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Artificial intelligence, Sustainability, and Firm Survival. An Empirical Analysis

Relatore:

Chiar.mo Prof. Roberto Fontana

Tesi di Laurea

di Elena Folli

Matr. n. 547479

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Abstract (English)

This thesis investigates the effect of sustainability and artificial intelligence on startup survival. First, it provides a review of the existing literature on the key concepts of sustainability and technological progress, with particular emphasis on artificial intelligence, highlighting how these factors influence firm development, management, and performance. The study then describes the sample used for the empirical analysis, which consists of startups operating across different sectors and characterized by varying degrees of environmental orientation. The sample is composed of 965 firms, 591 are non-sustainable and 374 are sustainable. It considers a period of 14 years, from 2011 to 2025.

The empirical analysis begins with a descriptive phase, examining the main patterns related to firm entry and exit, sustainability orientation, and selected performance indicators. Building on these findings, an econometric analysis is then conducted to assess whether the observed relationships hold in a multivariate setting. In particular, survival models based on the Cox proportional hazards specification are estimated, complemented by robustness checks using complementary log-log (cloglog) models.

The main objective of the study is to explore the relationship between sustainability orientation and the survival of startups that adopt artificial intelligence, as well as to analyze their modes of exit. The results indicate that sustainability plays a significant role in enhancing startup longevity. Moreover, among the performance indicators considered, access to funding emerges as a key determinant of exit mode: startups that receive funding are more likely to exit through acquisition rather than failure.

In conclusion, the findings suggest that the integration of sustainable practices, combined with the adoption of advanced technologies such as artificial intelligence, can significantly enhance the resilience and competitiveness of startups.

Abstract (Italiano)

La presente tesi analizza l'effetto della sostenibilità e dell'intelligenza artificiale sulla sopravvivenza delle startup. In primo luogo, viene proposta una panoramica della letteratura esistente sui concetti chiave di sostenibilità e progresso tecnologico, con particolare enfasi sull'intelligenza artificiale, evidenziando come tali fattori influenzino lo sviluppo, la gestione e le performance delle imprese. Successivamente, lo studio descrive il campione utilizzato per l'analisi empirica, costituito da startup operanti in diversi settori e caratterizzate da differenti livelli di orientamento ambientale. Il campione è composto da 965 imprese, di cui 591 non sostenibili e 374 sostenibili, osservate in un arco temporale di 14 anni, dal 2011 al 2025.

L'analisi empirica si articola inizialmente in una fase descrittiva, in cui vengono esaminati i principali pattern relativi all'ingresso e all'uscita delle imprese, all'orientamento alla sostenibilità e ad alcuni indicatori di performance. Sulla base di tali evidenze, viene successivamente condotta un'analisi econometrica al fine di verificare se le relazioni osservate si mantengano in un contesto multivariato. In particolare, vengono stimati modelli di sopravvivenza basati sulla specificazione dei rischi proporzionali di Cox, affiancati da verifiche di robustezza mediante modelli complementary log-log (cloglog).

L'obiettivo principale dello studio è esplorare la relazione tra l'orientamento alla sostenibilità e la sopravvivenza delle startup che adottano l'intelligenza artificiale, nonché analizzare le loro modalità di uscita dal mercato. I risultati indicano che la sostenibilità svolge un ruolo significativo nel favorire una maggiore longevità delle startup. Inoltre, tra gli indicatori di performance considerati, l'accesso ai finanziamenti emerge come un fattore determinante della modalità di uscita: le startup che ricevono finanziamenti hanno una maggiore probabilità di uscire dal mercato tramite acquisizione piuttosto che per fallimento.

In conclusione, i risultati suggeriscono che l'integrazione di pratiche sostenibili, in combinazione con l'adozione di tecnologie avanzate come l'intelligenza artificiale, può migliorare significativamente la resilienza e la competitività delle startup.

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Chapter 1. Introduction

Sustainability and artificial intelligence have gained increasing relevance in the global economic context. Due to the rise of environmental challenges and the rapid development of artificial intelligence (AI), institutions, governments and firms now find themselves having to modify the known economic models in order to create more sustainable and resilient economic systems. In addition, AI has emerged as an innovative technology able to adapt production processes and decision making across industries to the current scenario.

Using AI to address sustainable challenges presents both strengths and weaknesses. On the one hand, AI is capable of promoting environmental and economic sustainability, for instance, by improving resource efficiency, optimizing energy consumption and fostering informed decision making. On the other hand, the widespread use of this technology can raise significant ethical and resource consumption concerns. In fact, the relationship between AI and sustainability is characterized by trade-offs and effects on many different dimensions.

Current literature on these themes is characterized by research on specific aspects of the integration between AI and sustainability. In order to better address the emerging challenges a holistic and integrated approach is needed. Even if the body of knowledge is growing, the relationship between the adoption of sustainable business practices and the operational resilience of firms embracing these innovations appears to be underexplored.

This thesis aims to contribute to this debate by investigating the relationship between sustainability and firm performance in the context of artificial intelligence startups. The study aims to examine sustainability as a potential indicator of firm success through an empirical analysis based on a sample of 965 AI startups. Specifically, the differences between non-sustainable and sustainable firms in terms of outcomes, including survival, acquisition and failure are examined.

The dataset used in this study is composed of firms, largely startups. Information is collected from Crunchbase. This platform gathers material on all the aspects related to financing of firms. Moreover, the distinction between non-sustainable and sustainable startups derives from the application of a particular algorithm (developed on another project) that substantially considers the description of a firm's operations. The description is taken directly from the firm’s website, specifically the “about us” section. Based on some specific keywords provided for training, the algorithm looks for a combination of these keywords in the website’s description. On this basis, the startups are classified as sustainable or non-sustainable. A second phase of the categorization involved manually verifying the algorithm's results. This was done for a considerable portion of the sample.

The empirical analysis is based on descriptive statistics and statistical tests, which include chi-square tests and comparisons of key firm characteristics such as size, funding and revenues. Furthermore, Cox proportional hazard models are used to evaluate the relationship between sustainability and long-term firm survival. In order to verify the reliability of the results, robustness checks are also performed. In this context complementary log-log models and parametric models are used.

The thesis is organized as follows. Chapter 2 provides a broad review of the literature on the themes of artificial intelligence, sustainability and their interconnection. The key aspects, applications and research gaps are highlighted. Chapter 3 presents the dataset, descriptive statistics, and an analysis of the main distinctions between sustainable and non-sustainable firms. Chapter 4 contains an econometric analysis conducted to further examine the relationship between sustainability and firm performance. Finally, Chapter 5 contains the conclusion and presents the main findings, limitations and directions for future research.

Chapter 2: Literature review

2.1. Introduction

Rapid global transformations in current living conditions, consumption patterns and environmental conditions gave rise to new challenges that need to be addressed in order to ensure a continuous growing process and not compromise the future. In this evolving context, sustainability, artificial intelligence and their interconnection have emerged as increasingly important themes.

In environmental and economic sciences, sustainability is defined as the "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*". (United Nations, Brundtland Report, 1987) Generally sustainability includes three dimensions, the environmental, the economic and the social one which should be balanced in order to improve welfare. However, improvement might be hindered by the widespread belief that concentrating too much attention on climate will jeopardize growth and long-run well-being. In fact, a simplistic pattern of standard growth leads people to think that the commitment to reduce the implications of climate change will have negative effects on growth and welfare. The purpose of tackling climate change, instead, can create a new, appealing and sustainable growth story. In fact, dealing with climate change can produce higher growth, at least for some decades. Actually, underestimating the consequences of climate change is as damaging as weakening growth. Environmental sustainability is an extensive concept characterized by many trade-offs that need to be identified and deeply studied.

Current economic, social and environmental models require adaptation to the dynamic nature of present environments that are becoming increasingly complex and digitalized.

Artificial Intelligence has multiple definitions. In 1950 Alan Turing was the first academic to have the idea to use computer-based AI to replicate human behavior. He created a test to verify if a computer could communicate with a human, persuading the latter that it too is human. Soon after, John McCarthy introduced AI in 1956 to explore how machines could intelligently think, describing it as "*the science and engineering of making intelligent machines, especially intelligent computer programs*" (Zhao and Fariñas, 2022 pg. 9).

The Organization for Economic Co-operation and Development (OECD) defines artificial intelligence as "*a general-purpose technology that has the potential to improve the welfare and well-being of people, to contribute to positive sustainable global economic activity, to increase innovation and productivity, and to help respond to key global challenge*" (Zhao and Fariñas, 2022 pg. 10). While the European Commission declared that it relates to "*systems that display intelligent behavior by analyzing their environment and taking actions - with some degree of autonomy- to achieve specific goals*" (Zhao and Fariñas, 2022 pg. 10).

Due to this nature, artificial intelligence has a big potential that can be used to address complex problems that require innovative and advanced solutions. Its transformative advancements have reshaped various sectors such as healthcare, transport, agriculture, energy and the media.

Bodies in charge of tackling the increasingly complex problems related to sustainability in all its three meanings can take advantage of these new tools with their ability to ease and promote governance.

In the following paragraphs sustainability and artificial intelligence will be discussed more deeply shedding light on their interconnection, different areas of application and implications.

2.2. Main research areas

The application of artificial intelligence in tackling sustainability is quite recent, but there is a wide and expanding literature on this matter. Prior researches tend to focus on specific aspects overlooking the general picture, for this reason has been highlighted the need to further explore these themes and create a comprehensive study.

The most frequent and relevant themes analyzed in the selected literature are linked to many different contexts such as AI's contribution to sustainability goals, AI's impact on specific fields, the potential of artificial intelligence in sustainability reporting and business and management. The current literature is only focused on some aspects of sustainable development through AI, while other contexts result underexplored such as food security, environment, information management, transfer learning, strategy and ecosystem services. The major categories for research are related to environmental sciences; green and sustainable science and technology; environmental studies; engineering, electrical, and electronic; computer science, information systems; energy and fuels; management; telecommunications; business; and engineering, environmental.

In particular, artificial intelligence's impact on Sustainable Development Goals (SDGs) is just emerging and needs to be deeply studied due to its novel, dynamic and rapidly evolving nature. It has been integrated in different ways into the SDGs, in recent years in sustainable management and leadership programs. For instance, it has been applied for the assessment of water crises, in relation with agriculture and application in sanitation and health.

As some studies have highlighted, vital challenges for humanity's future can be solved through the use of artificial intelligence which also plays a fundamental role in the commitment of different countries, cultures and sectors. In fact, artificial intelligence creates competitiveness and value. The critical themes identified in the literature regard sustainability assessment and indicators, determinants of AI adoption, strategic management in AI-driven sustainability efforts and the outcomes of AI integration in reporting.

Furthermore, thanks to the rapidity of progress made in the AI sector the creation of new opportunities to meet the SGDs' goals is enabled by system-thinking approaches and data-driven insights.

2.2.1. AI for sustainability vs sustainability of AI

The studies conducted to explore the integration and interaction between artificial intelligence and sustainability can be divided into two major groups: AI for sustainability which refers to the applications of AI tools to tackle climate challenges, and sustainability of AI that addresses the implications of AI on the environment (Dhiman et al., 2024).

Artificial intelligence can potentially facilitate a sustainable development that aims at reducing human footprint. In fact, the capacity to enhance environmental governance not only addressing issues linked to the usage of natural resources is revolutionizing thanks to its wide application in many different fields such as energy efficiency, climate change mitigation, resource management, biodiversity conservation and much more.

The belief that artificial intelligence can have crucial environmental impacts is fundamental in its application and use in order to shift towards a sustainable transaction. For this reason, a comprehensive analysis is needed even if not easy to conduct because of the inability to focus on the whole and concentrating only on specific aspects. For this reason, the understanding of the broader landscape is incomplete.

Besides these positive effects that artificial intelligence can bring in many contexts, there are rising concerns about the ethical implications of unregulated AI implementation. For instance, transparency is a fundamental element in the assessment of data, in fact its absence can lead to algorithmic bias and data misuse. For this reason, the previously exposed advancements in SDGs can be threatened.

Sustainability reporting is of fundamental relevance in limiting the insufficiency of transparency and artificial intelligence's potential in this framework is undermined by the absence of adequate literature about this theme. The future goal needs to be the creation of a comprehensive framework that incorporates AI technologies and themes, such as decision support systems and innovation, into sustainability reporting, ensuring transparency, credibility and alignment with the SDGs. In fact, the use of artificial intelligence into sustainability reporting means merging technological advancements and strategic management.

Artificial intelligence can also be applied in supply chain management which has gained global priority. As highlighted in some studies, AI's contribution is crucial in the optimization of global supply chains thanks to the enhancement of transparency and efficiency, in particular in the agri-food context which has important impacts on environment and society. Other relevant areas are: logistics optimization, waste reduction and product safety improvement. In this framework the analysis conducted tends to overlook the social sustainability issues and environmental challenges.

It is relevant not only to consider the use of AI to achieve sustainable development but also the sustainability of using AI systems. The concept of sustainable AI is used to merge these two aspects. In fact, the massive employment of artificial intelligence could constitute a threat to environmental and social sustainability. The creation of AI governance and regulation, multidisciplinary collaboration and building trust in AI applications can help to address these issues. Artificial intelligence can promote environmental governance and diminish resource and energy intensity. Nevertheless, there are some aspects that need to be considered such as the excessive reliance on historical data, the uncertainty of human behavioral responses and risks in cybersecurity.

The interaction between artificial intelligence and the natural environment regards carbon emission measurement, energy consumption optimization and the energy cost of running large ML models. As said before, the environmental dimension needs to be balanced with the social one that focuses on ethical considerations, educational implications and issues of equality related to AI. The economic dimension looks at the economic growth, labor market dynamics and novel business models (Dhiman et al., 2024).

2.2.2. Applications (Industry 4.0, ML, DSS, SCM)

A central global trend is digitalization which is reshaping the way industries operate and also society and nowadays it is present in every human activity. For this reason, it is important to make a general and comprehensive analysis and not focus only on some aspects and dimensions of artificial intelligence.

The development of the digital sector, with the expansion of Internet of Things, robotics, and quantum computing, creates useful tools to promote sustainability incentives within the expanding context of Industry 4.0. The implementation of Artificial intelligence for sustainability applies in dependence on machine learning and innovation, decision support systems, environmental impact and supply chain management. The role of these improvements can be fundamental for sustainability reporting and decision making. Artificial intelligence can optimize resource utilization, reduce emissions and improve the efficiency of global supply chains (Di Vaio et al., 2020).

The merger between Industry 4.0 and sustainability has gained relevance in both academic and business research, technological advancements in IoT, robotics, quantum computing and additive manufacturing are transforming business models.

In this framework, sustainable business practices are supported by operational efficiency and resource management that are strictly linked and enhanced by these advancements (Mustafa et al., 2025).

Some studies focus their attention on economic benefits while overlooking trade-offs between advancing technological progress and adhering to sustainability principles and not considering long-term consequences. The rapid development of industry 4.0 contexts has made it challenging to integrate sustainability standards. The criteria to assess sustainability are many, but they need to be incorporated into the digital transformation driven by Industry 4.0.

2.2.3. Governance, standard and global distribution

The literature highlights the fact that artificial intelligence, actually, gains value when integrated with company-specific investments, including data infrastructure and stakeholder confidence. The lack of transparency constitutes a threat to the process of collecting and diffusing consumer data which leads to incongruities between expressed desires and actual behaviors.

Although standards have been mostly used related to climate and sustainability, it is relevant to acknowledge that compatibility standards have an enabling role for “green” technologies.

The focus must be the measurement of real-world impacts of industry 4.0 technologies on sustainability suggesting practical solutions for moderating adverse effects.

There are different tools that can be used in this context, one of them is Machine Learning that has been applied in finance and governance, and which now is gaining importance in sustainability reporting especially through AI-driven solutions. Carbon-intensive industries can apply this technology to deal with large datasets and enable predictive capabilities and decision support. By finding trends in historical data, Machine Learning can predict future scenarios which is fundamental for addressing sustainability strategies across many different sectors (i.e., transport, energy, agriculture). The big hurdle is to find a way to integrate these tools into sustainability reporting in order to support long-term innovation.

Another important tool is represented by Decision Support Systems which are used to enhance decision-making and promote sustainable practices across industries. It is relevant in the consolidation of complex datasets and generation of actionable insights, improvement of accuracy and transparency of sustainability reports. Decision support systems can be integrated with AI and ML to support more informed and responsible decision-making, in particular when data is fragmented or difficult to interpret. Unfortunately, this tool remains unevenly adopted across industries and there are many countries in which this technology is not used. Decision support systems raise concerns about the ethical aspect, the data can be manipulated or biased in decision-making.

Government intervention to regulate the rapidly changing world is fundamental. Standards can create shared rules for designing or measuring products and processes aiming at promoting interoperability rather than independence. They also facilitate the division of innovative labor, reduce entry costs and promote competition in the market for standardized goods and establish requirements for safety and performance. Unfortunately, standards can also have negative aspects such as the reduction in variety when we adopt a single technology and the creation of lock-in and switching costs that leads to market power and rents only for some parties. In the last few years, environmental challenges have led to standardization efforts.

Among the areas of study, one field that requires additional research is the integration of artificial intelligence into sustainability reporting. It has the ability to enhance sustainability especially when processing large amounts of complex data. Artificial intelligence can also be applied in analyzing and developing business models, underlining its effects on production and sustainable consumption as well as the enhancement of knowledge management systems.

2.2.4. Literature limits and gaps

In most cases the research topics are investigated by only summarizing either AI's contribution to sustainability goals or AI's impact on a specific field. Hence, there is also the investigation on the potential of artificial intelligence to improve sustainability reporting, particularly in relation to Environmental, Social and Governance (ESG) issues.

The effects of artificial intelligence on sustainable development are both immediate and long term, considering positive and negative outcomes. However, these developments are not homogeneously distributed, only the advanced nations have the ability and the possibility to obtain news technologies and accessibility is strictly associated with the economic potential and motives of a nation. For this reason, an ethical and regulatory framework is needed to ensure the equitable and sustainable use of this rapidly developing technology. So, it is uncertain if AI represents a true paradigm shift in sustainable development research and its application.

Current studies lack multilevel views, systems dynamics approaches, design thinking, psychological and sociological considerations, and economic value considerations.

The literature analyzes a wide spectrum of themes. The following paragraphs will focus more in detail on the relationship between AI and sustainability and the application in the economic field.

2.3. AI and sustainability: opportunities and risks

Artificial intelligence offers significant opportunities to support environmental sustainability, but its widespread adoption also raises economic, social and ethical concerns. While many studies emphasize the positive environmental impacts of artificial intelligence, such as improved energy efficiency and pollution monitoring, it is equally important to consider the risks associated with its large-scale deployment. These include increased inequalities between countries, governance gaps and ethical challenges related to transparency and accountability. In fact, disparities will be exacerbated between countries that are able to access these new technologies and countries that are unable to do so. For this reason, it is fundamental to balance negative repercussions, such as the increase of energy consumption, with benefits derived from a sustainable production system.

2.3.1. AI, climate change and economic growth

A simplistic analysis based on the comparison between marginal costs today and marginal benefits tomorrow overlooks important aspects of the process that aims at mitigating climate change. On the one hand there is a conservative vision that continues to fit in this known and oversimplified path. On the other hand, there is a more complex and innovative vision.

Conservative researchers state that a major attention on climate actions would inevitably lead to a cut on other government expenditures causing growth reduction, lower future tax revenues and larger investments to mitigate climate change. In this vision the present is characterized by high financial pressures because of the current debt level of the governments.

The other group of studies shows, instead, that addressing climate change issues can drive higher growth, at least in the short term, taking into consideration also societal well-being and including the enhancement of investments, innovation and system change. In fact, current growth levels are no longer sustainable without undertaking stronger climate actions.

Conservative studies are limited by the use of models that ignore market failures, risks and distributive biases. Moreover, using the wrong indicator to measure economic well-being leads to wrong conclusions, such as overlooking the risks brought by atmospheric concentrations of GHGs and the increase in extreme events, thinking that markets could handle these situations well. However, evidence has shown that markets are poor at making risk assessments of complex and unknown factors.

All these aspects lead to a pessimistic view that highlight problems in specifications and formulations of objectives.

Climate change is an example of systemic risk, for this reason the externalities created by one party strongly influence others. Climate change consequences and path are not certain, but inaction can only lead to a lowering in individual and societal well-being and investment reductions. Climate actions instead are linked to a growth-enhancing path.

In conclusion, giving priority to the reduction of climate-related risks strengthens entrepreneurs' ability and readiness to confront a broader range of uncertainties, allowing them to undertake projects with higher expected returns than would otherwise be feasible. As a result, economic growth is stimulated and this is a dynamic that would hold even under conditions of perfectly functioning risk markets. Consequently, robust climate change mitigation policies can play a growth-enhancing role, while inaction on climate change intensifies market distortions and amplifies their interconnected effects (Stern and Stiglitz, 2023).

2.3.2. The role of governance and the governance framework

The ability to overcome different market failures in infrastructure, transaction costs, finance and networks is fundamental to reach greater resource efficiency and to reduce climate change and enhance growth. Government intervention has a central role in making the economy reach a better equilibrium which can also be eased by the increasingly strategic use of artificial intelligence. These tools can identify productive patterns and anticipate challenges better than human design alone. The process of transformation needs to be fast because of the heavy challenges created by worsening of environmental conditions, such as the increases in the atmospheric Green House Gases (GHGs).

The difficulty of the green transition is strictly related to the requirement of long-term changes such as those in sources of energy, switching from non-renewable sources to renewable ones. Renewable energy sources are arduous to manage and store, but in the medium term it is more profitable anyway to sustain these types of transformations rather than continuing to use the same means. The transaction needs to be accompanied by political support and industrial policies. In order to improve on the current situation, it is fundamental to ensure benefits for society and develop new industries ensuring them the access to new technologies.

An increased incorporation of artificial intelligence in a management context raises problems and ethical implications regarding various issues such as data privacy, algorithmic bias and the development and deployment of responsible AI. For this reason, governments, industry professionals and members of civil society must work together and design inclusive rules and standards linking the integration of artificial intelligence with sustainability objectives.

Business and society can reach a win-win situation thanks to the revolutionary nature of AI, integrating in the goals for transparency and accountability the long-term effects on individuals and society. In this context artificial intelligence encourages transparency, indicates sustainable policies and decisions, it also hinders discrimination, fraud, conflicts of interest, etc. The reliance on algorithms that rapidly adapt to changes and core values by using big data is fundamental for the achievement of these goals. In an increasingly globalized world, the legal challenges are more complex, in fact an international regulatory framework is needed in order to balance the use of the new technology and the social and environmental aspects.

2.3.3. Social implications: labor, inequality and bias

The pervasiveness of artificial intelligence has the potential to threaten the achievement of many applications relevant to SDGs within the economy and society. An example of this is the introduction of technology in working contexts which can lead to job losses even if the net impact may not be negative. For this reason, it is important to draw a clear line between the acceptable and unacceptable use of artificial intelligence.

Automated operations requiring repeated motions are the perfect context in which new technologies can be applied, the substitution of humans in these processes reduces mistakes and boosts the overall efficiency together with ease of collaboration and communication among departments and teams. The distinctive feature of the digital lean is the ability to collect and analyze massive amounts of data in real time which is a significant advantage for businesses. In fact, it enables the gain of vital insights into their production processes and operations. Furthermore, this new technology facilitates working from a distance and improves the management of distributed teams.

The emergence of global challenges constitutes an obstacle to the achievement of environmental, social and economic goals.

In the challenges that must be considered when using artificial intelligence there is also a gender data gap. The majority of the data used to predict and use these tools is biased due to the fact that only part of the population (i.e., men) is considered. This aspect emerges in many different contexts such as disease management, car safety or voice and speech recognition systems. The artificial intelligence context is mainly constituted of male researchers that unconsciously introduce biases during the development stages. Gender equality is hindered by this bias together with culture and race.

2.3.4. AI for environmental sustainability: key applications

Energy and industrial management

The application of artificial intelligence in the energy usage context brings numerous environmental benefits, it helps reduce overall energy consumption, gain better efficiency and reduce carbon emissions. All these operations are fundamental to introduce sustainable manufacturing processes and reduction in waste. However the integration of artificial intelligence goes beyond simply optimizing energy and resource use, it contributes to the overall sustainability of the environment. For instance, building management systems with artificial intelligence's support leads to significant reductions in energy consumption and in emission of carbon dioxide.

Industrial processes can see substantive advantages with the improvement of sustainable manufacturing practices that help reduce energy use and produce less waste. In fact, these means identify inefficiencies and address them with an analysis on data collected from sensors. Artificial intelligence can help lower carbon emissions by integrating renewable energy sources and demand-response systems in buildings, while also promoting environmental responsibility by optimizing resource use, lowering energy consumption, and improving operational efficiency.

Mobility and urban planning

Artificial intelligence can also be applied in a more urban context, helping reduce fuel use and emissions thanks to the monitoring of traffic patterns and recommending effective routes to reduce congestion. In recent years, attention to electric vehicles has increased, as their adoption offers several environmental benefits, including lower traffic emissions, reduced air pollution, and greater driving automation. Rapid urban development has also highlighted the issue of light pollution, which can be addressed through smart LED lighting systems that use energy more efficiently and have a longer lifespan.

Natural resources, agriculture and pollution monitoring

Biodiversity, traffic management, energy usage and water management are some of the main contexts in which artificial intelligence helps environmental sustainability. The methods used regard predictive analytics and intelligence grid systems. The main goals are the optimization of energy storage, efficiency and distribution, while enhancing the reliability and integration of renewable sources.

AI combined with satellite imagery can monitor land use by detecting changes in vegetation, forest cover, and the impact of natural disasters. In agriculture, robotics enables early detection of crop conditions and potential problems, while automated data collection, corrective actions, and decision-making processes further improve efficiency. Although often overlooked, air pollution remains one of the greatest threats to human health, and integrating AI with air purification systems allows real-time monitoring of air quality and automatic adjustment of filtration performance.

2.3.5. Green AI and sustainability of AI

Nowadays the necessity of a green transition is evident. Undertaking clean and sustainable practices requires comprehensive sustainable measurements to enhance model's transparency in results not only in performance and accuracy, but also in the carbon footprint, reflecting energy and water consumption. The widespread use of this new technology requires a new approach, called 'Green AI', which promotes sustainable practices in the design, training, and use of models in order to reduce environmental impacts and carbon emissions. The difference between traditional machine learning and green artificial intelligence stands in the switch from significant energy, water consumption, and greenhouse gases emissions to general better conditions in terms of carbon footprint, air quality, small models, low computational complexity and logical transparency due to energy-effective solutions that use cloud centers and mobile/edge devices. This new approach ensures people's trust offering clear and logical decision-making processes, including social sustainability. According to the literature, green algorithms can improve energy efficiency and lower the environmental impact of AI models, while also supporting solutions to environmental challenges. Reducing energy consumption is a key goal for a more sustainable society and can be achieved by better matching local energy demand with regional power generation. However, the variable nature of renewable energy sources still creates challenges for the reliability of energy supply.

The application of artificial intelligence to sustainability can be defined as ‘Green by AI’. The areas of application are energy efficiency, smart mobility, sustainable agriculture, climate change and environmental policies. ‘Green-in AI’ is another framework that sees the integration of artificial intelligence into sustainable efforts. ‘Green AI’ focuses on achieving new and useful results while keeping computational costs low or, at least, not increasing them. In this approach, attention is given not only to better algorithms, but also to efficient hardware, optimized data centers, and more careful scaling of models.

2.3.6. Data, big data and limitations

Artificial intelligence relies on high-quality data architectures, and its full potential can only be achieved with reliable big data. Big data includes large, fast, and diverse datasets that need efficient and innovative processing to support insights, decision-making, and automation. For this reason, poor data quality is one of the main obstacles to effective machine learning. However, having too much data can constitute a disadvantage because we don't know what to do with them.

When AI handles personal and sensitive data, it is essential to protect privacy, comply with legal requirements, and clearly define the roles and responsibilities of both humans and AI systems, so that people can understand, interpret, and influence AI-based decisions, with governments playing a central role in this process.

2.3.7. Research gaps and need for a holistic approach

AI enables the development of common strategies in the conservation of the environment by analyzing large-scale interconnected databases. AI can understand climate change and model its possible impacts, supporting low-carbon energy systems with high integration of renewable energy and energy efficiency which are fundamental for addressing climate change. However, the high-energy requirements for AI operations can undermine efforts to achieve climate action. This aspect needs further research.

Studies have shown that there is a gap between advanced AI methodologies and deep sustainability expertise. Bridging this gap is crucial to the full realization of the promise of AI for sustainable development. AI boosts efficiency, resilience, and sustainability across a wide range of sectors, with specific applications shaped by each sector’s needs and the availability of data. The selection of AI algorithms is largely shaped by the specific needs, challenges, and data availability of each group. For instance, deep-learning and supervised machine-learning algorithms are applied in vegetation, water and clean energy; evolutionary algorithms enable efficient optimization in challenging scenarios (renewable energy layouts); fuzzy-logic algorithms offer interpretability and adaptability, being useful for modeling systems; natural-language-processing algorithms are emerging in health care and education.

Balancing sustainable and unsustainable trends that vary both geographically and temporally considering social and technological advancement is fundamental in the achievement of sustainable transformation. The environmental aspect cannot be considered as an independent framework, it has to be considered as part of a whole together with the economic and social context. Sometimes it is not easy to address environmental problems also because of the trade-offs between these three contexts. A simplistic and reductive logic is widely diffused and this hinders the achievement of development goals. In fact, in some contexts/disciplines is required to identify key objectives which sometimes are difficult to interpret and use in artificial intelligence tools creating data gaps.

The reliance on artificial intelligence requires protection against cyber-attacks that can threaten normal operations.

When using these new technologies, it is fundamental to balance the negative repercussions that can generate on the environment such as an increase in energy use and a rise in carbon emissions and the help that they can give in promoting energy efficiency and sustainable manufacturing. These objectives can be accomplished thanks to AI algorithms that individuate areas for optimization, reduction of energy-intensive processes and optimize resource allocation reducing waste production. Difficulties and moral dilemmas should not be overlooked, for this reason the integration of AI has to be tackled holistically considering both environmental and social consequences.

2.4. Economic aspects

Artificial intelligence is a potent tool that can be used also in the economic context.

The financial condition of firms influences the long-term survival and competitiveness of firms. There are many actors, such as investors, policy makers and various stakeholders, involved in the evaluation of organizations’ performance regarding sustainability in its three main dimensions. The difficulty in the access to finance leads to situations where firms need to face heavy challenges in specific sectors and management of working conditions.

The employment of artificial intelligence in this sector can affect workforce diversity in FDIs beyond impacting innovation and advancements. Employees are trained for the new skills to get the work done. The greater merger between artificial intelligence and the financial sector enables services to be available all day long and be personalized according to customers' requirements. AI can be applied in various sectors such as process automation, case handling, bot services, online assistance to customers, and their validations.

The perception, acceptance and usage of AI-based models is strongly influenced by economic logic. Therefore, the concepts from environmental, conventional and behavioral economics need to be incorporated in order to understand the power and the limitations of artificial intelligence in addressing sustainability challenges. This analysis falls into the field of Information System (IS) domain which focuses on the generation of economic and strategic value for firms by information technologies. In order to be effective in generating value, IS needs to be integrated by complementary assets, such as specific data infrastructures, human skills and stakeholder trust. Researchers are now trying to understand if the traditional debate on IS stands also for artificial intelligence which has a unique data understanding capability that could lead to overcoming traditional systems. Examining the economic value of artificial intelligence is fundamental to assess its tangible impact and support performance measurements of technological solutions applied to environmental sustainability. The technologies and approaches of artificial intelligence used to tackle climate crisis are the following ones: machine learning which is applied in the analysis of IoT data to support governance and metabolism of smart cities; natural computing which includes algorithm inspired by nature to optimize automated learning models or solve multi-objective issues; computer vision and natural language processing that extract information from imagines or videos and text analysis in order to comprehend public opinion or perceive the environment around (Nishant et al., 2020).

Artificial intelligence has the potential to contribute to the global economy with around 15.7 trillions of dollars by 2030.

2.4.1. Financial sustainability

Sustainable finance was born from the integration of ESG data in the investment management business and gained importance in the convergence of finance and sustainable development goals. In order to make the narrow definition more precise, Information Systems propose the incorporation of all the activities and factors that would make finance sustainable and contribute to sustainability involving artificial intelligence systems, applications and models. In order to assess the relevance of artificial intelligence systems in accounting, both positive and negative aspects should be considered. In fact, with this analysis the new technologies can be trained and specific aspects can be highlighted. The impact of artificial intelligence is seen in an enhancement of capabilities and productivity of quality financial reports for investors.

Artificial intelligence contributions stand in helping investors to collect and interpret data on environmental, social and governance risks. In this way more informed decisions for long-term financial sustainability are made.

Artificial intelligence's application in financial reporting improves investors' capacity of collecting, analyzing and interpreting massive amounts of information accounting for ESG related risks and opportunities facing companies and investor portfolios. Due to the high interconnection between the three sustainability areas, advancements in the economic sector can give rise to ethical and sociological effects (Al-Sartawi et al., 2022).

In specific sectors, such as the hydro one, artificial intelligence is able to create strategic financial operations and dynamics that aim at improving productivity and cost savings. Artificial intelligence ability lies in combining growth projections with future water availability and infrastructure condition assessment allowing managers to maximize decisions and investment in infrastructure (Goralski and Tay, 2020).

The financial sector undergoes relevant changes due to the major improvements in the new technologies, such as neural networks that imitate human behavior. In fact, accurate outputs can be produced by artificial intelligence, which is capable of replacing human effort, even if unable to replicate human intelligence (Duan, Edwards, and Dwivedi, 2019, cit. in Al-Sartawi et al., 2022).

Thanks to this process of automation, financial reporting sees improvements in transparency and reducing costs linked to complex manual processes. The relevance of artificial intelligence stands in the ability to conduct activities that humans cannot conduct themselves at that level.

There are different driving forces that can generate new growth stories, operating individually and together.

2.4.2. New Stakeholder Theory

In a context in which the assessment of ESG challenges is fundamental both for the sustainability of individual businesses and large-scale economic systems; inaction can only produce negative effects. For this reason the New Stakeholder Theory (McGahan, 2021, cit. in Helfat et al., 2023) has emerged, stating that the key stakeholders of a firm are the strategic resources suppliers (Barney, 2018, cit. in Helfat et al., 2023) and that stakeholder management is thus the process of credibly committing to sharing value with these resource providers, in order to induce them to make firm-specific investments that will boost overall value creation for the firm (Klein, Mahoney, McGahan, and Pitelis, 2019, cit. in Helfat et al., 2023). Production within firms has a team nature and so co-specialized investments by multiple stakeholders are needed.

This theory is unclear in some aspects, even if the commitments made by stakeholders are credible, their achievements are not well defined. Furthermore, stakeholders can fear opportunism from other stakeholders and firm's shareholders in making firm-specific investments. This fear is pressing for stakeholders that have been until now marginalized or exploited. This theory assumes that it is possible to determine ex-ante the value created from a given combination of resources and the relative contribution of each resource, however this is extremely unlikely in reality.

For these reasons this theory needs further research.

2.4.3. Examples of AI in sustainable firms in Finland

Artificial intelligence can be applied in practice in many different contexts. In Finland there are examples of technological tools employed in multiple areas such as refineries, real estate sector, food retail and media.

The introduction of robots in risky settings enhances employee safety. In fact, robots can substitute humans in inspecting hazardous facilities, arranging imaging, microphones and thermal imaging that can detect abnormalities.

Robot's application can extend to the research of safer energy grids in which artificial intelligence monitors maintenance needs and reveals abnormal activity. In many contexts, repetitive tasks can be done by robots that in addition classify and assist customers. This process is particularly relevant because it divides customers that need further assistance, a human one, from those that do not need it. Companies that integrate AI-powered risk management solutions are able to reach environmental, health, safety and quality standards thanks to semantic technology that utilize machine learning by sensing meanings from natural language (Sipola et al., 2023).

In the forestry industry machine learning-powered software was employed to analyze and gather information about the effects of companies' operations on the environment and people surrounding the company.

Optimizing heating and air conditioning is important in real estate and construction, so artificial intelligence applications can contribute significantly to achieve these goals. The advancements in intelligent energy grids focus on end-users partially producing their own energy. Artificial intelligence optimizes energy consumption through proactive buying and cost-effective storage. Sensory technology monitors air temperature to automatically regulate building conditions. AI systems customize heating and cooling to enhance energy efficiency across various buildings, contributing to a balanced energy grid. Research also shows that this technology benefits energy producers and a communications enterprise enhancing housing energy optimization, as well as another company reducing emissions in process industries.

AI-powered applications were not only adopted to regulate energy consumption of buildings, but also the energy consumption of machines and supply chain activities. Thanks to these tools enterprises can monitor their own energy consumption and waste generation.

In grocery retail, AI was employed in mitigating waste thanks to a greater ability to monitor product expiration dates, relieving humans from monotonous tasks and enabling them to engage in more productive assignments. In the specific sector of oil refining business, AI optimization was used to increase waste material utilization in the production of bioproducts.

Artificial intelligence also saw a particular employment in the media business context, where it created versatile and interesting content for media consumers. Its objective was to avoid media consumers to end up in filter bubbles. So, AI acts as a strategic catalyst capable of diversifying users' information exposure, thus stimulating a constant interest in the evolution of modern society.

2.4.4. Environmental and entrepreneurial sustainability

There is a positive correlation between AI development and sustainable entrepreneurship.

Sustainable entrepreneurship is founded on the concept that sustainable goods would provide economic advantage or profits (Dean and McMullen, 2007; Kuhlman and Farrington, 2010; Yaşlıoğlu and Yaşlıoğlu, 2020, cit. in Gupta et al., 2022), making sustainability and fairness its main goals. In this context, people are taught how to more efficiently utilize the available resources without compromising future generations' resource use. As already mentioned, sustainable entrepreneurship requires equilibrium/balance between economic, social growth and environmental protection.

Sustainable entrepreneurship does not only focus on starting new sustainable businesses, but also on the reformation and management of existing businesses in order to make them more sustainable. For this reason, there are no specific characteristics needed by an enterprise to develop sustainably.

Effect of entrepreneurship on environment

In order to realize sustainable business development, social, economic and environmental frameworks need to be studied and considered comprehensively. In fact, the development of sustainable entrepreneurship requires balancing economic and social growth. In a specific analysis conducted in a particular context such as China, it has emerged that there is a strong link between economics, environment development and entrepreneurship. The environment and economy have a U-shaped connection using the Kuznets curve, which shows that at an economic growth corresponds at first an environment decline, reaches a trough and then climbs again. This curve was proposed in 1995 to offer a link between income disparity and economic growth, following research has shown a direct link between environmental development and economic growth (Adu and Denkyirah, 2017; Dinda et al., 2000; Buehn and Farzanegan, 2013; Brock et al., 2010 cit. in Gupta et al., 2022). Furthermore, studies conducted in African nations proved a positive correlation between environmental resources and sustainable enterprise. This curve can efficiently measure sustainable development and many real-world factors. However, there are aspects that need further research.

In order to promote sustainable development, there are business strategies such as sustainable entrepreneurship that produce, maximize and detect activities aiming at environmental and social benefits (Muñoz & Cohen, 2018, cit. in Chen et al., 2025). In this context traditional business systems, production techniques and consumption patterns are substituted by environmental and social ones (Vallaster et al., 2018, cit. in Chen et al., 2025). Sustainable entrepreneurship, unlike traditional businesses that concentrate their efforts on only enhancing economic development, tries to balance ecological, social and economic goals (Rosário et al., 2022, cit. in Chen et al., 2025). For all these reasons sustainable entrepreneurship fits in the path of sustainable development, addressing current challenges without compromising the future (Rosário & Figueiredo, 2024, cit. in Chen et al., 2025).

2.4.5. Digitalization

The integration of the widespread digitalization process and the improvements in sustainable entrepreneurship have led different realities to experience general developments. Studies on newly born sustainable ventures in Mexico have shown that digitalization promoted social inclusion, connectivity and broader stakeholder integration (Fuerst et al. 2023, cit. in Chen et al., 2025). While globally AI helped promote sustainable entrepreneurship and sustainable development (Islam, 2024, cit in Chen et al., 2025). Furthermore, digitalization enhances entrepreneurial activity and sustainable competitiveness (Dabbous et al. 2023, cit. in Chen et al., 2025).

There are numerous hypotheses formulated in this context, such as that digitalization has a significant impact on SE in developing economies; governments have a significant impact on SE in developing economies; governments have a significant moderating effect on the digitalization and SE relationship in developing economies.

2.4.6. Decision-making changes and Lean Management

As already mentioned, the reduction of waste has an important role in the transition towards sustainable development. Traditional lean management has as its objective the elimination of waste production and continual development. Nowadays the increasing importance of digital technologies has given start to a new phenomenon defined digital lean. Enterprises that implement digital lean can reach numerous benefits. In fact, they can benefit from enhanced visibility, increased efficiency, improved decision-making, and data-driven continuous improvement (Radnor and Johnston, 2012, cit. in Ayoubi et al., 2023). Instruction diagnosis and resolution of issues can be addressed thanks to monitoring and analysis of manufacturing processes in real time. In this context the introduction of automation technologies in repetitive motions helps reduce the probability of mistakes deriving from human inattention and enhance overall productivity. Communication among teams and departments results easier with digital technologies consequently improving problems addressing efficiency and decision making.

In recent times, the increased adoption of digital technologies by businesses has gained popularity to the concept of digital lean. Due to the evolutionary nature of existing technologies and methodologies, the idea of digital lean undergoes continued changes. For this reason, it is fundamental to investigate the possibility of implementing this approach for businesses that want to improve operational and production efficiency.

It is a widespread conviction that the integration of artificial intelligence and digital technologies in businesses boosts general efficiency and performance. Furthermore, environmental benefits from these improvements, such as energy efficiency and sustainable manufacturing even if particular issues should be addressed, such as data privacy, scalability and responsibility of AI cooperation and practices (Ayoubi et al., 2023).

2.5. Entrepreneurship and Environmental Awareness

2.5.1. General concept of Ecological Awareness

Ecological awareness understands and recognizes the environmental issues and the responsibility of acting in an eco-friendly manner through eco-innovations that introduce new or significantly improved products, processes or organizational methods aiming at reducing environmental impact.

This concept is fundamental in the alignment of economic objectives and environmental responsibilities. A wider diffusion of ecological awareness among entrepreneurs affects their decision-making processes and strategic approaches. Higher levels of ecological awareness are linked to the adoption of sustainable practices in business models improving the shift towards the new paradigm (Wang and Chen, 2021).

Making known the advantages of sustainable practices stimulate entrepreneurs to invest in these new sustainable technologies and business models. The benefits are not only related to the environment, but also to businesses that become more appealing for consumers.

Ecological awareness is rooted in individuals' understanding of environmental challenges and the impact of human activities, with the aim of reducing associated harm. It encompasses both personal lifestyle choices and organizational practices. For these reasons, ecological awareness plays a fundamental role in fostering a culture of sustainability within organizations.

In this context, an increased environmental consciousness can push small and medium enterprises towards cost-effective and sustainable solutions that help enhance their competitiveness and resilience facing the relatively limited resource availability compared to larger ones.

Linear models of production and consumption need to be changed in order to better address environmental challenges and in this framework environmental consciousness has an increasingly relevant role in the transition towards sustainable practices such as reuse, recycling and responsible management of resources. These innovative business solutions beyond mitigating environmental harm, create value through sustainable development.

Ecological awareness thanks to entrepreneurs' example can expand in the business context to employees, customers and stakeholders encouraging the adoption of more sustainable behaviors. In this way green markets with sustainable products can develop and become more pervasive and less exceptional.

2.5.2. Entrepreneurs, sustainability and strategic challenges

Businesses are central actors in the sustainable transition through assessment of climate change, resource scarcity and environmental degradation. In fact, sustainable entrepreneurship is becoming a strategic imperative. (Filser, et. al., 2019, Gurtu, 2020, Hummels & Argyrou, 2021, cit. in Odeyemi et al., 2023). Sustainable entrepreneurship's relevance is highlighted in different contexts.

First of all, evolving expectations of consumers tend to be better addressed by businesses that embrace sustainability. In fact, consumers tend to search for products and services aligned with their own environmental values and thanks to sustainable entrepreneurship's ability of meeting consumers' needs, sustainable businesses are able to enjoy brand loyalty and market share (D'Adamo, et. al., 2022, George & Schillebeeckx, 2022, cit. in Odeyemi et al., 2023).

Secondly, the emergence of stringent environmental regulations proposed by governments and international authorities represents a boost in the adoption of sustainable entrepreneurship practices. In fact, sustainable businesses embracing this new paradigm can, beyond complying with regulations, position themselves as leaders in anticipating and exceeding future environmental standards. (Rosário, Raimundo and Cruz, 2022, Zhao, Liu and Shu, 2021, cit. in Odeyemi et al., 2023).

Furthermore, sustainable entrepreneurship through the assessment of resource efficiency and environmental responsibility is able to improve the long-term resilience of their operations. As a matter of fact, sustainable businesses mitigate resource depletion, supply chain disruptions and reputational damage risks which is fundamental in an era of environmental uncertainties. (Nyström, et. al., 2019, Settembre-Blundo, et. al., 2021, cit. in Odeyemi et al., 2023).

In conclusion, innovation, responsibility and profitability converge in sustainable entrepreneurship, making it fundamental for long-term success in a rapidly evolving world and not only an ethical choice.

2.5.3. Green business models

Green business models are fundamental pillars in the implementation of sustainable entrepreneurship aiming at meeting both environmental standards and economic success. The integration of eco-friendly practices into various aspects of business operations can be seen in three key models: circular economy, eco-innovation and supply chain management. (Awan & Sroufe, 2022, Iqbal, et. al., 2020, cit. in Odeyemi et al., 2023).

Circular economy, unlike traditional linear approaches, fosters a regenerative system continuously recycling and reusing materials. In this context products are designed to last in time, repaired easily, remodeled and recycled. In this way resource depletion is strongly reduced and the impact of the extraction and disposal of materials lowered. In order to do so businesses have to create, ease and incentivize take-back programs, recycling infrastructure and consumers' delivery of products for the remanufacturing process. Hence businesses provide conservation of resources and reduction of waste in landfills (Jannusi & Paul, 2022, Yazirlıoğlu, 2021, cit. in Odeyemi et al., 2023).

Eco-innovations develop products that are environmentally sustainable without compromising quality or functionality. The design process takes into consideration the entire lifecycle of the products utilizing renewable resources and recycled materials in order to reduce waste and consumption of finite resources. The environmental footprint linked to the disposal of these products will be minimized by the energy-efficiency, the ease of recycling or their biodegradable nature (Al-Shami & Rashid, 2022, Janahi, Durugbo & Al-Jayyousi, 2022, cit. in Odeyemi et al., 2023).

Innovative technologies can have a fundamental impact in many different contexts by enhancing the environmental performance through the adoption of energy-efficient processes and machinery, the use of renewable energy sources like solar panels and smart solutions for resource management. For all these reasons entrepreneurs identify the importance of these technologies which enable the achievement of environmental objectives together with competitiveness.

Sustainable supply chain management concerns the entire production process, from the source of raw materials to the final disposal. Suppliers need to be sustainable in order to be chosen by environmentally aware entrepreneurs. For instance, having fair labor practices, responsible sourcing of materials and compliance to social and environmental standards are some of the fundamental elements that are required in a sustainable supply chain. Furthermore, entrepreneurs aim at minimizing carbon emissions, reducing transportation-related environmental impacts and optimizing logistics for efficiency such as just-in-time inventory.

The increased reliance of entrepreneurs on sustainable models beyond improving longevity and resilience contribute to the shift towards a sustainable and circular economy.

2.5.4. Market turbulence and green entrepreneurship

As already mentioned, markets are changing due to the increased attention of consumers on environmentally friendly products. For these reasons green entrepreneurship aims at assessing these new needs with innovative products, technologies and business models (York & Venkataraman, 2010, cit. in Maisaroh et al., 2022). The new paradigm of green entrepreneurship tends to create integration among business, environmental and social benefits to reach superiority competitiveness (Lotfi et al., 2018, cit. in Maisaroh et al., 2022). Nowadays consumers give priority to health, security, quality and environmental impact beyond price when choosing a product.

In order to define a business as green entrepreneurship, four criteria must be met:

- The principles of business sustainability have to be internalized in every business decision by the company

- The products and services produced and offered by the company are environmentally friendly
- The company is greener or more environmentally friendly than competitors
- The company has an ongoing commitment to apply environmental principles in its business operation.

(Cooney, 2009, cit. in Maisaroh et al., 2022)

Green entrepreneurship is able to grant sustainability and economic prosperity to the company because of sustainable business profitability, sustainable conservation of the universe and sustainable welfare and social justice for the community as exposed by Elkington in the Triple Bottom Line of Business.

Green entrepreneurship has three dimensions: clean growth, socially aware business and environmentally friendly business as said by Dixon and Clifford (2007).

In this context there are six concept components related to green entrepreneurship. They refer to the distinction between green and non-green companies in terms of products and processes which are thought of in terms of markets and resources used; to the use of environmentally friendly technologies that enable the minimization of damaging technologies impact; the improvements in green entrepreneurship will impact general economic development and will also enhance the quality of businesses practices; lastly green entrepreneurship has as its goal social welfare through the balance of environmental and business practices (Haldar, 2019, cit. in Maisaroh et al., 2022).

2.5.5. Intentions, behaviors, and growth

Green entrepreneurship results strongly influenced by the relationship between the intention in engaging environmentally friendly entrepreneurship, the actual behavior of undertaking such entrepreneurship and family members' support. In fact, individuals that have a strong motivation towards environmentally beneficial actions result in being more inclined to participate in green entrepreneurial activities improving environmentally friendly products, services and business strategies. Moreover, family members play a crucial role in supporting and increasing the achievement of more sustainable tangible practices (Bansal et al., 2020).

2.5.6 Green Entrepreneurial Orientation

Organizations' entrepreneurial efforts to integrate ecologically sustainable practices and values to undertake sustainable decisions and actions to improve their environmental performance is defined as Green Entrepreneurial Orientation (GEO). However, the factors that determine GEO are not fully understood and the effects on the firm's performance are not clear. Furthermore, there are areas that result unexplored in terms of connection between GEO and its outcomes (Tuncer and Korchagina, 2024).

GEO and green entrepreneurship are concepts tightly related to each other but present some differences. GEO regards the readiness and willingness of a company to undertake innovative, proactive and risky actions, while green entrepreneurship focuses on the identification and transformation of business opportunities that can be considered environmentally friendly, considering costs, risks and uncertainties. In particular, it can be stated that green entrepreneurship is an entrepreneurial behavior that includes dual roles such as ecological environment orientation and market orientation (Li et al. 2022, p. 3, cit. in Tuncer and Korchagina, 2024).

Green entrepreneurial theory and entrepreneurship orientation theory compose the basis of GEO which concentrates on innovation, risk-taking and proactiveness in realizing green practices aimed at the creation of growth and value for businesses. Through these characteristics, green entrepreneurial activities identify and explore business opportunities. Green entrepreneurial orientation, instead, refers to the entrepreneurial efforts made by the organization in order to conduct practices and values that are ecologically sustainable, improving the environmental performance by undertaking sustainable decisions and actions.

2.5.7. Ecosystem and social change: drivers and barriers

There are particular drivers of the change in paradigm such as finance and policies. There are also barriers such as lack of resources and knowledge in sustainable entrepreneurship.

The process of funding enterprises or ventures always presents some challenges and especially financing environmental entrepreneurship. Green proofing can be an important tool to facilitate and manage green change dynamics thanks to a consultancy option.

Infrastructure, skills and education, funding, products, markets affordability and political will are some of the pillars that support environmental entrepreneurship (Diale et al., 2021). However, it is important to highlight that the financial key drivers cannot operate isolated and need non-financial support through behavioral change. Green finance mechanisms such as funding, credit, capital financing, investing in environmental entrepreneurship and crowdfunding are fundamental in order to support environmental entrepreneurship, but they are not enough alone.

For this reason, the social context plays a central role in the transition towards a more sustainable world. In fact, environmental innovation can be strongly supported by society and governments are fundamental in the contribution to subsidies and waiving of some costs. Environmental entrepreneurship is supported by networks, non-governmental stakeholders, financial structural support systems, tax exemptions and tax breaks. Furthermore, human capital and skill development are needed in order to contribute and boost the shift towards environmental entrepreneurship. Hence a holistic dynamic is needed. However, the ecosystemic theoretical model needs formal empirical validation.

2.6. Limitations and future directions

Artificial intelligence integration in sustainable practices, as already mentioned, is a new and dynamic theme, for this reason continuous research activity is required. The current literature highlights a critical gap because of the narrowness of studies that combine advanced applications of artificial intelligence with a deep understanding of sustainability.

The literature highlights methodological criticalities that hinder the global comprehension of the phenomenon. Many researches are conducted on specific databases, excluding governmental reports or reports conducted in languages other than English. The majority of the studies focus on advanced economies overlooking emerging countries.

Due to the innovative nature of these themes, it's difficult to collect historical data and for this reason are insufficient to analyze long-term tendencies. Furthermore, the data used is secondary data based on annual reports or simulations rather than empirical data deriving from real implementations of artificial intelligence.

Moreover, studies tend to focus on single dimensions neglecting social or economic aspects.

Acknowledged the limitations, future research should move towards a more holistic and technological advanced approach. The main aspects that need to be addressed refer to geographic and sectorial expansion; emerging markets and underrepresented areas; ethical implications and lastly specific technological innovations.

First, it is necessary to expand artificial intelligence's studies on sustainable reporting taking into consideration wider geographic areas and industrial sectors.

Second, emerging markets and underexplored sectors necessitate empirical research in order to identify challenges and opportunities specific to different contexts.

Third, the massive use of artificial intelligence has brought out concerns about data privacy, algorithmic biases and transparency challenges. For these reasons, these new technologies need to be distributed ethically and responsibly.

Lastly, through the implementation of specific innovative technologies many different challenges can be addressed. For example, explainable AI can improve transparency and responsibility in environmental decision processes. Furthermore, the application of hardware significantly enables the reduction of energy consumption and innovative devices can collect energy from the surroundings becoming self-sustaining. Finally, systems inspired by the human brain can be improved in order to do complex assignments using better energy efficiency.

2.7. Conclusions

This chapter has highlighted the increasing interconnection between sustainability and artificial intelligence in shaping modern economic and social systems. In fact, thanks to the rapid development of new tools, complex situations will be more easily managed and solutions can be found. Moreover, addressing climate change and environmental challenges fosters innovation, productivity, and long-term development.

Artificial intelligence emerges as a powerful enabler in this transition. In fact, artificial intelligence offers practical solutions to reduce environmental impact together with the enhancement of competitiveness. These practices aim at improving energy efficiency and optimizing resource allocation to support green entrepreneurship and environmental monitoring. However, AI’s potential can only be fully realized through high-quality data, responsible governance and sustainable technological measures such as green artificial intelligence.

Furthermore, environmental consciousness is reshaping entrepreneurial behavior. Green entrepreneurship proves that integrating sustainability into business models is not only an ethical choice but also a strategic one. Coordinated policy support and ecosystem development are highlighted as of extreme relevance in order to face challenges such as market barriers, financial constraints and regulatory complexity.

All in all, the relationship between sustainability, innovation, and entrepreneurship is not optional but structural. Future economic growth will increasingly depend on the ability of firms, institutions, and policymakers to align technological progress with environmental responsibility.

Chapter 3: Data and descriptive statistics

This chapter presents the descriptive statistics of the sample and explores the main patterns in the data use for this thesis. In particular, the chapter compares non-sustainable and sustainable firms in terms of exit outcomes, funding received and performance indicators such as firm size and revenues. This initial overview of the relationship in data is preparatory for the econometric analysis that will be carried out in the next chapter.

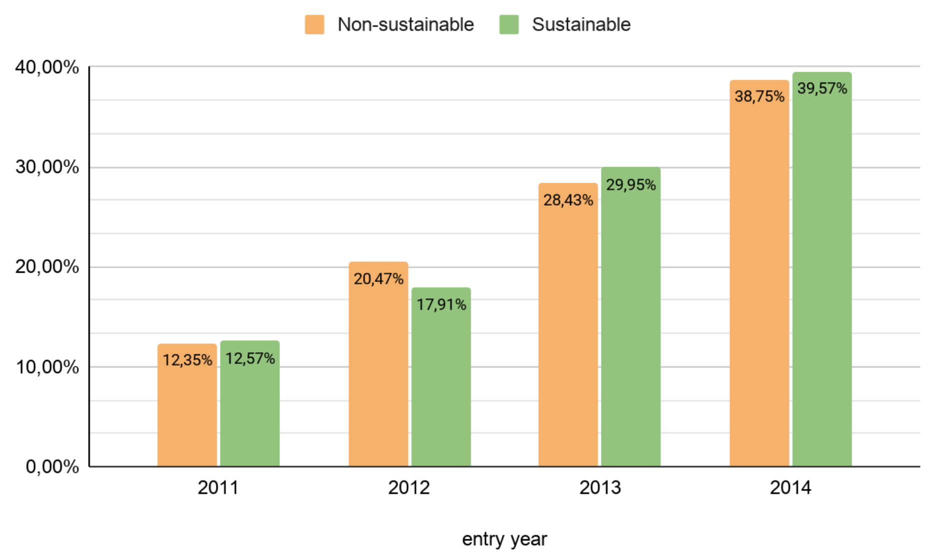
The sample used in this study includes 965 AI firms, 591 are classified as non-sustainable and 374 as sustainable.

The chapter is structured as follows. First, the patterns of entry and exit of firms are described. Second, the differences in exit outcomes related to various parameters of performance between sustainable and non-sustainable firms are analyzed. This analysis is accompanied by chi-square tests and t tests to better investigate the relationship between firm size, funding and revenues and firm's type of exit. Lastly, the conclusion paragraph summarizes all the findings.

3.1. Pattern of Entry, Pattern of Exit, and Exit Mode

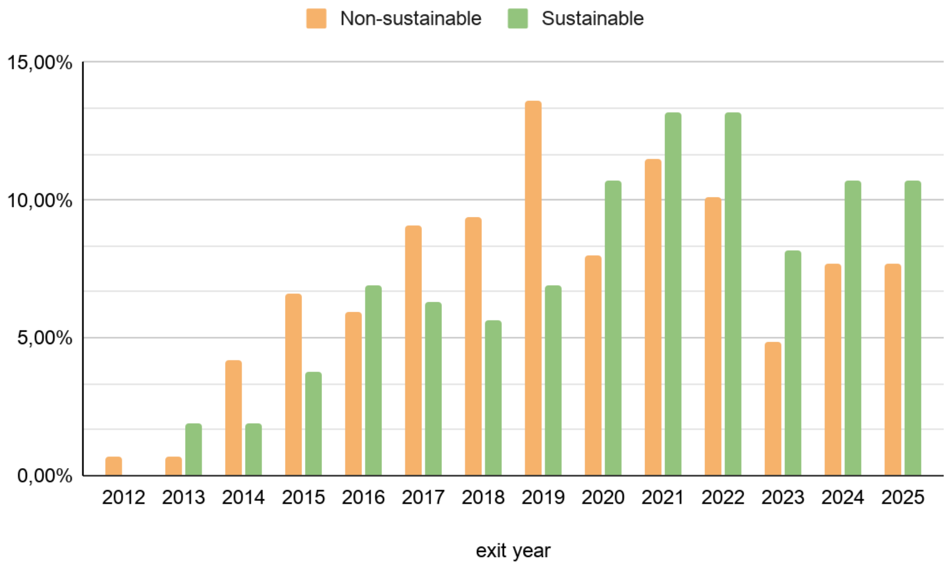
First, the pattern of entry and exit of firms in the sample are examined. The firms are divided into sustainable and non-sustainable in order to better show the differences between the two groups.

Figure 3.1: Patter of entry



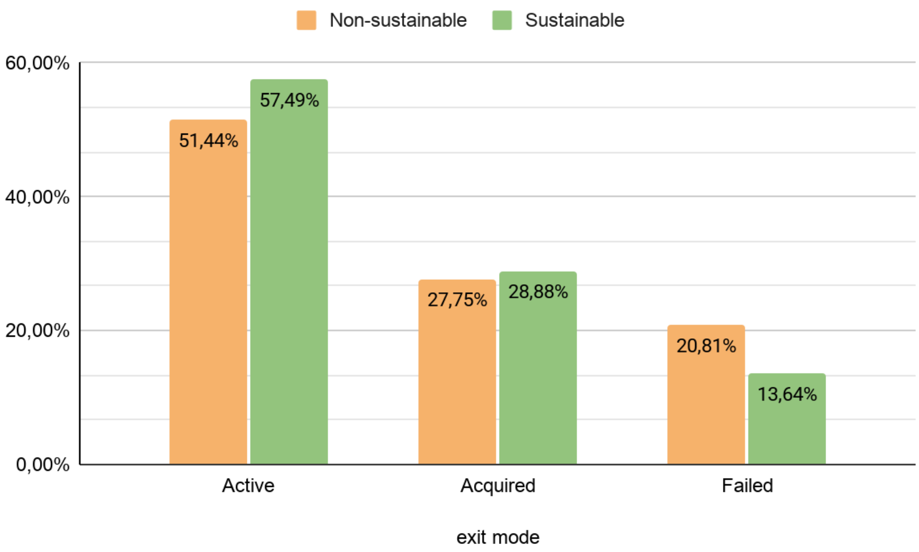
This graph illustrates that sustainable and non-sustainable firms have a similar entry pattern with the majority of entries concentrated in 2013 and 2014. Sustainable firms tend to enter slightly more than non-sustainable firms in 2013, 2014 and 2011. Non-sustainable firms entered more in 2012.

Figure 3.2: Pattern of exit



This graph shows the pattern of exit in percentage. Non-sustainable firms tend to exit principally in 2019, 2021 and 2022, while sustainable firms tend to exit in 2021, 2022 and 2020. The year characterized by the biggest difference in exits between sustainable and non-sustainable firms is 2019. Overall, it is possible to note that the year characterized by the majority of exits are 2019, 2021 and 2022.

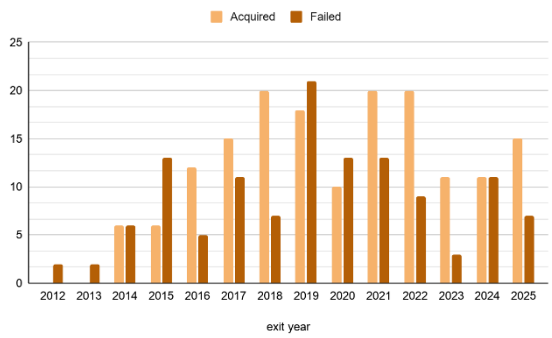
Figure 3.3: Exit Mode



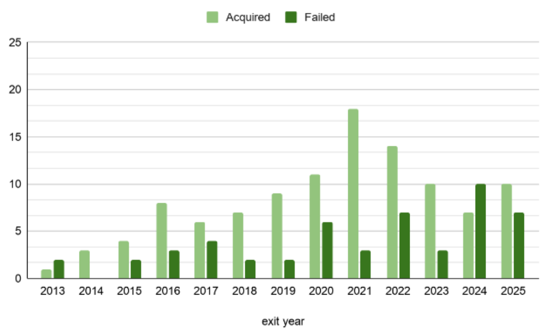
This graph illustrates the status of the firms in percentage at the end of the observation period. Firms in the sample can be active or can no longer be operative for two reasons: being acquired or failed. The major difference between sustainable and non-sustainable firms is seen among the failed firms. In percentage sustainable firms that failed are 13.64%, while non-sustainable firms that failed are 20.81% of the sample. This result shows that sustainable firms tend to fail less than non-sustainable firms, suggesting that sustainability is a condition that influences firms survival. The pattern of survival and acquisition, instead, are quite similar between the two groups but still showing that sustainable firms tend to survive or be acquired.

Figure 3.4: Exit year and type of exit for non-sustainable and sustainable firms

a. Non-sustainable firms



b. Sustainable firms



These graphs show for each year of exit the distribution of acquired and failed firms. Among non-sustainable firms, failures occurred mostly in 2019, while the years with the highest acquisitions were 2018, 2021, and 2022. The only years in which failures exceeded acquisitions were 2015 and 2020. In 2012 and 2013, there were only failures and no acquisitions. Among sustainable firms, the years with the highest failures were 2013 and 2024, while acquisitions occurred mostly between 2020 and 2022. In 2014, there were only acquisitions.

These graphs further demonstrate the previously stated conclusion that sustainable firms tend to be acquired more than they fail, while non-sustainable firms have a higher exit rate.

3.1.1. Association test

As a first test, we study the correlation between sustainability and firm survival. The aim is to investigate the possible relationship between sustainability and the mode of exit. The following chi-square test shows this relationship.

Table 3.1: Chi-Square Test between sustainability status and exit mode

Sustainability	***Exit mode***			***Total***
	Active	***Acquired***	***Failed***	
Non Sustainable (0)	304	164	*123*	***591***
	51.44	27.75	*20.81*	***100.00***
Sustainable (1)	215	108	*51*	***374***
	57.49	28.88	*13.64*	***100.00***
Total	**519**	**272**	***174***	***965***
	53.78	**28.19**	***18.03***	***100.00***
***Pearson$\chi 2(2)$* = 8.2024**			***Prob > $\chi 2$(p-value)* = 0.017**	

Sustainable firms have a higher probability of surviving (57.49%) compared to non-sustainable ones (51.44%). The failure rate is lower among sustainable firms (13.64%) than among non-sustainable firms (20.81%). The probability of being acquired is quite similar across the two groups.

The chi-square test suggests that the association between sustainability and exit mode is statistically significant (p = 0.017). Hence it is possible to state that sustainability influences the pattern of exit.

The subsequent analysis considers the relationship between firms' characteristics, such as size, fundings, and the revenues, and the mode of exit paying attention to the differences between sustainable and non-sustainable firms.

3.2. Firm size

The first indicator taken into consideration is firms' size where is measured in terms of employees. The sample is characterized by a majority of firms with large employee.

Table 3.2: Distribution of employee cohorts by sustainability status

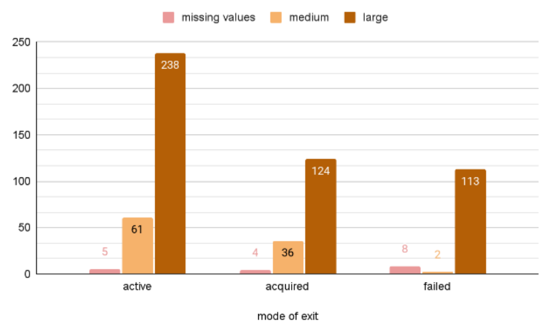
	Employee cohort			*Grand total*
Sustainability	***Missing values***	***Large***	***Medium***	
Non Sustainable (0)	2.88%	80.37%	*16.75%*	***100.00%***
Sustainable (1)	0.53%	79.14%	*20.32%*	***100.00%***
Grand total	**1.97%**	**79.90%**	***18.13%***	***100.00%***

In this table it can be seen that non-sustainable and sustainable firms are principally characterized by large size. There are missing values for both non-sustainable and sustainable firms, but they represent a small percentage of the total.

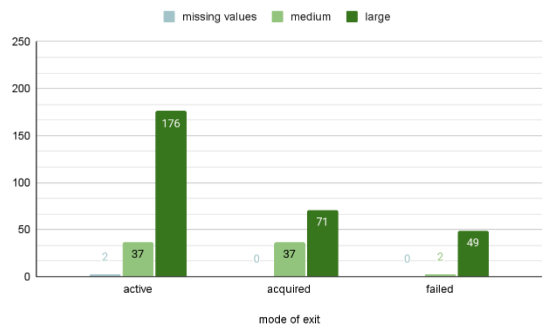
The following graph shows clearly the distribution of firms size and their mode of exit.

Figure 3.5: Employee cohort and exit modes for non-sustainable and sustainable firms

a. Non-sustainable firms



b. Sustainable firms



As said before, the majority of firms are characterized by large employee cohorts. In this graph it is evident that failed non-sustainable and sustainable firms are almost all large.

3.2.1. Chi-square tests of the association between employee cohort and exit type by sustainability status

In this section, the statistical significance through chi-square tests between the type of exit (acquisition or failure) and the firms' size for both non-sustainable and sustainable firms is analyzed.

Table 3.3: Association between the mode of exit and employee category for sustainable firms

Exit type	*Employee category*		***Total***
	Large	***Medium***	
Acquired	71	37	***108***
Failed	49	2	***51***
Total	**120**	**39**	***159***
Pearsonχ2(1) = 17.2231		***Prob > χ2(p-value) = 0.000***	

Focusing specifically on the mode of exit of the firms in the sample, this table illustrates that among sustainable firms with a large employee cohort the acquisition is the prevailing outcome. However, among all failed sustainable firms, almost all of them are large. This is certainly related to the small number of observations for the medium employee cohort. The chi-square test highlights that there is a statistically significant association ($p < 0.001$) between firm size and mode of exit.

Table 3.4: Association between mode of exit and employee category for non-sustainable firms

Exit type	*Employee category*		***Total***
	Large	***Medium***	
Acquired	124	36	***160***
Failed	113	2	***115***
Total	**237**	**38**	***275***
Pearsonχ2(1) = 24.2164		***Prob > χ2(p-value) = 0.000***	

Similarly, a chi-square test was conducted among non-sustainable firms and it is evident that the ones characterized by a medium employee cohort almost do not fail. The majority of acquired firms are large. Also, in this case the result of the chi-square test suggests that there is a statistically significant association ($p < 0.001$) between the type of exit and the firm size.

3.2.2 Overall findings

Based on the above-mentioned results, it can be argued that most of the firms in the sample are rather large. Non-sustainable and sustainable firms do not seem to differ in terms of size category. Furthermore, chi-square tests show a strong significance in the relationship between the mode of exit, acquisition or failure, and the size of the firm. In particular, it is emphasized that larger firms tend to be acquired rather than fail. The same reasoning also applies to medium-sized firms. Indeed, almost all firms belonging to the medium employee cohort are acquired, and only a small percentage fail.

3.3.Funding

Another important variable to study is funding. This section will explore the potential relationship between receiving funding and firm survival.

First of all, sustainable and non-sustainable firms are compared in terms of funding groups.

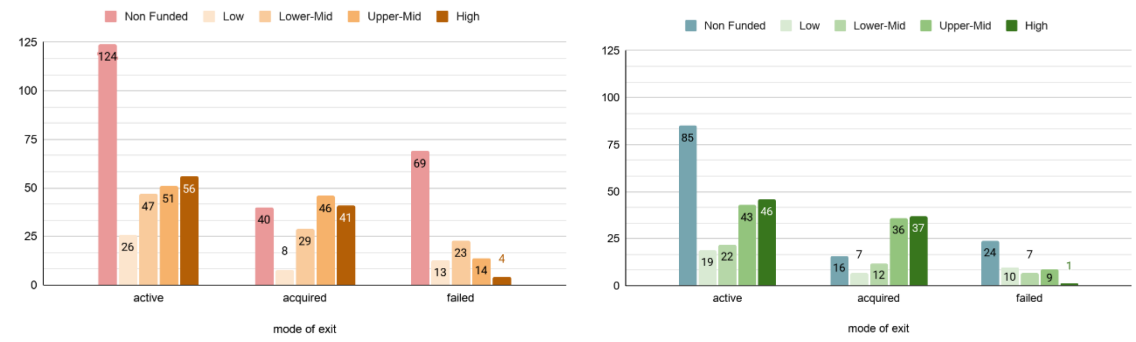
Table 3.5: Distribution of funding group by sustainability status

	Funding group					***Grand total***
Sustainability	***Non funded***	***High***	***Upper-Mid***	***Lower-Mid***	***Low***	
Non-Sustainable (0)	39.42%	17.09%	*18.78%*	*16.75%*	*7.95%*	***100.00%***
Sustainable (1)	33.42%	22.46%	*23.53%*	*10.96%*	*9.63%*	***100.00%***
Grand total	**37.10%**	**19.17%**	***20.62%***	***14.51%***	***8.60%***	***100.00%***

This table shows the distribution of fundings among non-sustainable and sustainable firms. In the sample not all firms received funding. Non-sustainable firms tend to receive less funding than sustainable ones. Non-sustainable firms that receive fundings are present in the upper-mid, high and lower-mid groups. In percentage terms, sustainable firms can be found more in high and upper-mid funding than non-sustainable ones, although the patterns do not differ much.

Figure 3.6: Funding group and exit modes for non-sustainable and sustainable firms

a. Non-sustainable firms b. Sustainable firms



These graphs illustrate the relationship between funding levels and exit modes for both non-sustainable and sustainable firms. A clear pattern emerges. Firms that receive low levels or no funding are more likely to fail, while those with higher levels of funding are more likely to be acquired.

The patterns do not vary significantly across the two groups, although some differences can still be noted. In particular, non-sustainable firms exhibit a larger proportion of failed firms among those that do not receive funding compared to sustainable firms. On the other hand, sustainable firms appear to benefit more from higher funding levels, with greater acquisition likelihood among funded firms.

Overall, results suggest that access to funding plays a crucial role in determining firms' exit outcomes.

3.3.1. Association between funding group and mode of exit by sustainability status

In this section, the statistical significance of association between the type of exit (acquisition or failure) of the firms and the amount of funding received for both non-sustainable and sustainable firms is analyzed through chi-square tests.

Table 3.6: Association between mode of exit and funding group category for sustainable firms

Exit type	***Funding group***				***Total***
	High	***Upper-Mid***	***Lower-Mid***	***Low***	
Acquired	*37*	*36*	*12*	*7*	*92*
Failed	*1*	*9*	*7*	*10*	*27*
Total	*38*	*45*	*19*	*17*	***119***
Pearsonχ2(1) = 23.7246				***Prob > χ2(p-value) = 0.000***	

This chi-square test illustrates that there is a statistically significant association ($p < 0.001$) between the type of exit and the level of funding received. In fact, the firms that receive higher funding exit mainly through acquisition, while those with low funding fail more often. This suggests that the type of funding received influences the mode of exit of the funded firms.

Table 3.7: Association between mode of exit and funding group category for non-sustainable firms

Exit type	***Funding group***				***Total***
	High	***Upper-Mid***	***Lower-Mid***	***Low***	
Acquired	*41*	*46*	*29*	*8*	*124*
Failed	*4*	*14*	*23*	*13*	*54*
Total	*45*	*60*	***52***	***21***	***178***
Pearson$\chi2(1)$ = 25.8398				***Prob > $\chi2$(p-value) = 0.000***	

Also, in the case of non-sustainable firms, the ones receiving high and upper-mid funding are more likely to be acquired, while those which receive low funding fail more often. In fact, the p-value of the chi square test ($p < 0.001$) highlights a statistically significant association between the exit type and the funding.

3.3.2. Average funding

Fundings are not equally distributed, and firms receive very different sums of money. In the following table is shown the average value of funding received by non-sustainable and sustainable firms.

Table 3.8: Distribution of average funding in USD by sustainability status

	Exit mode	*Average funding*
Sustainability		
Non-sustainable	*Active*	*59'800'945.53*
	Acquired	*175'856'547.9*
	Failed	*238'231'583.5*
	Total sample	*126'913'094*
Sustainable	*Active*	*317'877'646.7*
	Acquired	*1'092'695'393*
	Failed	*8'028'532.63*
	Total sample	***570'557'592.7***

This table displays the average sum of money received by the firms divided into sustainable and non-sustainable firms and for their status. Among sustainable firms the ones acquired received the higher sum of funding, while among the non-sustainables the failed ones are those that were mostly funded. Looking at the average amount of money, sustainable firms receive higher levels than non-sustainable ones.

We test the statistical difference with a series of t-tests.

Table 3.9: T-test of average funding and sustainability status

Group interval	*Obs*	*Mean*	*Std. err.*	*Std. Dev.*	*[95% conf. interval]*	
Non-Sustainable	358	15.57919	.1190967	2.253416	15.34497	15.81341
Sustainable	249	15.90181	.1524261	2.405243	15.60159	16.20202
Combined	607	15.71153	.0941815	2.320385	15.52657	15.89649
diff		-.3226205	.1911843		- .6980859	.0528449

diff = mean(0) - mean(1) t = -1.6875

H0: diff = 0 Degrees of freedom = 605

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 0.0460 Pr(|T| > |t|) = 0.0920 Pr(T > t) = 0.9540

Here a two-sample t-test was conducted to compare the average funding levels between sustainable and non-sustainable firms. The results show that sustainable firms receive slightly higher funding on average (mean = 15.90) than non-sustainable firms (mean = 15.58). However, the difference of 0.32 units is only weakly significant (t = −1.69, p = 0.092), suggesting that sustainability is not strongly associated with higher funding levels.

In order to better test the correlation between the average amount of money and the exit type other t tests have been conducted.

Table 3.10: T-test of average funding by exit type for sustainable firms

Group interval	*Obs*	*Mean*	*Std. err.*	*Std. Dev.*	*[95% conf. interval]*	
Acquired	92	16.37294	.241754	2.318823	15.89273	16.85316
Failed	27	14.12243	.3502935	1.820178	13.4024	14.84247
Combined	119	15.86232	.2202475	2.402617	15.42617	16.29847
diff		2.250509	.485406		1.289188	3.21183

diff = mean(Acquired) - mean(Failed) t = 4.6363

H0: diff = 0 Degrees of freedom = 117

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 1.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 0.0000

Here the two-sample t-test was conducted to compare the average funding levels between sustainable firms that were acquired and those that failed. The results show that acquired firms received significantly higher funding on average (mean = 16.37) compared to failed firms (mean = 14.12). The difference of 2.25 units is statistically significant (t = 4.64, p < 0.001). These results suggest that higher funding levels are associated with a greater likelihood of acquisition among sustainable firms.

The same test has been performed for non-sustainable firms.

Table 3.11: T-test of average funding by exit type for non-sustainable firms

Group interval	*Obs*	*Mean*	*Std. err.*	*Std. Dev.*	*[95% conf. interval]*	
Acquired	124	15.98902	.181359	2.019528	15.63003	16.34801
Failed	54	14.4657	.308546	2.267341	13.84683	15.08456
Combined	178	15.52689	.1653518	2.206068	15.20057	15.8532
diff		1.523322	.3419399		.8484918	2.198152

diff = mean(Acquired) - mean(Failed) t = 4.4549

H0: diff = 0 Degrees of freedom = 176

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 1.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 0.0000

This table shows the two-sample t-test conducted to compare the average funding levels between non-sustainable firms that were acquired and those that failed. The results indicate that acquired firms receive significantly higher funding on average (mean = 15.99) than failed firms (mean = 14.47). The difference of 1.52 units is statistically significant (t = 4.45, p < 0.001), indicating that higher funding is associated with a greater likelihood of acquisition rather than failure among non-sustainable firms.

3.3.3. Overall findings

These tests reveal similar patterns, highlighting that the exit mode (acquisition or failure) of the firms in the sample is closely associated with the amount of funding received. Indeed, as already mentioned, firms that receive funding tend to be acquired more often and fail less. Although the pattern is the same for acquired sustainable and non-sustainable firms, the latter receive proportionally lower amounts of money for funding (4-5 times more funding than failed firms) than sustainable firms (9-10 times more funding than failed firms).

3.4. Revenues

The other variable considered regards the revenues obtained by the firms. In this section, the relationship between the revenue level generated by the firm and their sustainability is analyzed. Furthermore, the possible correlation between the revenue group and the firms' exit type is examined.

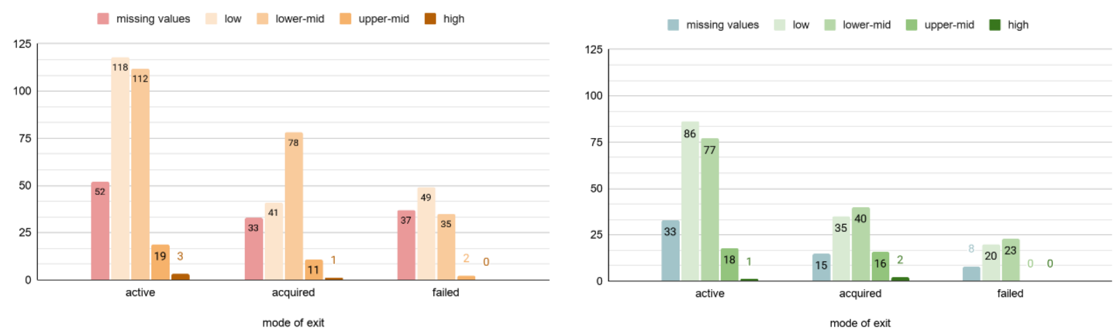
Table 3.12: Distribution of revenue group[1] by sustainability status

	Revenue group					*Grand total*
Sustainability	***Missing values***	***High***	***Upper-Mid***	***Lower-Mid***	***Low***	
Non-Sustainable (0)	20.64%	0.68%	5.41%	38.07%	35.19%	***100.00%***
Sustainable (1)	14.97%	0.80%	9.09%	37.43%	37.70%	***100.00%***
Grand total	**18.45%**	**0.73%**	**6.84%**	**37.82%**	**36.17%**	***100.00%***

The majority of firms in the sample tend to obtain low or lower-mid revenues. High revenues constitute only a small portion of the total. Sustainable and non-sustainable firms have similar patterns. However, some differences can be observed: sustainable firms are more present in high and upper-mid revenue groups than non-sustainable ones.

Figure 3.7: Revenue group and mode of exit for non-sustainable and sustainable firms

a. Non-sustainable firms　　b. Sustainable firms



Sustainable and non-sustainable firms have similar patterns, with most firms concentrated in low and lower-mid revenue groups. Overall, only a small number of firms generate high or upper-mid revenues.

Considering the type of exit (acquisition or failure), firms with high, upper-mid and lower-mid revenue levels are generally more likely to be acquired than to fail. This pattern is particularly evident among sustainable firms. In contrast, among non-sustainable firms, failure is more likely than acquisition only in the low revenue group. In both cases, high-revenue firms do not fail.

[1] Note: Revenue categories are defined as follows: High ($100M–$500M); Upper-Mid ($10M–$50M); Lower-Mid ($1M–$10M); Low (<$1M).

3.4.1. Association between mode of exit and revenue group category by sustainability status

In this section, chi-square tests were performed to observe the statistical significance between the revenue group obtained and the type of exit (acquisition or failure) for both non-sustainable and sustainable firms.

Table 3.13: Association between mode of exit and revenue group category for sustainable firms

Exit type	***Revenue group***				***Total***
	High	***Upper-Mid***	***Lower-Mid***	***Low***	
Acquired	*2*	*16*	*40*	*35*	*93*
Failed	*0*	*0*	*23*	*20*	*43*
Total	*2*	*16*	*63*	***55***	*136*
Pearson$\chi 2(3)$ = 9.5924				***Prob > $\chi 2$(p-value) = 0.022***	

This table shows that among sustainable firms, revenue levels are significantly associated with exit types. Firms in the highest revenue categories do not fail and exit only through acquisitions even if they constitute a minor share of the total sample. Firms belonging to low or lower-mid revenue groups tend to be more acquired than fail. This chi-square test states that there is statistical significance (p = 0.022) between the revenue groups and the type of exit.

Table 3.14: Association between mode of exit and revenue group category for non-sustainable firms

Exit type	***Revenue group***				***Total***
	High	***Upper-Mid***	***Lower-Mid***	***Low***	
Acquired	*1*	*11*	*78*	*41*	*131*
Failed	*0*	*2*	*35*	*49*	*86*
Total	*1*	*13*	*113*	***90***	*217*
Pearson$\chi 2(3)$ = 15.6457				***Prob > $\chi 2$(p-value) = 0.001***	

This table displays the distribution of revenues among non-sustainable acquired and failed firms. Firms belonging to the high, lower-mid, and upper-mid revenue groups tend to be acquired more than fail. Most acquired firms fall into the low or lower-mid revenue group. The difference in exit patterns among low-revenue firms is not particularly marked, while among lower-mid firms, it is more evident. Only low-revenue firms are more likely to fail than be acquired. Finally, no failed firms belong to the high-revenue group. The chi-square test conducted shows that the correlation between revenue group and type of exit is statistically significant ($p = 0.001$).

3.4.2. Overall findings

The patterns between sustainable and non-sustainable firms do not differ significantly, except that in the low-revenue group, more sustainable firms are acquired than fail, while among non-sustainable firms, more firms fail. In both cases, firms with high, upper-mid, and lower-mid revenues are more likely to be acquired than to fail. These results suggest that firms' exit behavior depends on the type of revenue earned.

3.5. Conclusions

This chapter has provided a series of descriptive statistics on the sample of firms that has been collected. The figures and tables presented above have explored the relationship between the mode of exit and a set of characteristics such as: size, funding, and revenues, broken down into sustainable and non-sustainable firms. Sustainable and non-sustainable firms show broadly similar patterns, although some differences can still be observed.

In terms of size, the firms in the sample are mostly large, and for both groups, acquired firms outnumber those that fail. However, among non-sustainable firms, the difference between acquired and failed firms is less pronounced than among sustainable firms. Medium-sized firms are almost all acquired.

Conversely, regarding funding, it is clear that firms receiving high or upper-mid levels of funding tend to be acquired more often, while firms receiving low funding tend to fail more frequently. This pattern is common to both sustainable and non-sustainable firms.

In terms of capital received, it is possible to note that sustainable firms tend to obtain more financing on average than non-sustainable firms, although the statistical significance is weak. The relationship between average funding received and acquisition is stronger, however. Indeed, both sustainable and non-sustainable firms that are acquired receive more funding than those that fail. This difference is particularly evident for sustainable firms.

Finally, regarding revenues generated, sustainable firms tend to be acquired more often across all revenue categories, while among non-sustainable firms, the only revenue group that tends to fail more is the low-yield category.

Overall, these findings suggest that firm performance, particularly in terms of funding and revenues, plays a key role in shaping exit outcomes. While sustainability appears to be associated with lower failure rates and slightly higher funding levels, these relationships are descriptive and do not imply causality.

The next chapter will investigate these dynamics more formally using econometric methods.

Chapter 4: Econometric exercise

This chapter presents the results obtained from the analysis of the variables in a multivariate framework. In particular, it checks whether the patterns observed in the previous chapter persist beyond a univariate setting. To conduct this analysis, several estimations have been employed.

First, the Kaplan–Meier estimator has been used to describe and graphically display the survival functions. This method provides a non-parametric estimate of the probability that startups remain active over time. In addition, the statistical significance of the differences observed across various subgroups has been tested using log-rank tests, which allow us to assess whether the variables in the sample effectively influence the duration of startups' survival.

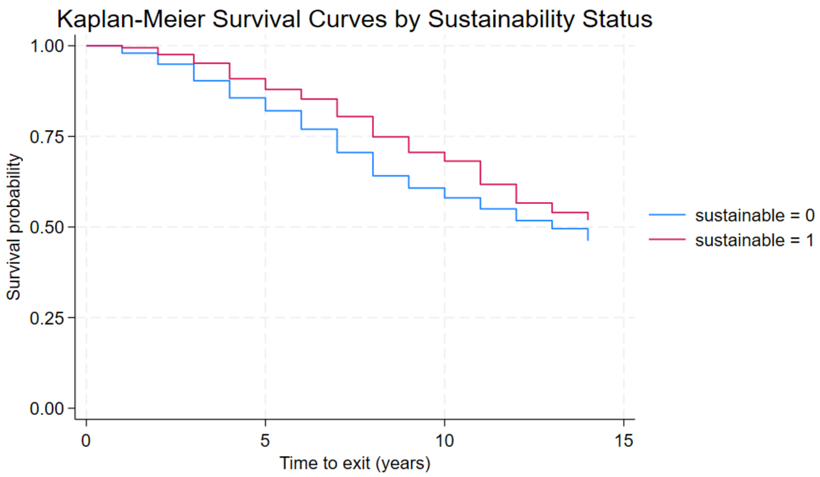
Subsequently, Cox proportional hazards models have been estimated to investigate the survival dynamics of the firms in the sample. These models are semi-parametric analytical tools used to estimate the effect of different variables on the hazard rate, that is, the risk that a given event, such as failure or acquisition, occurs over time. They allow us to identify what firm level characteristics proportionally shift the baseline hazard function without requiring its functional form to be specified a priori.

Specifically, the estimated models first analyze the probability of survival versus generic exit, including both acquisition and failure. Then, more detailed Cox models are presented to examine the probability of survival versus specific exit modes, namely acquisition or failure.

Finally, a set of robustness checks will be conducted to test whether the results hold under different baseline specifications. These checks have been performed using complementary log–log models as well as several parametric models (i.e., Weibull, Gompertz, and Exponential).

4.1. Non-parametric Kaplan-Meier analysis

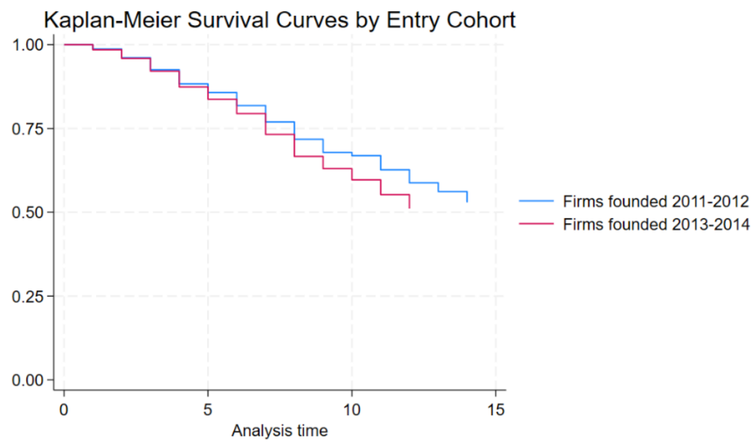
Figure 4.1: Kaplan-Meier Survival Curves by sustainability status



This graph presents the Kaplan–Meier survival curves by the sustainability status of startups. The vertical axis represents the probability of survival, while the horizontal axis shows the time to exit in years (from 0 to 15). The fact that the curve for sustainable firms lies above that of non-sustainable ones indicates that, at any given time *t*, these startups have a higher probability of remaining active compared to the others.

By the end of the observation period, the survival probability of sustainable startups remains above 50%. This figure therefore suggests that sustainability acts as a factor enhancing longevity. For both groups, the probability of survival decreases over time. However, sustainable startups exhibit greater resilience and a stronger ability to remain in the market in the long run.

Figure 4.2: Kaplan-Meier Survival Curves by entry cohort



This graph shows the Kaplan–Meier survival curves stratified by the founding year of startups, dividing the sample into two groups: the 2011-2012 cohort and the 2013-2014 cohort. The vertical axis reports the probability of survival, while the horizontal axis shows the time to exit expressed in years.

The figure indicates that startups founded in the 2011–2012 period were more resilient than those established in the subsequent two-year period, although during the first four to five years of life both groups exhibit almost identical survival patterns. This result suggests that market conditions at the time of entry, or differences in cohort composition, may have influenced firms' ability to remain in the market over the long term.

4.2. Log-rank tests

This section reports the results of the log-rank tests, which are used to assess the equality of survival functions across two or more subgroups within the sample. These tests have been carried out for the following variables: sustainability, funding, revenue, and cohort.

Table 4.1: Log-rank test by sustainability

Sustainability	***Observed events***	***Expected events***
Non-Sustainable (0)	*287*	*264.21*
Sustainable (1)	*159*	*181.79*
Total	***446***	***446.00***
Statistics $\chi 2(1)$	***5.11***	
Prob > $\chi 2$(p-value)	***0.024*****	

*Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The test evaluates the null hypothesis of equality between the survival functions of the two groups.*

This table shows the presence of a statistically significant difference in survival between the two groups (sustainable and non-sustainable startups). In particular, sustainable startups exhibit a higher probability of survival compared to non-sustainable ones.

Table 4.2: Log-rank test by funding group

Funding group	*Observed events*	*Expected events*
High	*83*	*92.87*
Upper-Mid	*105*	*90.31*
Lower-Mid	*71*	*58.56*
Low	*38*	*39.03*
Non funded	*149*	*165.23*
Total	***446***	***446.00***
Statistics $\chi 2(4)$	***8.16***	
Prob > $\chi 2$***(p-value)***	***0.086****	

*Note: Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1. The test evaluates the null hypothesis of equality between the survival functions of the two groups.*

The results reported in this table indicate that firms receiving high levels of funding tend to exhibit better survival than expected, and a similar pattern is observed for firms that do not receive funding. In contrast, firms belonging to the upper-mid and lower-mid categories tend to exit the market more frequently than expected.

The test shows only marginal statistical significance, suggesting the presence of a statistical tendency toward differences in survival across funding groups; however, the evidence is not as strong as that observed for the variable capturing sustainability.

Table 4.3: Log-rank test by revenue group

revenue group	***Observed events***	***Expected events***
High	*3*	*3.77*
Upper-Mid	*29*	*31.87*
Lower-Mid	*176*	*172.44*
Low	*145*	*171.21*
Missing	*93*	*66.71*
Total	***446***	***446.00***
Statistics χ2(4)	***15.72***	
Prob > χ2(p-value)	***0.0034****	

*Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The test evaluates the null hypothesis of equality between the survival functions of the two groups.*

High, upper-mid, and low categories show better performance in terms of relative survival. The lower-mid category behaves almost exactly as predicted by theoretical expectations, while the high and upper-mid categories exhibit slightly lower mortality than expected.

Table 4.4: log-rank test by cohort

cohort	***Observed events***	***Expected events***
2011-2012	*139*	*159.14*
2013-1014	*307*	*286.86*
Total	***446***	***446.00***
Statistics χ2(1)	***4.45***	
Prob > χ2(p-value)	***0.0348***	

*Note: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The test evaluates the null hypothesis of equality between the survival functions of the two groups.*

This table shows that the cohort of firms founded in 2011-2012 experienced fewer actual failures than predicted, indicating better survival performance compared to the sample average. In contrast, the

2013-2014 cohort recorded more observed failures than expected, suggesting that this group experienced higher losses than predicted by the equality model.

4.3. Semi-parametric Cox regression models

This section presents all the Cox models estimated. The aim of the analysis is to examine the influence of specific variables on the survival or exit mode of firms in the sample. The Cox model allows for this type of analysis.

In total, four models were estimated. The first model studies survival versus generic exit for all firms in the sample. In this model, variables are introduced sequentially to better verify that the model properly captures their effects.

The following three models instead analyze exit modes more specifically. The first of these examines the probability of acquisition relative to failure and considers only firms that have exited the market (446). The other two models analyze, respectively, the probability of acquisition versus survival and the probability of failure versus survival. These models are based on subsamples including active firms (519) and, respectively, acquired firms (272) and failed firms (174).

4.3.1. Survival vs. Exit

Table 4.5: Sequential estimations, Dependent variable: survival

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Sustainable	0.805**	(0.080)	0.809**	(0.080)	0.820**	(0.082)	0.813**	(0.081)	0.815**	(0.081)
Funding Group (Ref: Non funded)										
High			1.008	(0.138)	1.180	(0.187)	1.167	(0.184)	1.165	(0.184)
Upper-Mid			1.308**	(0.167)	1.522***	(0.212)	1.486***	(0.207)	1.482***	(0.207)
Lower-Mid			1.326*	(0.192)	1.471***	(0.217)	1.432**	(0.212)	1.436**	(0.212)
Low			1.094	(0.199)	1.184	(0.217)	1.165	(0.214)	1.156	(0.212)
Revenue Group (Ref: High)										
Upper-Mid					1.131	(0.689)	1.065	(0.649)	1.105	(0.675)
Lower-Mid					1.220	(0.721)	1.133	(0.670)	1.169	(0.693)
Low					1.048	(0.625)	0.954	(0.570)	0.987	(0.590)
Missing					1.917	(1.158)	1.718	(1.040)	1.767	(1.071)
Firm Age							0.875***	(0.043)	0.804**	(0.080)
Cohort (Ref: 2011-2012)										
2013-2014									0.808	(0.176)
Statistics										
Log-Likelihood	-2923.3472		-2919.7174		-2910.6842		-2906.847		-2906.3669	
LR chi2	4.90		12.16		30.23		37.90		38.86	
Prob > chi2	0.0268		0.0326		0.0004		0.0000		0.0001	
No. of subjects	965		965		965		965		965	
No. of failures	446		446		446		446		446	
Time at risk	9,380		9,380		9,380		9,380		9,380	

*Note: Reported values are hazard ratios (HR). Robust standard errors are reported in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.*

This table analyzes survival versus generic exit (both acquisition and failure) through five sequential Cox models that consider the full sample (965 startups).

The variable capturing sustainability shows stable estimated hazard ratios across all models. This indicates that sustainable startups have a lower risk of generic exit compared to non-sustainable ones. The stability and significance of this effect, even after adding controls (i.e. funding, revenues, age), suggest that sustainability has a robust and independent effect on firm longevity.

The inclusion of funding groups in the second model shows an acceleration of exit associated with fundings. Firms in the upper-mid (HR = 1.482***) and lower-mid (HR = 1.436**) funding groups exhibit a significantly higher risk of exit compared to non-funded firms. This suggests that funding acts as a catalyst for exit, likely through acquisition.

Revenue groups are not statistically significant in these models.

The age variable is highly significant (HR = 0.804**), suggesting that each additional year reduces the risk of exit.

The cohort variable is not statistically significant.

Overall, these sequential models show that the main drivers of survival and generic exit are sustainability, funding, and firm age.

4.3.2. Analyzing exit modes

Table 4.6: Different modes of exit

Variables	Model (6) Acquisition vs Failure		Model (7) Acquisition vs Survival		Model (8) Failure vs Survival	
Sustainable	0.939	(0.120)	0.920	(0.115)	0.636***	(0.107)
Funding Group (Ref: Non funded)						
High	2.480***	(0.502)	2.692***	(0.544)	0.136***	(0.064)
Upper-Mid	2.377***	(0.460)	3.164***	(0.613)	0.611**	(0.150)
Lower-Mid	2.476***	(0.538)	2.344***	(0.494)	0.972	(0.209)
Low	0.895	(0.264)	1.335	(0.391)	1.105	(0.262)
Revenue Group (Ref: Low)						
High/Mid	1.258	(0.184)	1.282*	(0.190)	1.120	(0.204)
Missing	3.437***	(0.706)	2.438***	(0.483)	1.326	(0.261)
Firm Age	0.865	(0.111)	0.895	(0.112)	0.643***	(0.106)
Cohort (Ref: 2011-2012)						
2013-2014	1.163	(0.330)	1.015	(0.281)	0.505*	(0.180)
Statistics						
Log-Likelihood	-1392.9823		-1722.5401		-1071.4945	
LR chi2	65.23		61.68		61.52	
Prob > chi2	0.0000		0.0000		0.0000	
No. of subjects	446		791		693	
No. of failures	272		272		174	
Time at risk	3,108		8,211		7,441	

*Note: Reported values are hazard ratios (HR). Robust standard errors are reported in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.*

This table presents models that analyze exit modes more specifically.

The first model examines acquisition versus failure and includes only firms that have exited the market. The second model analyzes acquisition versus survival, while the third focuses on failure versus survival. These latter two models consider only active firms and compare them with either acquired or failed firms.

The most relevant result emerges in the Failure vs Survival model. Sustainability acts as a strong protective factor against failure (HR = 0.636***), indicating a lower probability of failure for sustainable firms. Conversely, sustainability has no statistically significant effect on the probability of being acquired.

Funding shows different effects depending on the event considered. In the first two models, receiving funding (High, Upper-Mid, Lower-Mid) significantly increases the probability of acquisition (HR between 2.34 and 3.16), indicating that funded firms are more likely to be acquired.

In the third model, the high funding group has an HR of 0.136***, showing a strong reduction in failure risk compared to non-funded firms. This suggests that funding prevents failure.

Regarding revenues, the missing category indicates that firms without revenue data have a higher probability of acquisition relative to both failure and survival. In the Acquisition vs Survival model, firms with High/Mid revenues show a slightly higher probability of acquisition (HR = 1.282*) compared to Low-revenue firms, suggesting a role of financial performance in exit outcomes.

Firm age is significant only in the Failure vs Survival model (HR = 0.643***), indicating that older startups are more robust and less likely to fail.

The cohort variable is significant only in the third model, showing that the 2013-2014 cohort has roughly half the failure risk compared to the 2011-2012 cohort. This may reflect better initial selection or different market conditions.

In conclusion, sustainability protects against failure but does not accelerate acquisition, which instead strongly depends on funding.

4.4. Robustness checks

This paragraph presents the results of robustness checks conducted to further validate the findings.

First, robustness checks were performed using cloglog models. Complementary log-log models represent the discrete-time equivalent of the Cox model and allow the analysis of data grouped into time intervals while maintaining the proportional hazards assumption.

Subsequently, parametric models were estimated. Parametric models (Weibull, Gompertz, and Exponential) are statistical tools used to estimate the impact of variables on the probability of an event. They require specifying a functional form for the baseline hazard and allow modeling specific time patterns such as constant, increasing, or decreasing risks.

4.4.1. Complementary Log-Log results

This section presents the results of robustness checks using cloglog models.

Complementary log-log models require explicit specification of the baseline hazard. A logarithmic specification is commonly used to model monotonic hazard trends. The inclusion of time polynomials (linear, quadratic, and cubic) improves flexibility and allows capturing non-monotonic dynamics or more complex patterns in failure distribution. This approach preserves the proportional hazards assumption.

Table 4.7: Cloglog survival vs generic exit

Variables	Model (9) Cloglog logarithmic		Model (10) Cloglog linear time		Model (11) Cloglog quadratic time		Model (12) Cloglog cubic time	
Sustainable	0.811**	(0.080)	0.813**	(0.081)	0.809**	(0.080)	0.811**	(0.080)
Funding Group (Ref: Non funded)								
High	1.179	(0.191)	1.182	(0.192)	1.173	(0.190)	1.175	(0.191)
Upper-Mid	1.511***	(0.216)	1.511***	(0.216)	1.504***	(0.215)	1.503***	(0.215)
Lower-Mid	1.456**	(0.220)	1.451**	(0.219)	1.452**	(0.219)	1.454**	(0.220)
Low	1.161	(0.216)	1.160	(0.215)	1.160	(0.216)	1.163	(0.216)
Revenue Group (Ref: High)								
Upper-Mid	1.114	(0.684)	1.109	(0.681)	1.118	(0.687)	1.112	(0.684)
Lower-Mid	1.187	(0.706)	1.186	(0.704)	1.187	(0.706)	1.182	(0.702)
Low	1.000	(0.602)	0.999	(0.601)	1.002	(0.603)	0.997	(0.599)
Missing	1.798	(1.095)	1.778	(1.082)	1.805	(1.100)	1.800	(1.096)
Firm Age	0.799**	(0.079)	0.791**	(0.079)	0.819**	(0.081)	0.811**	(0.081)
Cohort (Ref: 2011-2012)								
2013-2014	0.828	(0.178)	0.830	(0.179)	0.824	(0.177)	0.830	(0.179)
time								
lnj	1.776***	(0.128)						
t			1.101***	(0.014)	1.357***	(0.073)	1.655***	(0.200)
t^2					0.982***	(0.004)	0.943***	(0.021)
t^3							1.00*	(0.001)
Statistics								
Log-Likelihood	-1744.956		-1752.809		-1744.435		-1742.844	
Wald chi2	125.38		115.22		122.67		114.05	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
No. of obs	9,380		9,380		9,380		9,380	
Zero outcomes	8,934		8,934		8,934		8,934	
Non zero outcomes	446		446		446		446	

*Note: Reported values are hazard ratios (HR). Robust standard errors are reported in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.*

This table presents the results of four complementary log-log models, which represent the discrete-time equivalent of the Cox proportional hazards model.

The analysis focuses on survival versus generic exit using a person-period dataset (9,380 observations based on 965 subjects), where exit includes both failures and acquisitions.

The results are robust and consistent with those obtained from Cox models. Coefficient signs and magnitudes remain stable, confirming that the findings are not sensitive to the specification of the baseline hazard.

4.4. Parametric models

This paragraph presents the results of robustness checks using parametric models (Weibull, Gompertz, and Exponential).

Among continuous-time parametric survival models, the Exponential model is the most restrictive, as it assumes a constant baseline hazard over time. The Weibull model allows the hazard rate to increase or decrease monotonically depending on a shape parameter (p) and can be interpreted within both proportional hazards (PH) and accelerated failure time (AFT) frameworks.

The Gompertz model, instead, assumes an exponentially evolving hazard over time and it is typically estimated within the proportional hazards framework.

Table 4.8: Robustness check with parametric models

Variables	Model (13) Weibull		Model (14) Gompertz		Model (15) Exponential	
Sustainable	0.810**	(0.081)	0.812**	(0.081)	0.827**	(0.076)
Funding Group	(Ref: Non funded)					
High	1.176	(0.186)	1.182	(0.187)	1.161	(0.168)
Upper-Mid	1.510***	(0.214)	1.516***	(0.215)	1.446***	(0.185)
Lower-Mid	1.464**	(0.236)	1.462**	(0.233)	1.388**	(0.197)
Low	1.158	(0.218)	1.157	(0.216)	1.151	(0.198)
Revenue Group (Ref: High)						
Upper-Mid	1.118	(0.665)	1.113	(0.668)	1.088	(0.604)
Lower-Mid	1.187	(0.682)	1.187	(0.687)	1.160	(0.623)
Low	1.000	(0.580)	1.000	(0.585)	0.989	(0.536)
Missing	1.812	(1.074)	1.788	(1.067)	1.681	(0.928)
Firm Age	0.788**	(0.079)	0.771**	(0.0780)	0.844*	(0.0769)
Cohort (Ref: 2011-2012)						
2013-2014	0.826	(0.181)	0.828	(0.182)	0.849	(0.170)
p	1.717	(0.069)				
gamma			0.137***	(0.013)		
Statistics						
Log-Likelihood	-922.527		-936.463		-985.617	
Wald chi2	43.12		46.25		35.61	
Prob > chi2	0.0000		0.0000		0.0002	
No. of subjects	965		965		965	
No. of failures	446		446		446	
Time at risk	9,380		9,380		9,380	

Note: Reported values are hazard ratios (HR). Robust standard errors are reported in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1. A parameter p > 1 indicates an increasing baseline hazard function over time.

Results are highly consistent across Cox and parametric models (Weibull, Gompertz, and Exponential). Coefficient signs remain unchanged and magnitudes are very similar, confirming robustness to alternative baseline hazard specifications. The Exponential model shows slightly attenuated effects, likely due to its restrictive assumption of a constant hazard rate.

4.5. Conclusions

The results presented in this chapter show how sustainability, funding, and age influence the survival dynamics and exit patterns of startups in the sample.

Sustainability plays a crucial role in enhancing survival and particularly in reducing the risk of failure. The funding variable shows that receiving capital increases the likelihood of acquisition relative to failure. Finally, firm age acts as a protective factor against failure, as older startups are less likely to exit the market through failure.

These findings are further confirmed by the robustness checks performed.

Chapter 5: Conclusions

This thesis has presented an analysis on the survival of sustainable and non-sustainable startups working in the artificial intelligence sector. The aim was to investigate the influence of various firms characteristics on the survival of firms in the sample. In order to reach this objective, different types of statistics have been used.

First of all, the literature available on the themes of AI and sustainability has been presented. The literature has highlighted aspects studied and the gaps. The literature has suggested that sustainability represents an increasingly important aspect. Nowadays it is fundamental to address environmental issues in order to reduce situations that put the entire world in danger. Artificial intelligence can constitute a useful tool, but it must be correctly regulated in order to minimize the possible negative externalities.

The analysis was conducted on a sample of 965 startups with different sustainability status, 591 are classified as non-sustainable and 374 as sustainable. During the analysis various variables have been considered, such as funding received, revenues earned and firm age.

Fundamental insights were provided by the initial descriptive and univariate analysis. In particular, it highlighted that sustainable firms show longer survival than non-sustainable ones. This evidence suggests that sustainability may act as a factor enhancing firm resilience. Furthermore, the access to funding appeared to be strongly associated with the mode of exit. In fact, funded firms showed higher probability of being acquired rather than failing.

Subsequently, multivariate analyses were performed using Cox proportional hazards models to test if the patterns observed in the univariate context remained valid when controlling for multiple factors simultaneously. The results confirmed the initial findings. Sustainability, funding and firm age can be considered as key determinants of survival and modes of exit. In particular, the results highlighted that sustainability significantly reduced the risk of failure. Funding, however, played a crucial role in increasing the likelihood of acquisition. Firm age also showed a protective effect, indicating that older startups tend to be more resilient over time.

The results were found to be consistent across the different model specifications, including the robustness checks performed using complementary log-log and parametric models. This further strengthened the validity of the findings. In fact, the results appear to be not sensitive to the assumptions about the baseline hazard function. The stability of coefficient signs and magnitudes across these approaches suggest this robustness.

This thesis contributes to the existing literature by providing empirical evidence on how sustainability affects startup survival in the artificial intelligence sector. The findings show that sustainability is also a strategic factor able to enhance firm longevity and reduce adverse outcomes such as failure and does not only belong to an ethical or normative dimension.

Some limitations should be acknowledged. The analysis is based on a specific sample and future research could broaden this work by considering different contexts and additional variables. Moreover, a deeper research of causal mechanisms could provide further insights into how sustainability practically affects firm performance.

In conclusion, this study demonstrates that sustainability, together with funding and firm age, plays a crucial role in determining the survival patterns of startups. Given the increasing growth of the artificial intelligence sector, the integration of sustainable practices may represent not only a societal imperative, but also a key driver of long-term business success.

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