recommendations based on past interactions or preferences to help discover new opportunities, improve productivity and optimise processes (Reisch & Krakowski, 2021). Beyond these benefits, AI enhances sustainable growth and prosperity (Zhou et al., 2019), reduces costs, fosters productivity gains (Wirtz et al., 2018), and empowers decision-making and strategic alignment, leading to operational efficiency, customer-centricity, and various growth opportunities (Anane-Simon & Atiku, 2023). At the same time, entrepreneurs can potentially anticipate market changes and identify risks to stay one step ahead of competitors thanks to AI predictive analysis and tailor their company products to meet market demand effectively (Kaplan & Haenlein, 2018).

One of the reasons why AI brings several opportunities to the entrepreneurs and therefore to the overall new venture creation comes from the fact that this technology plays a crucial role in the global economy, where a shift from a mechanical model—centred on tasks like machine control, equipment operation, and information storage—to a thinking economy that prioritises object and process identification, work organisation, decision-making, and knowledge updating makes the application of this technology perfectly suitable. This transition has placed a greater emphasis on information management rather than machine operation (Huang et al., 2019) and AI, in both economic models, has found applications due to its ability to efficiently handle repetitive tasks, such as enhancing production efficiency through factory automation (Huang & Rust, 2018).

Given AI's critical role in both the global economy and its ability to streamline repetitive tasks, its application can also extend to enhancing the entrepreneurial process, especially in managing social tasks and fostering creativity within new ventures.

The entrepreneurial process is typically described as an emotional rollercoaster (Shepherd, 2003; Shepherd and Cardon, 2009); therefore, social tasks, such as engaging resource holders (Fisher et al., 2020), constructing potential opportunities (Seyb et al., 2019), using social skills to make sales (Baron & Markman, 2000) and supporting creativity, can be potentially enhanced from AI’s support. The creative support enhanced by AI applications stems from a sub-field called computational creativity, which involves computers performing tasks that would be considered creative if done by humans (Johnson, 2012), enabling systems to interact with users in a way that fosters human-machine co-creation of innovative and novel products (DiPaola et al., 2013).

In the context of integrating AI within the entrepreneurial process, several barriers hinder effective implementation, with access to data and resource constraints being the primary challenges for small companies (Obschonka & Audretsch, 2019), as AI applications require massive datasets for analysis and training, which young startups often struggle to afford in terms of cost and time. Furthermore, the lack of data privacy regulations complicates adoption, as compliance with data protection laws and ethical guidelines requires expertise that many early-stage companies lack (Floridi et al., 2020). Also, resource constraints represent a potential competitive disadvantage for young entrepreneurs, where the lack of substantial computational power and skilled personnel lowers the possibility of entering the AI market. Finding talents with the required AI knowledge has been considered a challenging task for start-ups due to the high competition from well-established companies like Amazon Web Service, Google AI or OpenAI (Floridi et al., 2020) with access to cutting-edge infrastructure and significantly greater resources compared to small companies, which are often overshadowed by these industry giants (Floridi et al., 2020).

Nevertheless, for AI startups, the AI progress is transforming society and the know-how requirements that need to be continuously updated to be at the forefront of this technology development might represent an important obstacle to overcome. From this perspective, bigger companies exploiting AI and big data for entrepreneurial strategies might benefit from a considerable incumbent advantage over small ventures since they possess better "economic muscles" and direct access to infrastructure (Obschonka & Audretsch, 2020). As shown, the impact and implementation of AI can be seen from different viewpoints, as well as the fact that the implementation of this technology brings massive benefits, but at the same time, challenging aspects have to be taken into account when deciding to either embrace it as a process to optimise operational procedures or use it as a final company product.

2.4 Theoretical Framework Overview

Chalmers et al. (2020) framework comes from a literature review carried out by bringing together different authors' models (see A.1).

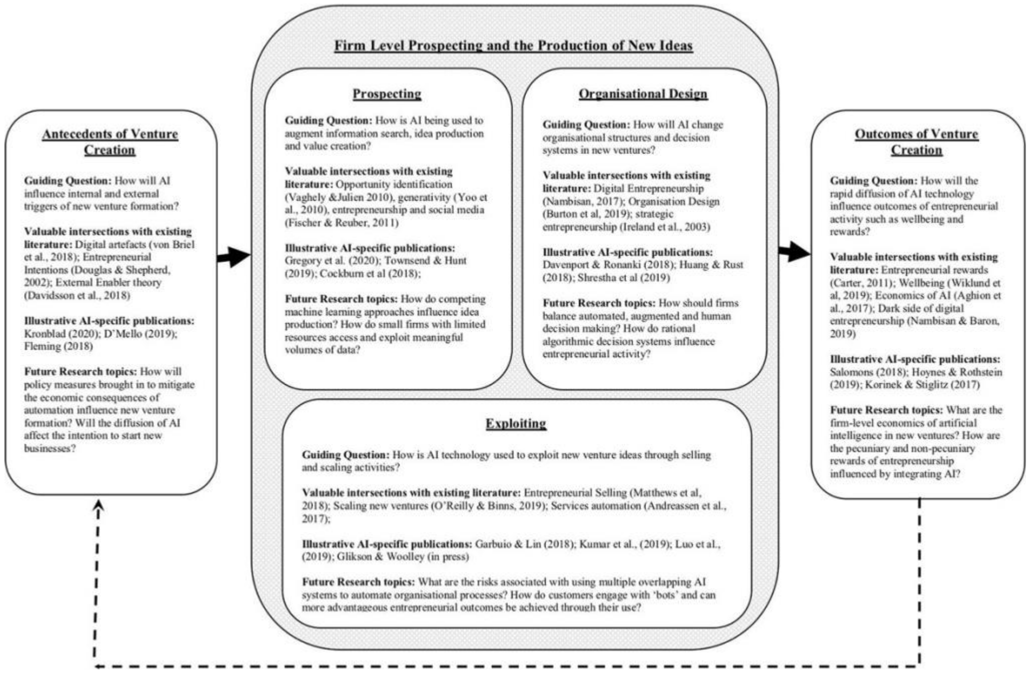

Figure 4. Artificial Intelligence and New Venture Processes and Practices (Chalmers et al., 2020, page 5)

Chalmers et al.'s framework (figure n.4) follows a linear path by examining how AI impacted the antecedents of venture formation, then considers how the technology shapes a range of firm-level activities before turning to the potential implications for entrepreneurial outcomes.

The framework's starting left-side paragraph, focusing on the antecedents of venture creation, explores how AI can influence individual decisions to engage in entrepreneurship, affecting both the likelihood of starting a venture and the selection of firm typologies. Triggers and idea generation, key components influenced by both individual factors and broader external systems, are significantly impacted by artificial intelligence in these early stages of entrepreneurial decision-making.

The central core of the framework delineates the new opportunities AI offers by revolutionising how new ventures explore and generate ideas through advanced data analysis and pattern recognition, while also highlighting critical research opportunities to better understand AI's influence on venture creation and industry structure, particularly in its transformation of decision-making processes, organisational structures, and customer interactions within new ventures. Concurrently, the authors emphasise that AI's impact on industry structures is prompting smaller ventures to devise innovative organizational designs and collaborative models in response to the dominance of large tech firms in the AI sector.

The last section considers the outcomes of venture creation, which argues the potential effects and rewards of AI-enabled entrepreneurship, highlighting the possibility that AI may reshape entrepreneurial rewards like well-being, financial returns or satisfaction.

Chalmers et al. (2020) framework highlights significant research gaps, beginning with the antecedents of venture creation, where the authors note the limited studies on AI's influence on individual entrepreneurial intention and venture typologies, and moving to the central core, where they identify a gap in understanding how AI could transform traditional methods of opportunity recognition and organisational design. Additionally, the authors acknowledge gaps in assessing the outcomes of AI-enabled entrepreneurship, as existing literature primarily focuses on performance and financial metrics, and propose expanding this focus to include broader impacts, such as satisfaction and well-being, to provide a more holistic understanding of entrepreneurial rewards.

The second framework considered belongs to Giuggili & Pellegrini (2022), which crosses out four thematic clusters with the five parts of Chalmers et al. (2020) schematisation to show the most relevant emerging areas. (Figure n.5)

	Antecedents of venture creation	Prospecting	Organizational design	Exploiting	Outcomes of venture creation
Education and research	AI implemented in digital learning as an enabler for antecedents of venture creation				AI combined with ethics as an enabler for outcomes of venture creation
Opportunity		AI coupled with neuroscience as an enabler for opportunity identification and exploitation			
Decision-making			AI applied to entrepreneurs' communication as an enabler for fundraising		
Performance				AI used alongside blockchain as an enabler for automation and scaling	

Figure 5. The AI-enabled Entrepreneurial Process – Framework (Giuggioli & Pellegrini, 2022, page 828)

The authors carried out a systematic literature review based on 60 articles (24 theoretical papers, 31 quantitative papers and 5 qualitative papers), where they identified four clusters representing the differences in the impact of AI on entrepreneurship, allowing for multiple entries of a paper across different clusters.

These clusters are the "education and research" cluster (12 papers), which is a general cluster primarily related to theoretical debates surrounding the recent evolutionary trends of the discipline and its implications for the educational sector; the "opportunity" cluster (11 papers), dealing with AI as an enabler for entrepreneurs to create new opportunities; the "decision-making" cluster (24 papers), considers AI as an enabler for entrepreneurs to make better predictions and, hence, better decisions and the “performance” cluster (18 papers), which refers to the improvements achievable thanks to AI according to the firm’s performance. Figure n.5 shows how the authors cross out the four clusters, with the findings coming from Chalmers et al. (2020).

The first intersection, involving "education and research" and "antecedents of venture creation," focuses on the application of AI to digital learning, which, according to the authors, has the potential to further understand and stimulate entrepreneurial intention and orientation, with increased engagement through AI-supported teaching strategies potentially improving and developing entrepreneurial intentions and orientations (Khalid, 2020). The following matching “opportunities” and “prospecting” sections refer to the potential that AI coupled with neuroscience can capture hidden mental processes and at the same time, contribute to the overall understanding of the role of intuition, emotions, implicit attitudes and insights in the entrepreneurial process (Nicolaou et al., 2019). In the third section, AI is presented as an enabler for improving entrepreneurial decision-making, particularly in organisational design, by offering ways to enhance communication, which is crucial for securing funding, as entrepreneurs who effectively convey their potential and project details are more likely to engage investors (Clark, 2008; C.M. Mason & Harrison, 2003). AI holds untapped potential to assess and measure the impact of communication on funding decisions, benefiting both entrepreneurs, who can adjust their approach to increase their chances of securing financial backing, and investors, who can make more informed, rational funding decisions.

The focus on “performance” should be directed toward the specific process of exploiting an opportunity, where AI combined with blockchain can act as a key enabler for automation and scaling by ensuring secure and validated data sharing in environments with low trust, leveraging the enhanced security provided by big data (K. Wang et al., 2019).

The final section on “education and research” explores the outcomes of venture creation in AI and its broad applications, emphasising the ethical implications outlined in Giuggioli & Pellegrini’s framework, which highlight the urgency of responsible AI use, as success should be measured not only by financial and economic returns but also by its alignment with the principle of equity (Zhang et al., 2021).

Further research should explore how entrepreneurs can harness the benefits of AI while mitigating risks and ensuring democratic and ethical governance through corporate social responsibility strategies, as some types of AI can profoundly impact a company’s economy, not only enhancing productivity but also reshaping business strategies themselves (Agrawal et al., 2019).

The Giuggioli & Pellegrini (2022) framework underlies other potential gaps from opportunities, decision-making and performance points of view, underscoring the opportunity to increase the understanding of how AI is improving entrepreneurial decision-making. For example, the authors suggest that this technology can enhance communication strategies, needed for entrepreneurs to secure funding and help investors in making more rational decisions. Thus, the integration of AI with technologies presents opportunities to transform entrepreneurial practices by automating processes and enhancing data security, yet its implications for scaling and risk reduction remain insufficiently studied.

3. Methodology

The following paragraph will provide an overview of how the methodology of this study will be structured and carried out while explaining the reasoning behind the decision to adopt the chosen study approach.

3.1 Research Design

The previous sections highlighted a potential issue regarding the relevance and reliability of findings coming from AI applications in sectors like new venture creation and entrepreneurship. It was specifically noted that some findings, particularly those reported in academic reviews, may not always be updated or, in some cases, lack credibility, raising concerns about the research's validity, which ultimately relies solely on academic literature without incorporating real-time or empirical data. The reason behind this phenomenon might come from the fact that any predictions and explanations of future scenarios might quickly become outdated due to the rapid progress in the fields of AI and big data, and they are potentially considered far-reaching, yet hard-to-precisely predict, future implications for the real world (Grace et al. 2018).

Therefore, a qualitative approach was considered for this research due to its strong potential for exploring new topics, understanding processes, and addressing "how" academic research questions. This method emphasises describing participants' processes and behaviours while adopting an inductive approach that focuses on analysing the lived experiences of interviewees (Hennink et al., 2020; Azungah, 2018). This approach, according to Thomas (2006, p.238), refers to the group of "approaches that primarily use detailed readings of raw data to derive concepts and themes", particularly suited to a qualitative approach. By collecting in-depth, real-time data from practitioners in the field, this method enables the study to uncover context-specific mechanisms and behaviors that are less accessible through quantitative or literature-based methods. This is especially critical in understanding the complex, iterative processes of integrating AI into entrepreneurial ventures, where nuances and situational factors play a significant role (Gartner & Birley, 2002).

A qualitative methodology directly addresses the above-reported limitations by prioritising the collection of real-time, experimental insights from individuals actively engaged in the study field (Lerman et al., 2020). This approach helps the research outstrip publications' temporal limitations, capturing evolving patterns and processes as they occur by focusing on participants' lived experiences and contextual narratives, ensuring that findings are grounded in the present realities of entrepreneurship and AI application rather than coming mainly from generalised data (Corley & Gioia, 2011). Still, Thomas (2006) supports that instead of being confined by a preexisting theoretical mechanism, qualitative research fosters the discovery of novel themes and patterns that reflect the fluid and innovative landscape of both fields.

The collection of qualitative data offers several advantages in entrepreneurship research and organisational scholarship, as it is open-ended, allowing researchers to gather insights without predetermining precise constructs and measures, while also providing concrete, vivid (Paivio et al., 1988), rich, and nuanced information (Weick, 2007) that captures the complexity of entrepreneurial and organisational phenomena.

The reason why quantitative approaches were not considered in this work, is due to the limitation of this approach to keep pace with such dynamism due to their reliance on fixed models and datasets (Langley, 1999). As a result, they may miss the iterative and emergent nature of entrepreneurial decision-making, where qualitative methods excel in capturing processes as they unfold in real time (Eisenhardt, 1989). These methods often rely on predefined constructs and variables, which can constrain the exploration of novel phenomena like the integration of AI into entrepreneurial ventures, and given the emergent and context-dependent nature of this research, a qualitative design was better suited to this work (Creswell & Poth, 2017). Nevertheless, qualitative studies have greater potential to produce insightful papers also because they already departed from mainstream methods and can potentially embark on taking theoretical risks (Bell et al., 2022).

The decision to overtake a qualitative approach also refers to the vicinity and length that this method has in social sciences (Myers, 2015), mainly used to acquire in-depth understanding by paying attention to the participants' views and experiences, which found an effective implementation in the field of entrepreneurial studies (Gartner & Birley, 2002; Suddaby et al., 2014). By incorporating qualitative research methods, this study, aside from addressing the limitations of academic literature, also bridges the gap between theory and practice, offering a more nuanced understanding of AI's role in the entrepreneurial venture while contributing to both academic discourse and the practical toolkit needed by entrepreneurs (Suddaby et al., 2014).

3.2 Sampling

A relatively small and purposively selected sample may be employed in a qualitative study (Miles & Huberman, 1994) to increase the depth of understanding of the overall research findings (Palinkas et al., 2013).

The sampling used for this study will start with purposive sampling based on semi-structured interviews. Purposive sampling is used to select respondents most likely to yield appropriate and useful information (Bourgeault et al., 2010) and to identify and select cases that will use limited resources effectively (Palinkas et al., 2013), employing strategies to ensure that specific cases are included in the final sample of the research study.

The motivation behind the adoption of a purposive strategy is based on the assumption that, given the aims and objectives of the study, specific personas may hold a different and important point of view about the ideas and issue in question and therefore need to be included in the sample (Robinson, 2013).

According to Campbell et al. (2020), the most popular forms of purposive sampling are stratified, cell, quota and theoretical sampling.

The quota sample will be adopted for this study due to its great flexibility which, rather than focusing on fixed numbers of cases being required with particular criteria, specifies creating categories and the minimum number needed for each one (Mason, 2002). Quota sampling will take into consideration participants from different sectors (health care, fintech, manufacturing, etc.) supporting the final focus point of this research, ensuring that diverse perspectives are taken into account, capturing how AI impacts different types of ventures and/or founders. Since new venture creation and AI are directly influenced by contextual factors such as organisational size, market conditions and resource availability, the quota sample makes sure that ventures at various stages of maturity provide a rich understanding of these contextual dynamics (Creswell & Poth, 2017).

While other purposive sampling methods can introduce bias by over-representing well-connected participants, quota sampling mitigates this risk by using predetermined categories to ensure key groups are not excluded, making it particularly valuable for capturing the diverse backgrounds of AI startup founders (Palinkas et al., 2013). For instance, the experiences of technical founders leveraging AI for product development might be different from non-technical founders using AI for operational efficiency, then, by setting quotas for each group, this study can potentially uncover these opposite impacts (W.K. Smith & Lewis, 2011).

The decision to embrace quotas over other purposive samplings has the potential to mitigate gaining overly homogeneous representation data from less prominent but equally critical groups necessary to the final research scope.
Despite its strengths, purposive sampling has some potential limitations directly related to selection biases. Since the study participants are chosen based on the researcher's judgement, there is a risk of excluding important perspectives that the researcher may not anticipate (Tongco, 2007). Also, this methodology may limit the diversity of viewpoints, especially if the sample does not voluntarily reflect the researcher's assumption about the population. In order to mitigate these challenges, this study adopts the quota sampling strategy to ensure an effective representation across key demographic and professional categories relevant to AI and entrepreneurship (Mason, 2002).
However, while the purposive sampling (quota) will be selected for the first phase of the study, the snowball sampling will be taken into consideration during the qualitative data-gathering process, which will facilitate the overall study sampling by collecting participants through existing study subjects' referrals (Sjödin et al., 2020). This method, also known as the "chain method" (Naderifar et al., 2017, p. 2), is efficient and cost-effective for accessing individuals who would otherwise be difficult to find, as the researcher initially selects a few samples through convenience or purposive sampling and then asks them if they know others with similar views or situations to participate. The snowball method facilitates better communication with participants, as they are acquaintances of the initial sample, creating a link between the researcher and the samples (Naderifar et al., 2017) and can also be combined with purposive sampling, where participants are selected based on their specific characteristics or group membership (Parker et al., 2020).
This sample, while efficient, also carries limitations, particularly related to the risk of selection bias and homogeneity because participants are reached through referrals, there might be the possibility of building up a sample that reflects a narrow social network, thereby excluding diverse viewpoints (Biernacki & Waldorf, 1981). For this reason, snowball sampling will be used alongside purposive sampling to ensure the inclusion of participants from diverse backgrounds and expertise levels, while cross-checking data saturation across these varied groups will ensure the robustness of the findings.
Table n.1, provides an overview of all 20 interviewers' characteristics.

Interviewee No.	Gender	Position	Sector	Location
1	F	CSO	Biotechnology Research	Berlin
2	M	Founder	Technology, Information and Internet	Berlin
3	M	Co-Founder and COO	Technology, Information and Internet	Berlin
4	M	Co-Founder and CEO	IT Services and IT Consulting	Berlin
5	F	CTO	Consumer Services	Berlin
6	M	Founder and CEO	IT Services and IT Consulting	Berlin
7	M	CEO	Health and Human Services	Berlin
8	M	Founder and CEO	Health, Wellness and Fitness	Enschede
9	M	Co-Founder	Defense and Space Manufacturing	Berlin
10	F	Co-Founder and CEO	E-Learning Providers	Berlin
11	M	Co-Founder	IT Services and IT Consulting	Berlin
12	M	Founder	Software Development	London
13	M	Co-Founder and CTO	IT Services and IT Consulting	Berlin
14	M	Co-Founder and CEO	Software Development	Berlin
15	F	Co-Founder	E-Learning Providers	Berlin
16	F	Founder and CEO	Technology, Information and Internet	London
17	M	Founder and CEO	Information Technology and Services	Frankfurt
18	M	Co-Founder and COO	E-Learning Providers	Berlin
19	M	Co-Founder and CTO	Construction	Tel Aviv-Yafo
20	M	Co-Founder and CPO	Business Consulting and Services	Berlin

Table 1. Interviewees Traits (Own Table)

<u>*3.3 Data Collection*</u>

The data collection of this study will be based on semi-structured interviews with entrepreneurs leading AI start-ups, with additional implementation of multiple case studies necessary, as manifested by Im et al. (2023), for developing new insight into the theoretically novel phenomenon.

Semi-structured interviews were chosen for this study due to their flexibility and adaptability to new and shifting phenomena, where new information or trends might emerge or change unexpectedly (Benlahcene & Ramdani, 2021). Also, they have been considered a helpful tool for gathering rich, detailed data that can illuminate how trends evolve, making them ideal for exploring new and ongoing trends in dynamic fields like AI and entrepreneurship (Javadian et al., 2020). Semi-structured interviews are the preferred data collection method for the research to better understand participants' unique perspectives rather than a generalised understanding of the whole phenomenon (McGrath et al., 2018). Thus, the primary benefit of this qualitative data-gathering method is that it permits the interview to be focused while still giving the investigator the autonomy to explore pertinent ideas that might come up during the interview (Adeoye-Olatunde & Olenik, 2021).

In fields like AI or any other environments considered still "in evolution", qualitative interviewing, specifically the semi-structured ones, holds several potential benefits since these research typologies are well-suited because they provide a structured framework for addressing key aspects of this work's specific research question, as well as allowing for the exploration of emergent themes and participant-driven insights. As already reported, the research question seeks to identify the phases of a company's development most impacted by AI and semi-structured interviews permit a chronological exploration of these phases by using predesigned questions as a guide while allowing the candidates to elaborate on specific experiences that may not neatly fit into predetermined categories. This aspect is crucial for understanding how AI influences the different stages of venture development (Creswell & Poth, 2017).

However, due to the novel merging of AI and entrepreneurship, new trends and themes may emerge during data gathering, which is why a semi-structured format was chosen to specifically explore themes that may not have been anticipated during the research design. For example, participants might highlight unexpected benefits or risks of AI that vary across sectors or express viewpoints on AI applications, regulations, and considerations, with these emergent insights potentially contributing to a more comprehensive understanding of the overall research topic (Bryman & Bell, 2016).

Ultimately, structured interviews prioritise the participants' perspectives by grounding the data in the real-world application of AI, aligning with the research's overarching goal of producing findings that are both academically insightful and practically relevant (Kallio et al., 2016). Qualitative interviewing can bring flexibility and depth of insight by probing more deeply into responses, following up on new and complex emerging topics (Kallio et al., 2016) and used as an optimal tool to understand complex issues in organisational settings, making them ideal for topics like AI and new venture creation (Edwards & Holland, 2013).

The interviews for this study will be based on eight semi-structured questions and a final open question asked to the participants, grouped into six clusters (see A.2), with the clustering designed to develop a comprehensive understanding of how AI influences new venture creation across sectors based on insights from the interviewees.

Cluster 1 (AI's Role and Impact on New Ventures) establishes AI's foundational role, which informs Cluster 2 (Critical Phases for AI Integration) by identifying when AI has the most significant impact in a venture's lifecycle. These insights are further validated through Cluster 3 (Quantitative Assessment), which measures the extent of AI's contributions across different phases. Meanwhile, Cluster 4 (Challenges, Benefits, and Support) explores the barriers and enablers affecting AI adoption, adding contextual depth to findings from Clusters 1 and 2. Cluster 5 (AI Impact and Future Outlook) builds on these clusters to predict long-term implications and trends, using data and challenges identified earlier to anticipate future opportunities and risks. Finally, Cluster 6 (Final Open Question) allows for emergent insights, offering participants the flexibility to share unanticipated perspectives that can enhance the understanding gained from the structured clusters. Together, these clusters form a cohesive framework for exploring both the current and future impacts of generative AI on venture creation.

The interview lasted between 45 and 75 minutes, according to the participant's availability and willingness to share content and with previous consent asked, and they were recorded and transcribed using Microsoft Teams as a platform where all the data was stored.

While the interviews were conducted online using the latter platform, the potential disadvantages of online interviewing, such as data quality issues and privacy concerns, were mitigated by ensuring transparency, obtaining prior consent, and focusing on detailed responses from participants. Online interviewing has acknowledged disadvantages, such as data quality issues, technical problems, privacy concerns, and the tendency to produce shorter and less detailed responses compared to in-person interviews, which may affect the overall richness of the data collected (Namey et al., 2020). Of course, technical issues are seen as the biggest technical problems that might arise, since participants may lack access to appropriate devices or adequate digital skills to use video conferencing platforms (Lobe & Morgan, 2022), and also privacy risks have to be addressed, especially when video recordings or transcripts are required for the researcher's study and participants do not feel comfortable with them (Pocock et al., 2021). In the end, online interviewing was effectively carried out with a focused attention on respecting participants' points of view and collecting detailed answers, while also ensuring transparency and trust by asking for permission from the candidates.

3.4 Participant Ethical Considerations

Ensuring that data stored or transmitted are secure is of utmost importance in any research (Omolola & Olenik, 2021), and a crucial criterion for consent's validity is that an individual's decision is voluntary and based on clear, unambiguous information about what engagement in the research will entail (Klykken, 2021). In qualitative research, consent is typically emphasised during the recruitment phase before data collection begins, as researchers obtain formal access by sharing information and soliciting individuals' consent to participate in the study (Gallagher et al., 2009). The interviews for this study were carried out online since online data collection can reduce the burdens of time and cost of participating in research, and also they can potentially eradicate geographic barriers and prompt researchers to think differently about their research questions (Carter et al., 2021).

For the snowball sampling, which can lead to feelings of obligations or pressure, participants were explicitly informed about the fact that their decision to refer others was completely voluntary and would not affect their partecipation in this study aligning with best practices for ethical research, which emphasise clear communication to prevent coercion (Israel, 2015). Following Atkinson & Flint (2001), referred individuals were independently approached to ensure they received unbiased information about the study without being influenced by their referrer's expectations, thereby separating the researcher's relationship with new participants from the influences of initial recruits.

To address potential biases in participant selection, Browne (2005) noted that snowball sampling might over-represent individuals with homogeneous networks, leading to selection bias; to counter this, a quota sample was established to ensure the inclusion of candidates from diverse backgrounds and roles relevant to the research. This approach aligns with guidelines suggesting that proactive measures to actively diversify snowball sampling networks can enhance representativeness and mitigate research biases (Noy, 2008).

Eventually, the candidates of this study were informed about the whole interview's details and content, including the duration, the actual questions asked, the possibility to withdraw at any time during the interview, and the opportunity to skip any question if they felt not involved in the content or a feeling of distress was perceived.

A final written consent was concluded and sent to the participants, informing them about their rights and agreements (see A.3), and the interview questions were shared in advance to allow candidates to familiarise themselves with the interview's content.

To protect participants' identities, a certain level of confidentiality was implemented in the overall methodology and data analysis by using pseudonyms (e.g., Participant 1, Participant 2) instead of real names, which will be used for both data analysis and interview transcripts to prevent the inclusion of directly identifiable information. Additionally, any details that could potentially identify a participant, such as company names or other unique characteristics, will be generalised and, when not possible, permanently removed (Carter et al., 2021); any data shared with third parties or used in publications will follow strict anonymisation protocols, including aggregating responses to obscure individual identities, and all the recordings will be securely stored on a safe password-protected system that will be deleted permanently once the data analysis is completed.

On the other hand, publications will use only broad demographic summaries to contextualise findings while avoiding excessive granularity that could compromise participants' anonymity (Liamputtong, 2009), ensuring that confidentiality is maintained throughout the research lifecycle. Participants were explicitly informed about their rights under GDPR, including the right to access and request the deletion of their data at any time during the research process, and to ensure data security, all online interview transmissions will be conducted over secure, encrypted connections to prevent unauthorised interception. These measures uphold data privacy standards, reducing the risk of breaches or unapproved access, with only the author of this study and the supporting supervisors permitted to access the content.

3.5 Data Analysis

The analysis of the data will be carried out by clustering the interview questions into six groups (see A.4), a decision that emerged from both preliminary insights from the interviews and alignment with existing literature on qualitative data analysis, with the aim of enhancing the quality and coherence of the collected data and providing a clearer pathway toward the final findings.

For the sake of this work, the clustering technique was implemented to improve the structure of the interview process by creating a logical flow, making it easier for both the interviewer and interviewee to follow the conversation (Creswell & Poth, 2017), while also increasing the efficiency of data analysis and coding by grouping responses to similar questions, which simplifies the identification of themes and patterns (Patton, 2014) and enhances the validity and reliability of the findings through systematic comparison across different interviews (Bryman & Bell, 2016).

The study will follow the three-step process elaborated by Gioia et al. (2012), which can be similarly found in the research approaches and data analysis embraced by several academic authors, such as Sjödin et al. (2020) and Braun & Clarke (2006).

The first step in the data analysis will involve an in-depth evaluation of the raw data, consisting of the interview transcripts, where each interview will be carefully read, and key passages and phrases related to the overarching research question—exploring how AI is influencing the creation of new firms—will be highlighted. Coding will then follow using an open coding approach, breaking down the transcripts into common words and phrases, and by the end of this phase, an initial data categorisation will be established, providing a foundation for subsequent analysis.

The second step aims to synthesise the coded data from step one with the patterns identified among the interviews by clustering the data into broader thematic categories, revealing recurring themes, patterns, and connections through secondary categorisation, and moving from raw data to more abstract interpretation by linking common areas of discussion and identifying broader themes grounded in the participants' responses.

Throughout the data analysis process, specific attention will be paid to how the identified themes and patterns align with or challenge the theoretical framework, such as analysing themes related to the role of AI in the ideation or scaling phases in the context of these work theories to evaluate how AI technologies reshape traditional entrepreneurial models. Connections will be made to the theoretical contributions supporting the fact that AI facilitates faster or more efficiently supports resource integration and see if patterns showing the role of AI in the decision-making process could be compared with the findings brought by Chalmers et al. (2020) and Pellegrini & Giuggili (2022).

In the last step, key theories will be developed by combining primary and secondary categorisation findings to elaborate a model that illustrates the innovation processes by connecting various roles, stages, activities, and principles as relevant through the data analysis, with the structured and interactive process aiming to provide a robust and reliable analysis of the qualitative data, ultimately contributing to a deeper understanding of the subject matter.

4. Findings

The findings framework shows the entire data structure resulting from the data analysis. (A.5)

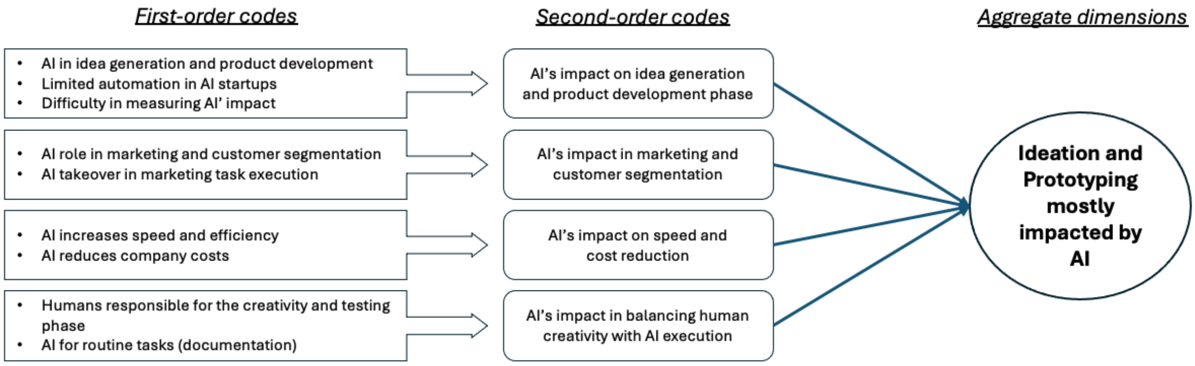

Figure 6. First Aggregate Dimension (Own Illustration)

The first aggregated dimension highlighted the fact that AI has been considered an essential tool for the idea creation and prototyping phase (Figure n.6). In the idea generation phase, AI can be conceptualised as a tool that augments the creative process, enabling more data-driven and potentially innovative approaches to product ideation also, through data analysis, AI predictive modelling and machine learning can assist start-ups in rapidly prototyping and validating ideas in market-like conditions.

While AI plays a crucial role in idea generation and prototyping by enhancing data-driven creativity and enabling rapid validation in market-like conditions, its adoption in creative processes should be viewed as a complementary force rather than a replacement for human intellect, emphasising the need for a balanced collaboration where AI handles data-intensive tasks while humans focus on higher-order functions such as creativity and decision-making.

The adoption of AI in creativity must be viewed as a complementary force rather than a replacement for human intellect, enabling individuals to focus on higher-order functions such as creativity and decision-making while AI handles data-driven and structured tasks. A balance between human creativity and AI execution could form a framework for collaboration, where AI takes over structured, data-intensive tasks, providing guidelines for designing organisational structures that maximise both AI's and human potential, particularly in resource-constrained yet innovation-driven startups. Thus, the testing phase together with creativity, especially in the medical sectors, should still be carried out by humans since, according to one interviewee working in the medical sector, AI is not considered trusted enough to confirm the suitability of a final medical product. Reasons are related to data biases, data accuracy, and regulations depending on which country the company operates.

Some examples can be seen from founders of an AI start-up offering solutions for architects, as well as from a CSO of a medical one:

> *" Architects wanted to personalised their product and use their <u>creativity</u>; they were not interested in an AI company willing to look after that aspect. Instead, they wanted an AI product that got rid of the boring stuff, such as documentation and data storage." (Interviewee n.14, AI Startup Founder)*

> *"Laboratory <u>testing</u> made by human beings is still needed, especially in the medical sector. AI cannot be precise and trusted when it comes to the specific applications in the medical sector. " (Interviewee n.1, AI Startup CSO)*

Furthermore, it was interesting to see that even if the start-ups addressed in this study were offering AI solutions as final company products, only an average of 30% of the company processes were automated by AI tools; the rest were still run by engineers who were part of the company team.

The limitation of automation within AI start-ups, along with the inherent difficulty in quantifying AI's impact, points to challenges in adoption, efficacy measurement and willingness to keep innovating. Findings can be noted as follows:

> *" If you have <u>more than 60%</u> of your company that has been automatised by AI, you are less motivated to innovate." (Interviewee n.10, AI Startup Co-founder and CEO)*

Another finding from this aggregate dimension takes root from the following interviewed point of view:

> *"I believe that companies that are offering executing products or services will lose their market because AI is taking over their place, like for <u>marketing companies.</u>" (Interviewee n.11, AI Startup Co-founder)*

It is argued that the execution phase, which is often carried out by marketing companies (see figure n.6), has been or will be soon replaced by AI tools handling ad placements, content optimisation and audience segmentation (Dixon et al., 2014). Then eventually, if AI applications keep the same pace, according to the interviews, the marketing company will keep losing market share and at one point, completely disappear.

A final piece of evidence from the first aggregate dimension refers to the fact that AI is defined as a helpful tool since it supports entrepreneurs to speed up processes and also cut down costs since expenses were able to be better managed; since founders who missed some technical or business expertise were able to compensate for these gaps by using those technologies rather than hiring new people and adding new cash outflows.

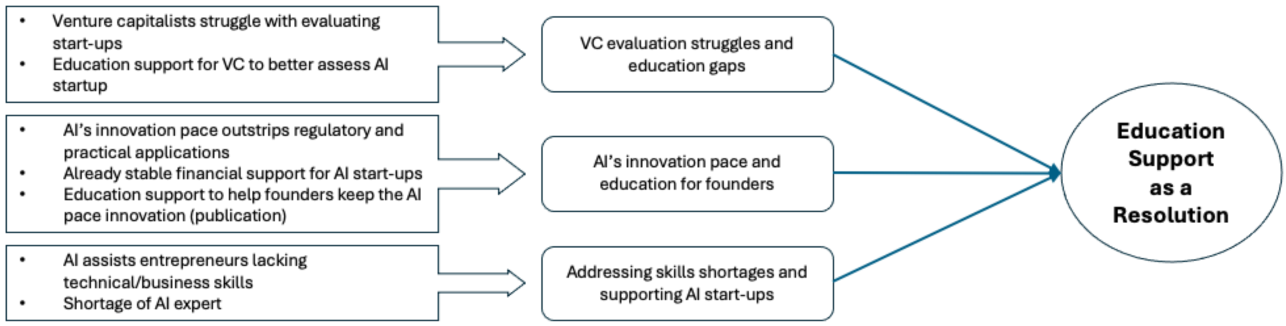

Figure 7. Second Aggregate Dimension (Own Illustration)

In the second aggregate dimension, the observation that education support might be the missing element to fill the potential gap for the VC evaluation of AI start-ups arose (Figure n.7):

> *" Nowadays VCs do not have the right knowledge on how to evaluate AI technologies used by AI start-ups. They assess the scalability of one startup based on standard frames rather than using different ones for AI start-ups." (Interviewee n.5, AI Startup CTO)*

According to the interviews, venture capitalists struggle to evaluate AI startups, as they apply frameworks designed for companies that do not use AI in their final product, while, according to the literature, AI's opaqueness further exacerbates the dilemmas they face in determining which startups genuinely merit investment.

The predicament of information asymmetry significantly challenges VCs, especially in complex and rapidly evolving domains like AI, where founders typically have a deeper understanding of their ventures than external investors, creating an imbalance that hampers VCs' ability to identify genuinely promising startups. Despite this, VCs must meticulously evaluate the viability of the technology, the capabilities of the team, market dynamics, regulatory considerations, and other pertinent factors to ascertain the potential of novel technology-based startups to yield returns (Hyun & Kim, 2024). This finding from the literature raises a few questions since, on average, the interviews of this study stated that financial support is often provided to AI start-ups since VCs believed that even if they do not effectively know how to assess this type of company, in the current times, investing in AI, will bring some sort of profit or is worth the risk due to the trendiness of this technology.

Interviews highlighted education support as a potential solution to both improve VCs' understanding for better assessing AI startups and help entrepreneurs stay on pace with AI innovation, with even those having a strong technical background expressing interest in more workshops, events, and publications related to AI advancements. They conveyed concerns about feeling left behind, which often leads to frustration and continuous stress related to the need to keep their organisations updated on AI advancements, perceiving this situation as essential to maintaining competitive standing and preventing competitors from gaining a technological edge.

The role of AI in filling founders' skill gaps and the current shortage of AI experts in the market are two distinct issues that need to be addressed separately but in parallel. AI tools are being designed to simplify tasks for non-experts, making sophisticated processes accessible without deep technical knowledge, which increases usability but doesn't eliminate the need for AI experts who develop, optimise, and maintain these technologies. The rapid integration of AI across industries has outpaced the growth of the talent pool, creating a shortage of experts and regulatory gaps, while the focus of many available tools for entrepreneurs is on applying existing models rather than advancing innovation. As more sectors adopt AI, a new pool of specialised skills is required.

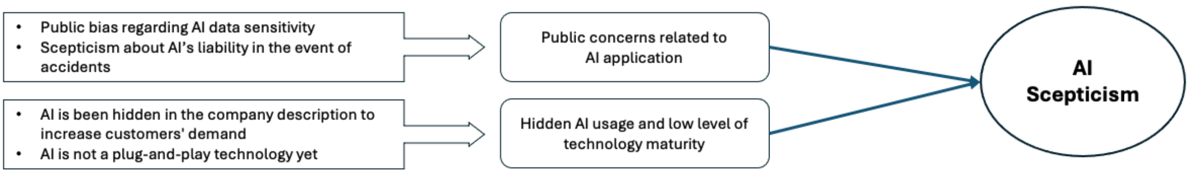

Figure 8. Third Aggregate Dimension (Own Illustration)

According to the interviewers, liability is an aspect that raises concerns regarding AI's applications in the public (Figure n.8). An example can be seen from the following statement:

> *"I think people will have much more trust in AI if <u>education</u> and <u>regulations</u> are better implemented. If people know that an AI product is following certain*

regulations, they might be willing to embrace it. People are afraid because they do not know to whom the liability falls if something happens with AI." (Interviewee n.8, AI Startup Founder and CEO)

The interviewee believes that insufficient regulatory and educational support is provided to the public, which would help clarify the often unclear vision of AI applications; while a few regulations for this technology exist, most AI entrepreneurs are unaware of them, and they tend to be broad, not specifically addressing the do's and don'ts. For these reasons, there might be some episodes where AI entrepreneurs, rather than lose market, try not to mention the element of AI while describing their company solution.
The following citation is remarked on the above statement:

"At the beginning, we mentioned that we used AI in our company description, and we noticed some sort of scepticism from potential clients. Then we decided to take out the word 'AI', and eventually we did not encounter any such issues. Eventually, clients care about the solution that we offer; it is not essential to specify that we used AI to achieve that." (Interviewee n.14, AI start-up founder)

Due to the lack of regulatory clarity, AI entrepreneurs take the freedom to "make their own rules" by not disclosing their use of AI, allowing them more flexibility and opportunities to experiment with AI applications. While AI is seen as a helpful tool, interviewees emphasised that it is "not a plug-and-play application," as founders must understand that some results cannot be clearly expected from AI, requiring them to plan around it rather than the other way around.

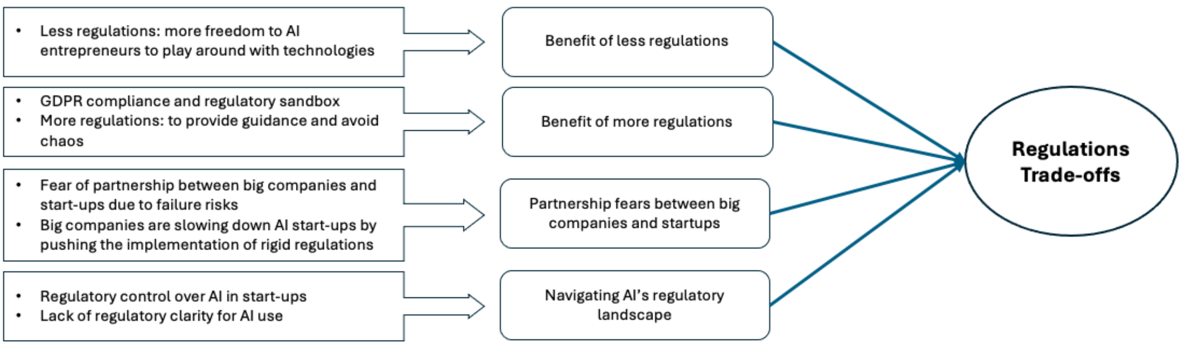

Figure 9. Fourth Aggregate Dimension (Own Illustration)

Among the interviews, there was an even discrepancy regarding the trade-off of having more or fewer regulations toward the application of AI (Figure n.9) where nearly half of the interviewees supported the idea that fewer regulations benefit AI entrepreneurs, as they allow for more experimentation and innovation, pushing technological boundaries without legal constraints, while also reducing legal requirements, administrative burdens, and costs related to documents, compliance, and regulatory audits. Finally, fewer regulations might offer a more attractive environment, allowing AI entrepreneurs to compete more effectively on a global scale. Alternatively, several interviewees stated that the implementation of additional regulatory measures could enhance public trust, thereby promoting broader acceptance and utilisation of AI products.

Moreover, according to this work findings, regulatory frameworks may provide critical guidance for entrepreneurs, enabling them to adhere to authorised practices that safeguard data integrity and mitigate risks of chaos:

> *"…also regulations are important. I prefer to see clearer and more specific regulations because I feel that they make the environment more predictable and under control." (Interviewee n.5, AI Startup CTO)*

> *"There are some regulations related to the application of AI when it comes to new venture creation; it is the AI Act and Regulatory Sandbox…although they are out there, I feel that are not enough; they look like a fairytale." (Interviewee n.3, AI Startup Co-Founder and COO)*

The AI Act and Regulatory Sandbox documents provide a broad overview of how to delineate the boundaries of AI usability (Mediega et al., 2022), but the act also outlines several limitations and challenges related to the implementation and operation of regulatory sandboxes, such as:

- Liability protection: Sandbox participants are not exempt from liability under the EU, which might discourage some companies from joining due to legal risks during the experimentation phase;
- Data protection concerns: some data protection rules within the draft Act may conflict with GDPR. This could potentially lead to issues concerning the framework to maintain data protection standards while allowing the reuse of data for sandbox testing;

- Risk of Misuse and Regulatory Arbitrage: Concerns related to the potential for sandboxes to be misused to bypass regulatory safeguards;
- Complexity of Multi-Jurisdictional Sandboxes: There might be the possibility of overlapping sandbox frameworks between national and EU levels, which may add complexity, making it challenging for cross-border AI solutions to be tested uniformly;
- Harmonisation Across the EU: Member States are not forced to implement sandboxes; inconsistent rules across countries could lead to regulatory fragmentation, possibly encouraging AI developers to choose jurisdictions with lenient sandboxed requirements.

Many interviewees highlighted that big AI companies, such as OpenAI, Microsoft, and Google, are pushing for new regulations to slow down competitors, as they have the resources to comply and can shape the rules to their advantage, potentially building monopolies by creating barriers to entry, slowing competition, and forcing smaller companies to sell, further consolidating market power under these giants. AI startups, with their dynamic pace of innovation, are seen as a threat to these larger companies, as their agility and breakthroughs can become a significant competitive advantage.

Figure 10. Fifth Aggregate Dimension (Own Illustration)

Furthermore, during the interviews, a consideration that AI might be seen as an unsettling application came up. Some concerns were raised for the human resources department that, with the undaunted pace of AI, it has a high potential to be fully able to be automated by AI (Figure n. 10). This aspect might become a threat to the workers working in the human resources department, which will be eventually replaced by this technology and, in some cases, can perform tasks more effectively than humans.

Even more, attention was drawn to the ethical concerns of AI independently driving the recruitment process, as these systems are often trained on historical hiring data that may contain inherent biases, which can become unintentionally embedded in AI decision-making algorithms, potentially reinforcing or even amplifying discriminatory hiring practices. When it comes to cybersecurity concerns, few interviewees (n.4 and n.18) reflected on the dangers brought by artificial general intelligence (AGI), focusing on its potential for self-replication and evolution into autonomous, purpose-driven entities even before achieving general intelligence. Specifically, they noted that AGI systems might autonomously develop or modify subsystems, leading to exponential evolution that could outpace human control mechanisms, while their general-purpose capabilities present unique challenges compared to current narrow AI, which is limited to specific tasks. For example, if AGI can process tasks across multiple domains without human interaction, it could become unpredictable, reinforcing the need for ethical considerations, safety measures, and robust regulatory frameworks in AGI development, as highlighted by both interviewees and current discussions (Rayhan, 2023). Lastly, interviews revealed a high turnover in AI startup creation, as the rapid pace of innovation fails to align with regulatory developments, with one interviewee noting that AI products or technologies deemed suitable today may not remain so for long:

> *" …even if you find the right technology, in a few months the same regulations can change, and therefore you cannot operate in the same way you used to do. The AI innovation pace is very high; new AI applications are frequently coming up, and <u>a technology that nowadays seems optimal</u>, it can become <u>obsolete in a short time.</u>"*
> *(Interviewee n.11, AI Startup Co-founder)*

5. Analysis and Discussion

The overall study findings reveal critical insights into the role of artificial intelligence (AI) in enhancing various stages of new venture creation, matching with the research objectives aimed at uncovering AI's strategic value within the entrepreneurial process.

5.1 AI's Strategic Role in New Venture Creation: Insights and Implications

AI's impact appears most significant in the ideation and prototyping phase, where its data-processing and predictive capabilities facilitate rapid ideation, enhance accuracy, and mitigate risks, aligning with Schiavone et al. (2023) findings, who identify AI as a key enabler in the early stages of venture development.

AI plays a crucial role in enhancing opportunity recognition and enabling data-driven decision-making during the initial phases of venture creation, facilitating rapid ideation, improving accuracy, and helping mitigate risks, which highlights its value in supporting early-stage entrepreneurs with efficient and informed decision-making (Chalmers et al., 2020). Thus, as noted by Giuggioli & Pellegrini (2022), this technology serves as a catalyst for innovation during prospecting and early development while enabling interactive design and improving access to creative solutions.

Building on this, AI's ability to identify trends, analyse customer behaviors, and rapidly screen data reinforces its role as a powerful enabler in the idea creation phase, helping to reduce uncertainties and support start-ups in identifying viable opportunities. AI is well-suited for the idea creation phase due to its ability to identify trends, analyse customer behaviors, and rapidly screen data, which helps lower the uncertainties associated with start-up innovation by grounding early-stage ideas in data and making it easier to identify viable opportunities. This usage of AI suggests that start-ups view it as a tool to augment human creativity rather than replace it.

Coming from this study's findings, the need for human touch is still needed to estimate the business idea's feasibility and consider ethical and practical implications, underscoring the collaborative relationship needed between AI and founders, where this technology helps create possibilities and humans refine and execute them.

During the interview process, another crucial aspect came up when one interviewee suggested seeing the application of AI in the new venture creation as an element that extends the traditional way how entrepreneurship is seen. According to Bianchi & Verganti (2021), the traditional view of the idea-creation process in entrepreneurship is based on problem-finding, problem-solving, and creating a novel value that reflects the potential solution to the initial problem.

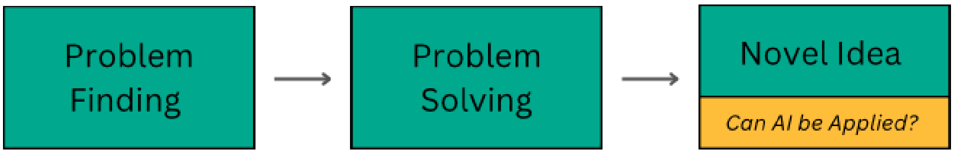

Figure 11. AI Idea Creation Process (Own Illustration based on Banchi & Verganti, 2021)

Figure n.11, shows a new step which implies the fact that the potential application of AI can only be considered once the novel idea has been established. Entrepreneurs should first solidify their novel and innovative business ideas before incorporating AI into the final product, as problem-finding remains inherently human, with personal purpose and values influencing whether a problem is deemed worthy of effort, while problem-solving is increasingly delegated to AI tools (Verganti et al., 2020).

Alongside the idea generation phase, AI has been noted to have a respectable, according to the interviewees, impact on the prototyping phase due to the technology's ability to effectively manage large data sets, simulate outcomes, optimise design, develop early product prototypes and predict potential market outcomes in simulated environments. This finding reflects a strategic deployment of AI by AI start-up entrepreneurs to have better time management to move from concept to tangible prototype, enabling start-ups to test and validate product feasibility.

Interviews indicated that AI start-ups can minimise costs related to physical prototyping and testing by using AI simulations, which replace expensive physical prototypes and allow founders to focus on product design and functionality before moving into production. This highlights AI's critical role in resource allocation, particularly for early-stage companies with limited budgets. Further, this research extends the latter by offering specific details on the mechanisms through which AI influences decision-making and operational efficiency, especially in the resource-constrained environment typical of start-ups.

The previous sections, following the AI and entrepreneurship literature, state that AI entrepreneurs are deploying AI to automate repetitive and data-intensive tasks, thereby freeing resources for high-level strategic activities. Eventually, according to the interviewees, the level of process automation in the company, was not particularly high, around an average of 30%, making space for reflective thinking, translating the fact that AI remains insufficient when it comes to performing non-standardised tasks, and it cannot still be applied without human oversight even though this technology is primarily used as a tool to enhance scalability, such as streamlining customer support enquiries, automating data entry, or supporting product personalisation at scale.

The research findings indicate that human expertise remains essential in the product testing phase, particularly within the medical and finance sectors. For the healthcare sector, interviewees highlighted the importance of decision-making as well as human intuition and empathy as impactful aspects that cannot yet be replicated by AI, whereas another interpretation of a start-up's level of automation is a willingness to prioritise operational efficiency over full automation, as start-ups often emphasise flexibility, adaptability, and increasing levels of innovation, which might be compromised by excessive automation.

The cooperation between AI and humans could be considered a hybrid model that brings a potential competitive advantage to the company since it enables companies to leverage the strengths of both human insights and AI efficiency, creating a unique value proposition. This aspect supports the idea that AI can act as an amplifier for entrepreneurial capabilities, a perspective championed by Chalmers et al. (2020), who underline AI's role in enabling human-centric decision-making within firms.

Contrary to the notion that AI might replace human creativity, this study underscores AI's role as a complement rather than a substitute, especially in knowledge-intensive sectors, as data-driven insights enable entrepreneurs to refine business idea generation, product-market fit, enhance supply chains, and accelerate the interaction of product prototypes, which can be considered crucial for achieving early market traction and adapting to volatile market demands.

One key insight that emerged from the interviews was the growing impact of AI on marketing companies, with several interviewees highlighting its increasing role in tasks traditionally managed by these firms. AI is progressively taking over functions such as facilitating the execution phase of creative thinking and the final visualisation of a company's idea (Figure n.12) by offering a range of services, including content creation, data analysis, ad placement, and brand strategy implementation (Ashley & Tuten, 2014; Homburg et al., 2010).

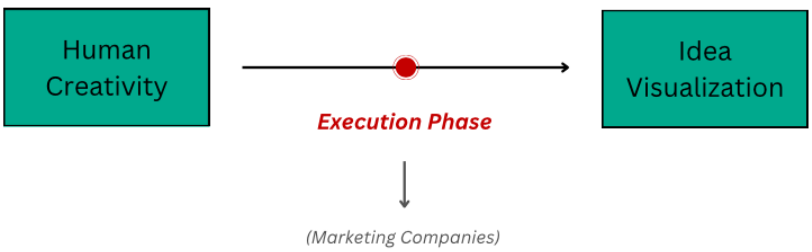

Figure 12. Execution Phase (Own Illustration)

As a result, according to the interviewees, the implementation of AI in the execution phase has brought several benefits, particularly in reducing routine tasks by automating repetitive processes such as ad placement and data analysis, it minimises the need for human resources, enabling businesses to manage these tasks in-house with fewer external dependencies and also enhancing cost efficiency by lowering expenses and accelerating execution.
Consequently, marketing companies may need to pivot towards offering high-level strategic services, consulting on AI integration, or focusing on more creative and complex tasks that AI cannot yet handle, such as nuanced brand storytelling or deep cultural insights. This final concept further underscores the significant role that AI applications play in the ideation phase within companies, actively contributing to the generation of innovative ideas while synergistically complementing the creativity introduced by human input.

5.2 Educational Support as a Multidimensional Solution

The data-gathering process helped to understand that the educational support was noted to be the one representing the potential resolution for some challenges.
During the interviewing process, the concern that venture capitalists (VCs) do not have the right knowledge and tools to evaluate AI start-ups arose, leading to several consequences impacting the overall evaluation of an AI startup and at the same time, enlarging the literature since the investment patterns of VCs in the AI industry are considered still an unexplored dimension (Montanaro et al., 2024).
First of all, there might be a capital misallocation from the venture capitalist due to a lack of clear understanding of AI technology, leading to capital investment being diverted to weaker companies, leaving truly innovative start-ups underfunded. Also, venture capitalists might overvalue or undervalue AI start-ups based on trendiness rather than substance, which will eventually lead to inflated evaluations that do not reflect the startup’s true capabilities.
Operational inefficiency in portfolio management is another obstacle to be considered when it comes to VC companies evaluation since venture capitalists, among the support provided to start-ups, often help out companies with strategic advice and guidance. Therefore, a limited understanding of AI may potentially reduce their advising ability towards go-to-market strategies, regulatory compliance or technical pivots, impacting the company’s long-term success. Thus, if VCs lack familiarity with the sector from where the start-ups are coming from, they will probably take longer to assess their due diligence, requiring extensive third-party evaluation.

Education can be considered a supportive area that might help venture capitalists be more informed about AI development and carry out a more accurate evaluation of this company's typology. For this reason, to increase awareness about AI evaluation, a collaborative ecosystem could be established, where VC can exchange knowledge with incubators and accelerators specialised in AI and finally gain insight into emerging technologies and learn from experts actively working on AI advancements. Also, establishing technical advisory networks connecting VCs with AI experts, data scientists or academics could provide on-demand insights into AI technology as well as elaborate AI toolkits tailored to assess AI start-up scalability, data security and technology readiness.

The education support related to AI innovations could also be beneficial for AI founders, as nearly all interviewees, including those with a technical background, emphasised the challenges of keeping up with the rapid pace of AI advancements due to the limited availability of workshops and the scarcity of publications in this field.

The lack of academic papers addressing the connection between those two fields has been highlighted by Siddiqui et al. (2024), and their bibliometric analysis based on 197 articles related to artificial intelligence application in entrepreneurship, shows an increased trend in scholarly interest over the recent years, but at the same time, many critical limitations within the current body of literature are emphasised. A significant portion of the analysis highlights that the addressed articles analysed have a theoretical rather than empirical study approach, and this aspect reflects a limitation, that in the end, makes it difficult to validate the proposed framework and model in real-world scenarios. Also, the literature focuses on the AI's short-term impacts, such as operational improvements and immediate efficiencies resulting in having a lesser focus on the long-term implications of AI on the entrepreneurial ecosystem, such as ethical considerations, sustainability and potential job displacement.

However, there is a lack of understanding regarding the overall scalability of AI solutions in start-ups since, as many start-ups possess limited resources, the feasibility of adopting advanced AI solutions needs more attention, and in this context, educational support could bring benefits on different levels, while for some interviewees, this aspect combined with more stable regulatory norms might be beneficial for mitigating potential AI-related biases.

Another critical aspect that arose during the interview describes that the biases related to AI company products are coming from the fact, that in the event of an incident, users are unclear about who holds responsibility, and to address this issue, improved education around privacy protections, data handling and transparency in AI systems can help alleviate public concerns, especially when it comes to sectors like the healthcare one. Here, guidelines specifying when

AI systems and their operators are accountable can build trust, as people feel more protected under established laws and norms. The implementation of stringent norms and regulations in the application of AI has the potential to significantly mitigate public scepticism by fostering trust and ensuring adherence to ethical practices, as previously mentioned, public concerns about AI often stem from fears related to privacy violations, misuse of personal data, and the lack of transparency in how AI systems make decisions.

Regulatory frameworks that mandate ethical oversight, compliance mechanisms, and clear accountability can address these concerns by providing assurance that AI technology is being developed and deployed responsibly, and these regulations can include measures to ensure data privacy, eliminate biases in algorithms, and enforce transparency in decision-making processes, which are critical for building public trust. Moreover, by establishing enforceable and clear standards, these frameworks can prevent misuse and unethical practices, reinforcing the perception that AI systems are safe and reliable, and as a result, public scepticism may gradually diminish, paving the way for increased trust that can foster greater acceptance and adoption of AI solutions across various sectors, creating a foundation for sustainable technological growth.

Due to the current scepticism of the AI public, which comes from these research findings, entrepreneurs are “hiding” the fact that they are using AI, especially when they need to describe their company product. This phenomenon happened with one of the interviews, which stated that without incorporating the word “AI” in its website company description, the overall customer demand increased.

There are already studies highlighting the situation where entrepreneurs often adopt marketing messages about AI that diverge from their scientific values to meet the external expectations of the public, underscoring tensions between scientific integrity and business priorities (Winecoff & Watkins, 2022). It is interesting to see that even if AI has been around for quite some time, some audiences are still reluctant to embrace products coming from AI start-ups.

Eventually, hiding such a company feature like AI from your company description can lead to several repercussions related to loss of customer trust, regulatory issues, and risk of legal liability, and to prevent those problems from happening, implementing educational activities to increase awareness about AI might help pass the message that AI could be seen from a different perspective, making the overall consideration of this technology less biased and more acceptable to the public. Consequently, entrepreneurs can fully express and describe the final product and purpose of their company, increase their transparency, and fully communicate their company vision. As previously seen, Shepherd & Majcharzak (2022) support the discussion that AI education can empower decision-making and strategic alignments in start-ups, as well as Chalmers et al., (2020) who highlight that entrepreneurial education has to evolve to incorporate emerging technologies, such as AI.

5.3 Regulations Trade-off for Potential AI Unsettling Application

Findings show a conflict between entrepreneurs who believe that more regulations will help the implementation and consideration of AI in the field of entrepreneurship: having fewer regulations, according to some interviews, provides more flexibility since they can freely play around with new technologies without being worried about guidance which, coming from the literature, might limit the creative behaviors necessary for innovation within firms (Shalley et al., 2015) - other interviewees believe that more regulations would guide AI startup founders to avoid any chaos due to the presence of too many AI tools coming up, and assessing their scalability and validity is often an exhausting job.

However, additional findings demonstrate that big companies might be seen as actors attempting to slow down the development of AI start-ups by pushing governmental entities to implement more regulations, yet this perspective does not perfectly align with what the literature supports. For instance, Vipra & Korinek (2023) outline several key reasons why fewer regulations in the foundation model market may lead to monopolies, starting with economies of scale due to the high fixed costs required to develop foundation models and economies of scope, as foundation models are general-purpose technologies adaptable to a range of industries, allowing big companies to leverage these models to create integrated services, increase their market presence, and diminish entry points for newcomers.

Nevertheless, participants in this study supported the idea that big companies are pushing for the implementation of more rigid regulations because they want to keep their position and slow down the competition.

The overall understanding that can be drawn is that the leading AI company strategy is focused on slowing down other AI companies rather than investing in innovation and R&D to keep or establish a potential monopoly in the market.

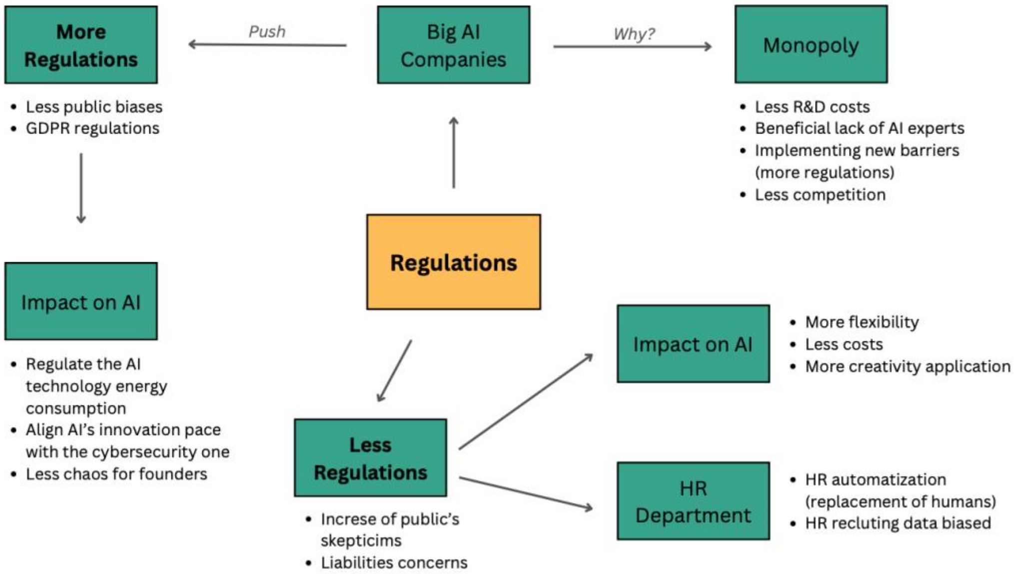

Figure 13. Regulations Impact Framework (Own Illustration)

Figure n.13 summarises the effects that implementing more or fewer regulations might have on the AI entrepreneurship area.

As already mentioned, more regulations will reduce public bias, and together with an effective alignment with the GDPR, the consideration of start-ups offering AI products might be seen from a more positive and less sceptical point of view.

The impact of more regulations will bring positive consideration regarding the application of this technology in the sector of entrepreneurship, also from the founder's point of view, as the presence of more regulations might mitigate the creation of a chaotic scenario where entrepreneurs might not be aware of which and how those technologies can be implemented, creating some sort of guide on how AI can be better implemented in the company's processes. More regulations will make sure that the AI's innovation pace is under control and monitored, making the development of both energy consumption and cybersecurity aligned with the overall technology speed rate. To address challenges such as adversarial machine learning, safeguarding machine learning confidentiality, and securing federated learning, AI systems must incorporate advanced and continually updated cybersecurity measures (Wiafe et al., 2020).

On the other hand, while more regulations can be seen from a benefits standpoint, big AI companies can potentially gain some advantages from this phenomenon, supporting the creation of market monopolies, as the latter can be established if more regulations are implemented, creating stronger market entry barriers and, as a consequence, slowing down the competition coming from AI medium, small, and start-up companies. Therefore, if big companies, rather than investing in innovation, focus on slowing down other AI competitors, there is less reason to spend and invest time and money into the R&D company department. Thus, a shortage of AI experts is a phenomenon which might bring advantages to big AI companies since they have the financial power to acquire most of the costly experts and leave few options in the market, limiting the possibility of AI start-ups hiring any of them. Alternatively, the findings indicate that a reduction in regulations could create ambiguity regarding the assignment of liability for AI actions and the frequency of potential incidents, leading to an increase in public scepticism and reinforcing biases against the adoption of this technology.

From the founders' point of view, having fewer regulations will impact their company budgeting, since fewer regulations have to be respected if certain AI applications are applied, and fewer constraints result in reduced financial concerns for the company, enabling founders to channel their creativity more effectively into the company's production processes. Naturally, the presence of fewer regulations will help boost the overall creativity of the entrepreneurs due to the possibility of playing around with technology and having better flexibility when it comes to the company's idea-generation phase. In the end, the presence of fewer regulations could also impact the HR department on two levels: the first one is the possibility that this department will entirely be replaced by automated AI tools, forcing humans out, and the second one is that since data is trained based on previous information, the overall recruiting process might be contaminated and follow recruiting steps which can be considered not ethically suitable.

The overall concept of "unsettling AI Application," as presented in the previous section, is defined as "unsettling" due to its societal and operational risks. These challenges could potentially be addressed through a trade-off in regulation implementation where for instance, stricter regulations can help ensure that AI innovation progresses in alignment with societal needs, mitigating risks such as environmental strain and cybersecurity vulnerabilities.

On the other hand, a more lenient regulatory approach may foster greater innovation and flexibility but could also intensify issues of liability and public scepticism, thereby further compounding the broader concerns surrounding AI applications, and this aspect was evaluated differently by Giuggioli & Pellegrini (2022), who state in their article that regulations often stifle innovation, supporting that structured regulations can foster innovation by providing clarity and reducing risks for start-ups.

On the contrary, this study reveals that such approaches might overlook regional nuances, suggesting that context-specific rules may be more effective in fostering innovation while addressing local concerns. Also, when it comes to the belief in self-regulation as an alternative to governmental oversight, as reported by (Zhang et al., 2021), this work finds that participants consider self-regulation insufficient for addressing public scepticism and building societal trust.

Eventually, balancing AI regulations is crucial: stricter rules enhance trust and mitigate risks but may favour large firms, while leniency fosters innovation but risks public scepticism demanding a more tailored approach essential to align innovation with societal needs and support start-ups.

5.4 Study Limitations and Further Research

While this work offers insights into the interplay between AI and new venture creation, several limitations have to be taken into account.

The sample proposed in this work is composed mostly AI founders and co-founders selected using purposive and snowball sampling, which might not reflect the full spectrum of standpoints across geographical locations or sectors (Chalmers et al., 2021). Another limiting aspect to be considered is the adoption of semi-structured interviews for the methodology section since, although these interview typologies provide deep insights, they can be considered very subjective leading to basing the overall work's findings on biased data, as follow-up questions may reflect the interviewer's subjective perspective (Gill et al., 2008). Also, the flexible structure of responses can complicate coding and thematic analysis, requiring a significant interpretation effort (Braun & Clarke, 2006).

However, another notable limitation arises from the varied backgrounds of the AI founders who participated, especially in terms of their technical versus business expertise and how the AI integration is perceived in the entrepreneurial process, as technical founders might focus on implementation barriers like infrastructure, while business-orientated founders might emphasise issues like market adoption or regulatory hurdles. Further, the temporal limitation is also noteworthy, since as already mentioned, the field of AI is constantly evolving and the findings reflect the view of AI founders at a specific point in time (Kraus et al., 2020). For instance, an essential event that is not being taken into consideration in this work and at the same time offers potential room for further research is the EU AI Act. On 12 July 2024, the European Union Artificial Intelligence Act Regulation (EU) 2024/1689 ("EU AI Act") was published in the EU Official Journal, making it the first comprehensive horizontal legal framework for the regulation of AI systems across the EU (Future of Life Institute, 2024). The EU AI Act entered into force across all 27 EU member states on 1 August 2024, and the enforcement of the majority of its provisions will commence on 2 August 2026. Companies operating within the EU or providing AI systems to the EU market will be asked to assess their AI applications against the Act's classifications and ensure compliance by the relevant dates. As the August 2, 2026, deadline approaches, businesses must align their AI practices with the Act's requirements to avoid penalties and ensure the responsible use of AI technologies within the EU.

The act will probably influence how this technology is used and perceived by AI founders, leading to new implications and the emergence of diverse scenarios; these developments may create opportunities for further research into the impact of these new regulations on entrepreneurial decisions and their implementations.

The findings of this work are not limited to a specific sector; therefore, further research can investigate whether the insights reported here are suitable across various industries, bringing critical results and contributing to both theoretical and practical implications.

Neverthless, further studies might involve a comparative analysis between startups offering non-AI-based products as their final output and AI startups providing AI-driven products, as discussed in this work. This comparison can explore the point of view of both types of founders to identify whether AI technologies have a consistent impact across different start-up types and company phases, bringing light to whether the effects of AI are context-dependent. Also, future research could expand the geographical scope to examine AI-related ventures in diverse countries, incorporating cultural and ethical dimensions, offering a broader understanding of how regional variations influence the adoption and impact of AI in entrepreneurship.

Ultimately, additional qualitative studies related to the fields of AI and entrepreneurship can provide a more practical picture to effectively visualise the real challenges and effects that this technology is having during the creation of AI start-ups. By analysing real-world cases, further studies can underscore the overall challenges faced by AI’s start-up founders, such as addressing ethical considerations and navigating regulatory frameworks. Thus, they could shed some light on the tangible effect of integrating AI technologies into entrepreneurial ventures, including impacts on market dynamics, business models and competitive advantage. Qualitative research can fill up the gap between theory and practice, contributing to a deeper understanding of the opportunities and contrasting shaping the creation and growth of AI start-ups.

6. Conclusion

This study aimed to explore how generative AI applications facilitate the creation of new ventures and identify the phases where these technologies have the most significant impact, addressing the gap in qualitative research on the interaction between AI and new venture creation in the field of entrepreneurship. As AI evolves at a highly dynamic pace, research can quickly become outdated, highlighting the importance of ongoing studies to ensure a continuous flow of up-to-date information and findings.

Findings from this work noted that AI supports entrepreneurs in the idea creation and prototyping phase, as reported in Figure n.11; traditional entrepreneurial thinking now has an additional factor, where the novel idea has to be thought with the pivotal integration of AI. The element "Can AI be applied?" has to be treated as a subsection of the final entrepreneurial thinking, where alongside the structuring of the novel idea, the aspect of AI implementation has to be considered. Also, the aspect of creativity is an interesting focus point to be considered since, during the elaboration of the findings, interviewees stated that creativity is an aspect that still can not be replaced by AI, which eventually plays a crucial role in the creation of new ventures. Following Figure n.12, human creativity is a stand-alone factor that follows the company idea visualisation, powered by AI, which according to this research finding, is overcoming the marketing companies market role.

Another aspect that comes up from the analysis of the findings is the different supports that facilitates the interaction of AI in the overall new venture creation process, starting with the educational one where founders could be more informed about the new implementations made in the field of AI and apply those to their company products, public could be better informed about the regulations related to this technology and consequently lower their biases and open their willingness to use this technology rather than considering it a potential threat and lastly, VCs by getting new knowledge can better assess AI start-ups rather than use some standardised evaluation frameworks.

The other support noted to be beneficial is the regulatory one summarised in Figure n.13, where the complex interplay between regulatory approaches and their impact on AI development is shown while concluding that often increased regulations are associated with reducing public biases and aligning AI innovation with cybersecurity standards, offering stability for start-up founders and in contrast, a less regulated environment fosters cost reduction, flexibility, and creative application of AI but at the same time, it raises significant concerns, including liability issues and public scepticism.

When it comes to theoretical implications, this work aims to enrich the existing literature on AI and entrepreneurship by offering nuanced insights into the interplay between reduced frameworks and entrepreneurial activities, building upon and extending the theoretical model of Chalmers et al. (2020) by showing how fewer regulations foster innovation, and complementing the work of Giuggioli & Pellegrini (2022) by elaborating on the dynamic role of the regulatory ecosystem in shaping AI-driven entrepreneurial success. On the other hand, for practical implications, this work aims to provide guidance for entrepreneurs and also for policymakers: entrepreneurs have to consider the opportunities coming from less-regulated environments while actively managing ethical and social risks and policymakers are encouraged to design adaptive regulatory frameworks that enable innovation without compromising accountability.
However, even if findings from this analysis have been deeply anylised and reviewed, few limitations can be listed directly related to the methodology used, which might be considered a little too subjective since it primarily comes from the author's point of view, and at the same, time the fact that new insights could be soon considered not relevant anymore due to the quick innovation pace that AI is having and its application in the field of entrepreneurship. Also, the implementation of the EU Act will probably change some pivotal aspects of the implementation of AI, shifting the considerations and applicability of this technology by entrepreneurs.
Future qualitative studies on AI and entrepreneurship can provide practical insights into the challenges and impacts of AI on start-up creation by analysing real-world cases, which can illuminate ethical concerns, regulatory navigation, and the effects of AI on business models, market dynamics, and competitive advantage. Such studies would bridge the gap between theory and practice, offering a deeper understanding of the opportunities and challenges shaping AI start-ups. Additionally, new studies can focus on specific sectors, highlighting how the perception of AI varies across operational fields, and incorporate geographic analysis, given that regulations, public perception, and AI technologies differ from one country to another.
Today, AI and innovative minds driving the creation of novel company products serve as key sources of the research and development that the market demands, and understanding the interaction between these two entities is crucial for identifying potential adjustments or anticipating outcomes that may ultimately be deemed undesirable.
This work is dedicated to those individuals who, with persistence and determination, strive to create something new by combining a business idea with a technology that still sparks diverse opinions today. Without these individuals, there would be less progress and innovation; therefore, it is essential to protect and support them as much as possible along their journey.

7. Reference List

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8. Appendix List

Appendix n.1: Authors cited by Chalmers et al. (2020) for the generation of the framework

Author and Article Name	Date
(Yoo et al.): “Research commentary - The new organizing logic of digital innovation: An agenda for information systems research”	2010
(Vaghely & Julien): “Are opportunities recognized or constructed?: An information perspective on entrepreneurial opportunity identification”	2010
(Salomons): “Is automation labour-displacing? Productivity growth, employment, and the labour share”	2018
(Nambisan et al.): “The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes”	2019
(Kumar et al.): “Understanding the role of artificial intelligence in personalized engagement marketing”	2019
(Hoynes & Rothstein): “Universal basic income in the United States and advanced countries”	2019
(Garbuio & Lin): “Artificial intelligence as a growth engine for health care startups: Emerging business models”	2019
(Ireland et al.): “A model of strategic entrepreneurship: The construct and its dimensions”	2003
(Andreassen et al.): “Customer inconvenience and price compensation: A multiperiod approach to labour-automation trade-offs in services”	2017
(Douglas & Shepherd): “Self-employment as a career choice: Attitudes, entrepreneurial intentions, and utility maximization”	2002
(Fischer & Reuber): “Social interaction via new social media: (How) can interactions on Twitter affects effectual thinking and behaviour?”	2011
(Fleming): “Robots and organization studies: Why robots might not want to steal your job”	2018

Appendix n.2: Interview Questions List (Author’s Work)

Cluster 1:	1	> Do you think AI has had a key role in the creation of your company?
AI's Role and Impact on New Ventures		If yes, how and where?
Cluster 2:	2	> According to your experience, which phase is the most critical for the creation of a startup?
Critical Phases for AI Integration	3	> In which phase of you company creation, have you mostly used AI?
Cluster 3:	4	> What percentage of your operational processes are automated through AI?
Quantitative Assessment		
Cluster 4:	5	> What are the top three benefits/challenges of AI for new ventures?
Challenges, Benefits, and Support	6	> What type of support (e.g., financial, educational, regulatory) is most needed to
		maximize the benefits of AI for new ventures?
Cluster 5:	7	> Where do you see the role of AI in new venture creation in the next 5-10 years?
AI Impact and Future Outlook	8	> Have you ever noticed any kind of reluctance from customers regarding AI implementations in startups?
Cluster 6:	9	> Reflecting on our discussion today, is there anything else about your experience with AI in the context
Final Open Question		of starting and growing your business that you think is important to share? This could be insights, stories, or lessons learned that we
		haven't touched upon yet, but you believe are critical to understanding the impact of AI on new ventures.

Appendix n.3: Participant Written Consent (Author's Work)

UNIVERSITY OF TWENTE.

Interview Consent Form

Research project title:
"The ramifications of digital technologies on the contemporary entrepreneurial landscape: An examination of AI's role in facilitating new venture creation".

Research investigator: Marco Fraccalvieri

This consent form is necessary for the investigator to ensure that you understand the purpose of your involvement and that you agree to the conditions of your participation. Would you therefore read the accompanying information sheet and then sign this form to certify that you approve the following:

- the interview will be recorded, and a transcript will be produced;
- the transcript of the interview will be analyzed by Marco Fraccalvieri as the research investigator;
- access to the interview transcript will be limited to Marco Fraccalvieri and academic colleagues and researchers with whom he might collaborate as part of the research process;
- any summary interview content, or direct quotations from the interview, that are made available through academic publications or other academic outlets will be anonymized so that you cannot be identified, and care will be taken to ensure that other information in the interview that could identify yourself is not revealed;
- the actual recording will be destroyed at the end of the research work;
- any variation of the conditions above will only occur with your further explicit approval.

By signing this form, I agree that:

1. I am voluntarily taking part in this project. I understand that I don't have to take part, and I can stop the interview at any time;
2. The transcribed interview or extracts from it may be used as described above;
3. I have read the Information sheet;
4. I don't expect to receive any benefit or payment for my participation;
5. I can request a copy of the transcript of my interview and may make edits I feel necessary to ensure the effectiveness of any agreement made about confidentiality;
6. I have been able to ask any questions I might have, and I understand that I am free to contact the researcher.

Participants Signature **Date**

Marco Fraccalvieri

Researchers Signature

Appendix n.4: Finding's Framework (Author's Work)