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**AUTOMATING STARTUP EVALUATION:
FROM QUALITATIVE DESCRIPTIONS TO A
MULTIDIMENSIONAL, TEXT-BASED MEASURE
OF MATURITY AND INVESTMENT READINESS**

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Supervisor: Prof. Marco Remondino

Candidate: Veronica Mariannelli

Matriculation: 3320923

Email: s3320923@studenti.unige.it

Automating startup evaluation: from qualitative descriptions to a multidimensional, text-based measure of maturity and investment readiness

Introduction

In recent decades, the world of startups has found itself playing a central role in the analysis of economic, technological and social transformations. Startups are not only one of the main engines of innovation, capable of profoundly changing market dynamics or increasing productivity, but they contribute to reshaping markets, industries, and innovation trajectories (Zacharakis and Meyer, 1998). The assessment of the maturity of startups, especially in their initial phase of life, is a question that the academic community has been facing for some time but until now it has remained an open question. In fact, it remains only partially addressed in the literature, as it is characterized by often heterogeneous approaches that are difficult to replicate (Gao et al., 2021). In this scenario, there is a strong need to develop analytical tools capable of combining technical rigor, operational capacity and scalability, in order to support investors' decision-making processes and entrepreneurs' strategic choices (Davila et al., 2003). Business ecosystems have become increasingly complex and require multidimensional approaches that go beyond traditional evaluation logics based only on financial indicators or non-formalized expert judgments (Franke et al., 2008).

In particular, investment selection and screening activities are influenced by information asymmetry between entrepreneurs and investors, the presence of cognitive biases that characterize decision-making processes and also operational constraints due to the time and resources available for this activity (Singhal et al., 2022) (Busenitz and Barney, 1997). Traditional practices are fundamentally based on a qualitative interpretation of narrative documents which, due to their unstructured nature, makes a systematic and replicable analysis difficult. This has the consequence that startups are evaluated through a process that is not very standardized, difficult to scale and highly dependent on subjectivity. This criticality is even more evident if we consider the growing importance of dimensions such as sustainability, technological innovation and organizational capacity, which can hardly be captured through traditional evaluation tools (Aspelund et al., 2005) (Colombo and Grilli, 2005). The lack of a shared language and objective metrics limits comparability between startups and reduces the effectiveness of financial resource allocation processes.

In the literature, models for the analysis of startups are widespread, ranging from frameworks based on organizational and strategic dimensions to tools focused on risk assessment and performance evaluation (Chandler and Hanks, 1993). Among these, the concept of IRL (Investment Readiness Level) is particularly relevant, which is based on a classification of startups based on their degree of investment readiness. However, these approaches have significant limitations. These tools are in fact often limited by a reduced level of operationalization and a poor analytical granularity. In fact, they are mainly based on self-declared data or subjective evaluations, thereby raising reliability concerns. They are also not easily scalable and are poorly suited for contexts characterized by the availability of unstructured data. In particular, textual descriptions of startups in natural language are an extremely important source but still little used in systematic analysis processes (Barry, 1994)

(Dubini and Aldrich, 1991). Moreover, as explored in Chapter 1, these models rarely systematically integrate fundamental dimensions such as technological innovation and sustainability, which today represent key factors for the competitiveness and attractiveness of startups to investors. This theoretical and applicative gap is one of the central elements on which the contribution of this work is grafted.

At the same time, the growing availability of unstructured textual data (presentation documents, business plans and informative reports) is an opportunity that is still little used. These data represent relevant strategic information, but their narrative structure requires tools capable of transforming them into observable and measurable data. Precisely for this reason, recent developments in the field of natural language processing and AI open up possibilities for overcoming these limitations. The integration between textual analysis techniques and structured evaluation models therefore represents a particularly promising research frontier, as will be developed in Chapter 4, able to bridge the gap between the wealth of information of qualitative data and the need for quantitative synthesis required by decision-making processes.

This PhD thesis introduces and develops the SUS²A (Strategic Unbiased Startup Sustainability Awareness) framework, with the aim of positioning itself in the gap created between the theoretical models for assessing the maturity of startups and the methods represented by automatic natural language analysis technologies (Baum and Silverman, 2004). This study offers as a fundamental contribution the design of a structured system capable of transforming unstructured textual data into replicable quantitative indicators. More specifically, this study aims to transform qualitative documents into more structured and replicable quantitative indicators, reducing at the same time interpretative ambiguity and increasing the possibility of comparing startups with each other (Dhochak et al., 2024). In particular, the framework is part of the studies on Investment Readiness Level (IRL), deepened in Chapter 1, enriching the theoretical framework through greater analytical granularity and operational formalization based on textual evidence. In this sense, SUS²A can be interpreted as an evolution of existing models, capable of integrating qualitative and quantitative dimensions into a single coherent system.

SUS²A is based on a multidimensional conception of startup maturity, based on eleven fundamental categories, including team, strategy, finance, technology, validation, ESG and scalability, identified through a literature analysis. This theoretical structure is then translated into a granular system consisting of 500 binary questions, designed to systematically detect the presence or absence of certain characteristics within the analyzed texts. This structure and methodological choice represents an element that distinguishes this work, as it makes it possible to overcome, through an explicit and verifiable formalization of the evaluation criteria, the vagueness that characterizes qualitative approaches. The construction of such a system of questions derives directly from the bibliometric analysis developed in Chapter 2, which allows the researcher to rigorously identify the relevant dimensions and to translate them into a structured operational framework. The choice to use a system of binary questions also makes it possible to reduce interpretative subjectivity, favoring the replicability of the results and making the model applicable on a large scale, even in contexts characterized by high information heterogeneity.

The present study is developed as a progressive process divided into three closely interrelated and interconnected phases (Behrens et al., 2012). Firstly, a theoretical conceptualization phase, where the key categories and questions for the analysis of the maturity of startups are defined and identified and systematized through a literature analysis. Secondly,

the operationalization phase, where these dimensions are translated into a structured system of questions and a quantitative scoring model. Finally, the automation phase, where the evaluation process is implemented with an automated textual analysis tool (Si et al., 2023). This last phase compares deterministic approaches based on keyword matching techniques and semantic approaches based on advanced language models (LLMs), with the aim of evaluating their reliability, scalability and degree of agreement.

This articulation reflects a logical progression that guides the reader from the definition of the problem to the proposal of an operational and technologically advanced solution, developed and validated in Chapter 3 and Chapter 4.

The entire thesis is therefore developed as a unitary path divided into four main chapters. Chapter 1 introduces the SUS²A theoretical model and the connection with the concept of Investment Readiness Level (IRL), providing the conceptual framework of reference. Chapter 2 deepens the construction of the framework through a bibliometric analysis and the definition of the categories and 500 questions (Dhochak and Doliya, 2020). Chapter 3 is dedicated to the definition of the scoring model and its empirical application, showing the results obtained from the analysis of startups. Finally, Chapter 4 develops an agent model that simulates the interaction between startups and investors in different conditions and in different market regimes, making available values related to the intrinsic properties of startups and market values that are easily comparable within the same market situation and in different regimes.

This structure allows the reader to be progressively accompanied along all phases of the research path, offering an integrated view that connects theory, methodology and empirical evidence and highlighting the incremental contribution of each chapter. Chapters 1 and 2 jointly contribute to the theoretical and methodological construction of the model, forming the basis of the first scientific contribution. Chapter 3 corresponds to the empirical application and validation phase of the framework, while Chapter 4 develops a further contribution, focused on automation and the use of agent-based modeling techniques. This articulation makes it possible to maintain both narrative coherence and clarity in the presentation of scientific contributions.

To further clarify the integrative logic connecting the four papers, it is useful to make the cumulative argument explicit. Chapter 1 establishes the theoretical necessity of SUS²A by demonstrating the insufficiency of existing IRL and startup maturity frameworks along three dimensions: granularity, domain completeness, and text-processing capability. Chapter 2 operationalizes this theoretical gap by showing — through a systematic bibliometric analysis of 1,297 articles — which dimensions of startup readiness the scientific literature considers most critical, and by translating these findings into 500 validated binary indicators through a Delphi expert process. Chapter 3 empirically tests the resulting instrument on 41 startups, comparing a deterministic keyword-matching approach against an LLM-based semantic evaluator to establish reliability and identify the framework's diagnostic patterns. Chapter 4 extends the framework beyond static screening by embedding SUS²A as a quality measure within an agent-based simulation of startup-investor dynamics across different market regimes, demonstrating its utility as both an analytical and a modeling instrument. Each chapter therefore builds on the previous one: the theoretical gap identified in Chapter 1 motivates the bibliometric design of Chapter 2; the validated instrument from Chapter 2 enables the empirical application of Chapter 3; and the empirical findings from Chapter 3 provide the calibrated measure used in Chapter 4. This sequential dependency is not merely narrative but

methodological: no chapter could stand alone without the foundation provided by the preceding one.

The empirical results highlight how the model is able to systematically analyze a certain number of startups, identifying recurring patterns and structural gaps (Emir Hidayat et al., 2022). Specifically, a lack emerges in the values related to the categories of ESG and talent management, against a greater focus on more traditional categories such as product and market. Furthermore, by comparing deterministic and semantic approaches, the comparison highlights a high level of agreement, attributing validity to the model as an effective and replicable preliminary screening tool (Bertoni et al., 2011). These results, discussed in particular in Chapter 3 and Chapter 4, reinforce the idea that a structured and automated approach can significantly contribute to improving the quality of evaluations, reducing the margins of error and increasing the transparency of decision-making processes.

The originality of the work lies in bringing together a traditional idea based on textual analysis with an advanced computational methodology, thus contributing to the academic debate on several levels. The contributions of this study are in fact placed along a continuum that crosses the different chapters: in the first part it reinforces the construct linked to the concept of maturity, then it arrives at an operational structuring, in the third phase it adds an empirical validation and finally extends the application to a comparative agent simulation. This progression allows to highlight not only the originality of the individual results, but also the systemic value of the entire proposed framework. The framework presented, unlike other existing models, introduces an analysis of the level of maturity of startups with a higher level of granularity, allowing to obtain a defined, detailed and quantitative representation of the characteristics of startups. This tool is not only a means of analysis, but a real paradigm in the way startups can be analyzed and evaluated, integrating scientific rigor, methodological innovation and potential through the use of emerging computational methods and describing each fundamental step along the four chapters.

On a theoretical level, the work proposes a new formalization of the concept of maturity of a startup, going beyond static and one-dimensional visions. From the point of view of the methodological level, a replicable process of automated textual analysis is introduced. This type of analysis makes it possible to overcome the subjectivity that characterizes qualitative evaluations. From the point of view of the application and practical level, this work offers a potentially relevant tool that could be useful to investors, incubators and policy makers who aim to evaluate a large number of entrepreneurial realities in a systematic and comparable way.

The thesis is structured in four papers, each dedicated to a specific phase of the research path. The first paper focuses on the theoretical construction of the model, analyzing the literature and defining the categories and the set of questions. The second is focused on the construction of the scoring model and its application as a structured evaluation tool. The third analyzes the automation of the process and assesses reliability through a comparison between different textual analysis techniques. Finally, the fourth paper simulates the relationships between startups and investors in different market regimes through agent modeling. Altogether, these contributions make it possible to outline a coherent path that makes it possible to move from theoretical conceptualization to empirical validation of an automated evaluation system.

This articulation in papers therefore reflects a synthesis of the contents developed in the four chapters, while ensuring a clear identification of the scientific contributions and an overall coherence of the research path. In this sense, the papers do not represent isolated elements, but

integrated parts of a unitary design that finds its complete and detailed explication in the chapters. In this study, theory, methodology and practice are put together and the foundations are laid for future development in the field of automated analysis of startup maturity, in particular in the transformation of qualitative data into quantitative data. SUS²A is therefore an attempt to redefine the way startups are analyzed and evaluated objectively, introducing a paradigm based on the transformation of textual descriptions in natural language into structured knowledge and supporting the evolution towards more objective, transparent and scalable decision-making processes.

In the light of this structure, the research questions not only guide the development of the four chapters, but are distributed transversely, ensuring consistency between theoretical objectives, methodological development and empirical validation. In the light of what emerged from the analysis of the literature and the objectives of this study, the research aims to answer a series of research questions, organized coherently with the three phases that structure SUS²A. A first area of analysis is focused on the theoretical and conceptual dimension of startup maturity. The research questions the way in which the concept of entrepreneurial maturity is defined, in a systematic and multidimensional way, overcoming simplified approaches. In particular, the first research question is:

RQ1: How can the maturity of startups be contextualized and structured in a multidimensional framework based on existing literature?

A second area of analysis is based on the process of operationalization of the theoretical construct. The goal is to understand if and how it is possible to transform abstract dimensions into observable and measurable indicators, reducing the interpretative errors typical of qualitative evaluations. The second research question is therefore the following:

RQ2: How is it possible to operationalize the maturity of a startup through a structured and granular system of indicators based on textual data?

Finally, the third and fourth areas of analysis are the methodological and applicative dimension. In particular, we want to refer to the automation of analysis processes. In this context, the role of AI for the evaluation of startups is analyzed, comparing alternative approaches and their reliability. The research questions are as follows:

RQ3: How can the startup evaluation process be automated through natural language text analysis techniques applied to unstructured textual data?

RQ4: What is the level of reliability and agreement between deterministic approaches based on keyword matching and semantic approaches based on advanced language models in determining the maturity of a startup?

These questions are the common thread on which the entire research work is developed, defining a path that goes from the theoretical definition of the model to its operational translation and subsequent empirical validation, with the aim of obtaining more structured, replicable and less subjectively dependent tools for the analysis of startups.

CHAPTER 1

SUS²A: A framework for assessing Investment Readiness Level in Start-ups. Literature review and model description.

Abstract

Frame of the research. The research is set within the evolving global economy, emphasizing the increasing importance of technological advancement and sustainability as key factors determining startup success. It frames the necessity for a comprehensive approach to evaluate and improve startup investment readiness by integrating strategic management, innovation, and sustainability principles.

Purpose of the paper. The purpose is to introduce the Strategic Unbiased Startup Sustainability Awareness (SUS²A) model as a diagnostic tool to help startups assess their investment attractiveness and identify improvement areas. This aims to facilitate targeted strategies that meet investor expectations and global sustainability goals operating as a structured textual proxy of the strategic intent formulated by the founders.

Methodology. The methodology involves a comprehensive literature review to explain the rationale for the model, followed by a multi-dimensional approach to evaluate startups across several domains, including strategic business management, innovation management, sustainability, financial viability, market potential, and team competency. It uses specific indicators within these domains to conduct a detailed analysis of a startup's strengths and improvement areas through the SUS²A model's structured assessment framework, which has been formally refined through expert validation panels and redundancy-reduction criteria to systematically map the 500 binary checkpoints.

Results. Preliminary results demonstrate the SUS²A model's effectiveness in identifying critical gaps in startups' strategies and operations. It offers a nuanced understanding of the Investment Readiness Level (IRL), enabling targeted improvements to increase investor attractiveness by balancing innovation and sustainability. The benchmark analysis validates the high alignment between deterministic script matching and probabilistic semantic processing.

Research limitations. The limitations include the model's dependence on available data for evaluation and the potential necessity for customization across different startup ecosystems and sectors. Additionally, it notes the structural boundaries of a document-based proxy filter and the need for further experimentation beyond the initial sample of 41 startups to obtain conclusive multi-sectoral results, thereby requiring a prudent moderation of claims regarding absolute generalizability.

Managerial implications. The research provides significant managerial implications by offering startups a comprehensive framework to evaluate and enhance their IRL. It also presents investors with a structured method to assess startup potential beyond traditional financial metrics, aligning startup strategies with investor expectations and contributing to sustainable economic development.

Originality of the paper. The originality of the paper lies in the SUS²A model and its integration of strategic management, technological innovation, and sustainability in evaluating

startups. This addresses a gap in existing literature and practice, presenting a scalable and comparable diagnostic tool in line with modern business trends and investor priorities.

1 Introduction

In the last twenty years, startups have played a fundamental role in driving technological innovation, economic growth, and sustainable development. The intersection of technology and sustainability has emerged as a critical area of focus, necessitating a nuanced understanding of how startups can leverage these dimensions to attract investment and ensure long-term success. This paper introduces the *Strategic Unbiased Startup Sustainability Awareness* (SUS²A) model, a novel framework designed primarily to evaluate and improve startup attractiveness to investors. The SUS²A model is grounded in the principles of strategic management, technological innovation, and sustainability, offering a comprehensive diagnostic tool that employs a scalable and comparable measurement approach. The following part outlines the context and relevance of integrating technological innovation and sustainability in startup evaluation and investment, reviews relevant literature on startup assessment and the integration of sustainability and technology in business models, and presents research questions aimed at exploring the integration of technological innovation and sustainability in startup evaluation through the SUS²A model and its implications for startup development and investor decision-making.

Technological innovation and sustainability are increasingly recognized as foundational concepts for the success and resilience of startups in the contemporary economy (Aldianto et al., 2021; Daraojimba et al., 2023; Salamzadeh et al., 2022). This recognition is grounded in an evolving understanding of economic success, which now integrates environmental stewardship and technological advancement as critical components (Javaid et al., 2022; Oláh et al., 2020). This integration reflects a paradigm shift in global business practices, where the traditional metrics of financial performance are being supplemented with considerations of environmental impact and innovation capacity (Arabeche et al., 2022; Le et al., 2023; Vasile et al., 2022).

Under an organizational behavior and structural contingency lens, early-stage startups are distinctively characterized as highly organic systems rather than mechanistic ones (Freeman, 1969). As classic business doctrine emphasizes (Rugiadini, 1979), small flexible enterprises rely heavily on fluid roles, open horizontal communication channels, and decentralized expertise to cope with extreme environmental volatility and rapid technological shifts.

The dynamic nature of the startup ecosystem, characterized by rapid technological advancements and shifting market demands, necessitates a comprehensive approach to innovation that is both forward-thinking and grounded in sustainable practices (Davis, 2022; Elia et al., 2021; Kaggwa et al., 2023). Technological innovation in this context is not merely the introduction of new products, services, or processes but entails a broader conceptualization that includes the disruption of traditional industries through sustainable and environmentally friendly methodologies (De Propriis and Bailey, 2020; Kivimaa et al., 2021). Such innovation is increasingly driven by the need to address complex global challenges, including climate change, resource scarcity, and social inequality, thereby aligning economic objectives with broader societal goals (Segovia-Hernández et al., 2023; Tödtling et al., 2022). Consequently, the SUS²A framework operationalizes these abstract organic traits into clear, verifiable checkpoints within its "Team" and "Strategy" domains, determining whether structural

flexibility translates into systemic scalability or highlights vulnerabilities related to operational chaos.

Sustainability, as applied within the startup context, includes a multi-dimensional approach that seeks to balance economic growth with environmental protection and social responsibility (Adhikari et al., 2023; Suriyankietkaew et al., 2022). This approach is premised on the principle of meeting the current needs without compromising the ability of future generations to meet their own, necessitating a long-term perspective on value creation that transcends immediate financial gains (Doh et al., 2021; Grossi et al., 2022). The broad range of issues covered by sustainability includes, but is not limited to, reducing carbon footprints, enhancing energy efficiency, promoting social equity, and ensuring economic inclusivity (Hariram et al., 2023; Sovacool et al., 2022).

The integration of technological innovation with sustainability strategies poses a unique set of challenges for startups, necessitating a nuanced understanding of the complex interplay between these dimensions. On one hand, this integration demands a commitment to research and development (R&D) aimed at fostering innovation that adheres to principles of sustainability (Chege and Wang, 2020; Chiarini et al., 2020). This commitment often requires startups to venture into uncharted territories, exploring new business models and operational strategies that prioritize long-term environmental and social value over immediate profitability. On the other hand, the successful integration of sustainability and innovation requires startups to manage the complex regulatory, social, and environmental contexts in which they operate (Lüdeke-Freund, 2020). This is critical for ensuring not only compliance with existing regulations but also the ability to anticipate and adapt to future changes in the socio-economic environment. The capacity to understand and respond to these external pressures is essential for maintaining the startup's relevance, value-creation capacity, and competitiveness in an increasingly sustainability-conscious market (Ninduwezuor-Ehiobu et al., 2023).

Moreover, the intersection of technological innovation and sustainability in startups is not only a response to external pressures but also a strategic approach to investment attraction (Bellucci et al., 2020; Lüdeke-Freund, 2020). Investors are increasingly prioritizing sustainability and innovation in their decision-making processes (Alkaraan et al., 2023; Ikram et al., 2021), recognizing these factors as indicators of a startup's potential for long-term success and resilience. This shift in investor priorities underlines the importance of startups aligning their strategies with sustainability and innovation principles, not only to attract investment but also to forge a path toward sustainable development.

From a managerial viewpoint, the strategic integration of technological innovation and sustainability requires a comprehensive approach that balances immediate operational needs with long-term strategic goals (Tsai et al., 2020), ensuring that startups are not only innovative and competitive but also sustainable and responsive to the broader societal challenges.

2 Literature Review and bibliographic analysis

The literature on startup assessment and investment readiness shows the complexity of evaluating startup potential and investor attractiveness (Granz et al., 2020; Trautwein, 2021). Traditional evaluation metrics often focus on financial performance (COZGAREA et al., 2023; Guo and Xing, 2023), market potential (Parzen et al., 2022), and the entrepreneurial team's expertise (KRAIEM et al., 2023).

In the core literature of entrepreneurial finance, the screening, selection, and pricing of early-stage innovative ventures are historically framed around mitigating deep information

asymmetries, moral hazard, and adverse selection risks (Gompers and Lerner, 2001). Traditional pre-investment screening operates as an intensive, resource-heavy due diligence process rooted in the bounded rationality of individual venture capitalists.

The seminal work of Gompers and Lerner (Gompers and Lerner, 2001) remains foundational in this regard: their analysis of the venture capital cycle demonstrates that VC screening is not a neutral analytical exercise but a structurally constrained process shaped by fund lifecycle pressures, reputational incentives, and the inherent difficulty of evaluating pre-revenue ventures under radical uncertainty. Critically, Gompers and Lerner establish that information asymmetry between entrepreneurs and investors generates systematic mispricing and selection bias that cannot be resolved through qualitative judgment alone. Their framework implicitly calls for more granular, formalized, and replicable screening instruments — precisely the gap that SUS²A is designed to address. By operationalizing 500 binary indicators derived from validated bibliometric evidence, SUS²A transforms the due diligence process from a resource-intensive, heuristic-dependent activity into a structured, scalable diagnostic protocol that directly mitigates the information asymmetry problems identified by Gompers and Lerner.

However, recent studies suggest that these metrics are increasingly being supplemented with criteria related to technological innovation and sustainability (Alänge et al., 2022; Alizada, 2023). This shift reflects a broader understanding of value creation in the startup ecosystem, where sustainable and innovative practices are seen as indicators of a startup's ability to adapt and thrive in the face of global challenges.

In order to fully explore the literature for similar proposed methods, a bibliographic analysis was carried on. In particular, this investigation involves a comprehensive analysis of a wide range of articles and publications from the Web of Science (WoS) database. As depicted in Figure 1, the present study analyzed 180 articles published from 2010 to 2023. The keywords used to retrieve the publications listed in the WoS database are Sustainability, Environmental, Green, Technology, Innovation, Technological Change, Startup, New Venture, Framework, Model, Approach, Tool, Venture Capital, Investor Support, Investment Decision, Funding. Following this step, the initial number of publications was limited to scientific articles published in English and belonging to the categories of Management, Economics, Business, and Business Finance.

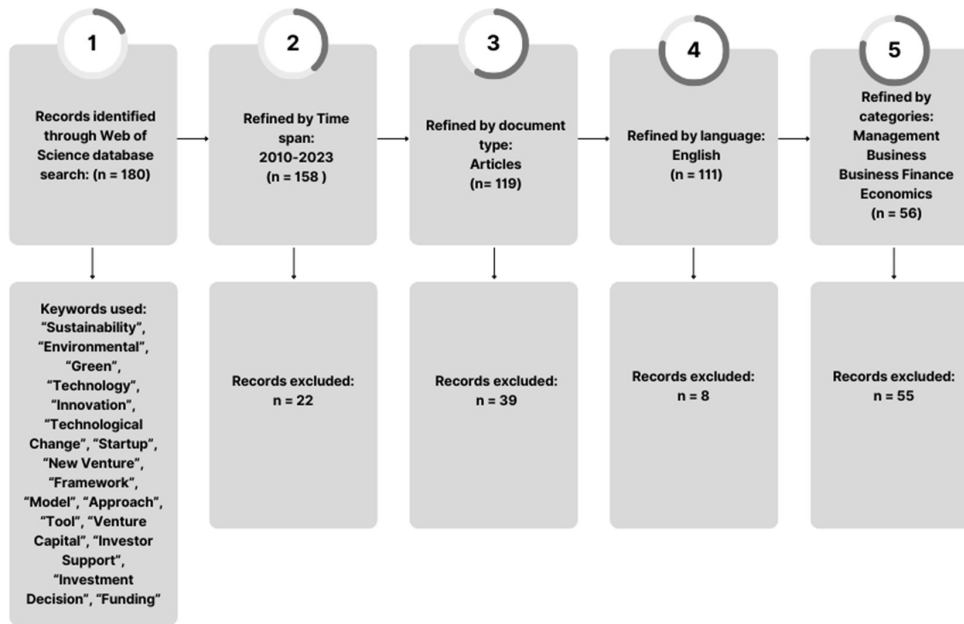


Figure 1 - bibliographic search on WoS (keywords and synthetic results)

The query used in WoS reflects a targeted search for scientific literature articles addressing the themes of sustainability, technological innovation, and funding in relation to startups. This query was constructed by combining different keywords to cover a broad range of topics related to sustainability, technology, entrepreneurship, and funding.

The query is as follows:

((TS=("sustainab" OR "environment*" OR "green")) AND (TS=("technolog*" OR "innovat*" OR "technolog* change*")) AND (TS=("startup*" OR "new venture*" OR "start up*" OR "start-up*")) AND (TS=("framework*" OR "model*" OR "approach*" OR "tool*")) AND (TS=("investor* support*" OR "investment* decision*" OR "funding*" OR "venture* capital*"))))*

The specific parts of the query reflect: sustainability; technological innovation; startups/new ventures; frameworks, models, approaches, and tools; investor support and investment decisions. More specifically, the query employs a structured approach to identify scholarly articles and research papers at the intersection of environmental sustainability and entrepreneurship within the context of technological innovation. It aims to extract literature that:

- Explores the adoption of sustainable, environmental, or green technologies and innovations by startups and new ventures.
- Examines the frameworks, models, approaches, or tools deployed by these ventures to integrate sustainability into their business operations.
- Investigates the role of investor support, including venture capital and investment decisions, in facilitating or enhancing the growth and development of technology-oriented startups with a focus on sustainability.

Sustainability: specific keywords include "sustainab*" which could cover "sustainability" or "sustainable," "environment*" for environmental topics, and "green" for ecological themes.

Technological Innovation: keywords include "technolog*," "innovat*," and "technolog* change*."

Startups and New Ventures: keywords cover various expressions of "start-up," including "new venture*," "start up*," and "start-up*."

Frameworks, Models, Approaches, and Tools: this section focuses on articles that may present frameworks, models, approaches, or tools. Keywords include "framework*," "model*," "approach*," and "tool*."

Investor Support and Investment Decisions: this part refers to aspects related to investor support and investment decisions. Keywords include "investor* support*," "investment* decision*," "funding*," and "venture* capital*."

To establish a rigorous connection between this extensive bibliometric mapping and the subsequent conceptual layout of SUS²A, the prominent semantic clusters generated through the Biblioshiny pipeline were directly cross-referenced with the operational weights and qualitative parameters of the checklist. The thematic prominence of keywords such as "Innovation Performance," "Venture Capital Screening," and "Sustainable Entrepreneurship" guided the initial formulation of 7 core analytical macro-areas, ensuring that the empirical architecture of SUS²A reflects the critical criteria demanded by contemporary international literature. As described in detail in the following chapters, this initial macro-structure was subsequently refined through iterative expert validation panels: the 7 initial macro-areas were first reorganized into 9 operational categories (Chapter 2) and ultimately structured into 11 strategic categories (Chapter 3), reflecting a deliberate process of analytical enrichment driven by the research advisory committee and the requirements of the empirical application phase.

As it emerges from this search, several frameworks and models have been proposed in the literature (Di Paola et al., 2018; Kostin et al., 2022; Pradhan et al., 2017; van Rijnsoever, 2022; Wu et al., 2019) to assess startup readiness for investment, with varying degrees of emphasis on sustainability and technology. For instance, the Lean Startup methodology (Rahmani et al., 2023; Rutitis and Volkova, 2021; Vlies, 2023) emphasizes rapid prototyping and customer feedback loops to drive innovation, but it does not explicitly address sustainability. Conversely, the Triple Bottom Line (TBL) framework (Loviscek, 2020; Ozturkoglu et al., 2021; Singh and Srivastava, 2022) focuses on evaluating a company's performance in three dimensions: social, environmental, and financial, encouraging businesses to pursue sustainability goals. However, there is a gap in the literature regarding frameworks that holistically integrate technological innovation and sustainability into startup evaluation and investment decision-making processes.

Furthermore, the methodological transition from unstructured qualitative business texts to quantitative indicators implemented in this study draws from established content-analysis practices in marketing and management literature. Specifically, the translation of narrative data into structural dimensions aligns with frameworks used to evaluate corporate identity in relation to perceived brand image via automated text mining (Crawford Camiciottoli et al., 2014). In these frameworks, language is processed to measure strategic consistency and the adherence of managerial declarations to institutional standards, providing a solid, cross-disciplinary foundation for the textual measurement architecture of the SUS²A model.

Sustainable business models often require startups to manage complex trade-offs between short-term profitability and long-term environmental and social goals. At the same time, leveraging technological innovation for sustainability presents opportunities for startups to differentiate themselves in crowded markets and address pressing global challenges. The literature highlights several success stories of startups that have successfully integrated sustainability and technology (Baaziz, 2019; Conway and Hemphill, 2019; Nyadu-Addo and Mensah, 2017; Zeng, 2018), but systematic approaches to evaluating and improving such integration remain limited.

The SUS²A model addresses these gaps by providing a comprehensive framework for evaluating and improving startup attractiveness to investors through the dimensions of technological innovation and sustainability. As briefly pointed out, SUS²A represents a transformative approach to evaluating the readiness and maturity of innovative startups. Its comprehensive methodology, which incorporates advanced analytics and self-administration, provides a tool for researchers, advisors, investors, and entrepreneurs alike. By offering detailed scoring across various dimensions of enterprise operation and strategic orientation, SUS²A can facilitate informed decision-making, targeted improvements, and enhanced investor readiness, positioning it as a crucial instrument in the landscape of startup development and innovation.

This leads to the formulation of two critical research questions for the core of the present paper:

- 1) How does the SUS²A model integrate technological innovation and sustainability in startup evaluation?

This question seeks to explore the methodological underpinnings of the SUS²A model, examining how it incorporates sustainability and technological innovation into its evaluation criteria. It involves a detailed analysis of the model's evaluation areas and categories, its scalable and comparable measurement approach, and the method for facilitating effective diagnosis and action planning. This analysis will provide insights into how the model bridges the gap between sustainability and technological innovation, ensuring startups are not only innovative but also sustainable in their operations and business models.

- 2) What are the implications of using SUS²A for startup development and investor decision-making?

This question delves into the practical implications of employing the SUS²A model for startups and investors. It seeks to understand how the model can influence startup strategy, development, and the ability to attract investment. It also explores the implications for investors in terms of identifying startups that not only promise high returns but, at the same time, contribute to sustainable development.

3 The central concept of Investment Readiness Level (IRL)

SUS²A provides a "cognitive map" that serves as an automatic filter for systematically assessing the condition of startups, spin-offs, and innovative SMEs in terms of their readiness for businesses and investors, using the Investment

Readiness Level (IRL) and its variations through detailed scoring. It's important to note that there's no analytical and established description in literature for the underlying nine stages

of maturity that the classical IRL indicator expresses for attributing a specific level of IRL, unlike the technology readiness level (TRL) indicator.

IRL acts as a tool that accompanies the lifecycle of a startup, spin-off, or innovative SME, offering a representation of its actual conditions, collateral risks, improvement areas, and enables the association of necessary action plans, effort levels, costs, and tracking of outcomes.

Its methodology consists of:

- Extended and deep analytical basis
- Characterised categories and areas
- Flexible delivery modes
- Scoring based on consistent metrics
- Traceability of results

Its prerequisites make it possible to:

- Use weighting algorithms
- Develop an updatable Analytical Base
- Allow self-administration modes
- Establish a Methodology for advisory
- Issue standardised reports.

In other words, IRL represents a structured approach to gauge a startup's maturity and readiness for investment. Originally conceptualized by Steve Blank (Blank, 2013), the IRL provides a framework analogous to the Technology Readiness Level (TRL) used by NASA (Mankins, 1995), but specifically tailored for startups. It serves as a metric system that evaluates the readiness of a startup to receive and effectively utilize investment based on various criteria, including business model validation, market fit, scalability potential, and the robustness of the management team.

However, a critical review of existing investment readiness models reveals severe structural insufficiencies that limit their operational and academic validity. Traditional IRL frameworks are significantly constrained by macro-level subjectivity, relying heavily on self-reported entrepreneur questionnaires that lack internal validation or granular verification. Furthermore, these existing models operate on macroscopic categorical scales that fail to capture the multi-dimensional nuances of modern ventures, completely omitting integrated structures for tracking emerging non-financial variables like formal ESG compliance or open innovation readiness. Most importantly, traditional frameworks are structurally incapable of processing the massive volumes of unstructured textual data that constitute the primary repository of startup strategic planning.

To make this insufficiency explicit, it is useful to map it across three dimensions that the SUS²A framework specifically addresses. First, existing IRL models operate at a macro-level of granularity: they classify startups into broad readiness stages (e.g., IRL 1 through 9) without specifying the observable indicators that justify each classification. SUS²A replaces this opacity with 500 binary checkpoints, each mapped to validated bibliometric evidence, transforming a qualitative judgment into a verifiable, auditable score. Second, prior frameworks treat sustainability (ESG), open innovation readiness, and talent management as peripheral considerations, whereas the bibliometric analysis underlying SUS²A demonstrates that these dimensions have become central predictors of investment attractiveness in the current

ecosystem. Third, and most fundamentally, existing IRL tools are document-agnostic: they rely on self-declaration rather than textual evidence extraction, making them vulnerable to the strategic misrepresentation that Gompers and Lerner (2001) identified as a systemic risk in early-stage financing. SUS²A addresses this by anchoring every indicator to explicit textual evidence present in the startup's documentation, functioning as a document-based proxy filter rather than a self-assessment checklist. This combination of granularity, domain completeness, and textual grounding constitutes the theoretical advancement of SUS²A relative to the existing IRL literature.

IRL's importance lies in its ability to transform the often subjective and speculative process of startup evaluation into a more objective and structured assessment. It offers both startups and investors a common language to discuss progress and pinpoint specific areas that need improvement before a startup can be considered ready for investment. This framework not only facilitates better decision-making for investors but also provides startups with clear milestones and targets for development, making the journey towards investment readiness more transparent and navigable.

The role of IRL in startup assessment is multifaceted, contributing to a more comprehensive and nuanced evaluation of a startup's potential for success and sustainability. Here's how IRL contributes to the startup assessment process:

1. **Objective Benchmarking:** IRL offers a standardized method for assessing startup maturity across various stages of development. This standardization allows for objective benchmarking, where startups can be compared against established criteria, helping investors identify ventures with the highest potential for success.
2. **Identifying Strengths and Weaknesses:** By breaking down the investment readiness into specific levels, IRL helps startups identify their strengths and weaknesses in critical areas such as product development, market validation, and business strategy. This detailed analysis enables targeted improvements, ensuring that resources are allocated efficiently to areas that will most significantly impact investment readiness.
3. **Facilitating Investor Communication:** The IRL framework provides a common vocabulary for discussions between startups and investors. It shifts the conversation from a binary "yes" or "no" investment decision to a more constructive dialogue about what startups need to do to reach the next level of readiness. This facilitates better mentoring and guidance from investors and other stakeholders.
4. **Enhancing Strategic Planning:** Startups can use their IRL assessment to inform strategic planning and prioritization. Understanding their current level of investment readiness helps startups set realistic goals and timelines for reaching the next level, ensuring that efforts are aligned with enhancing their attractiveness to investors.
5. **Improving Capital Efficiency:** The focus on reaching specific readiness levels before seeking investment ensures that startups are more likely to use the capital they receive efficiently. By addressing key risks and validating their business model before seeking significant funding, startups can reduce waste and increase the likelihood of successful growth.
6. **Encouraging Sustainability:** Although not explicitly focused on environmental sustainability, the IRL framework encourages startups to build solid foundations for long-term success. This includes developing sustainable business models that are resilient to market changes and capable of delivering consistent value over time.

Crucially, within the architectural design of SUS²A, a strict epistemological distinction must be established between measuring a startup's intrinsic operational maturity and measuring the structural completeness of its documentation. The SUS²A model scales primarily as a document-based proxy filter. It evaluates the exact capacity of the entrepreneurial team to formalize, structure, and articulate their strategic planning within a technical and professional vernacular aligned with institutional investor expectations. Consequently, a lower score generated by the model does not automatically signal an unviable business concept, but rather highlights a formal fitness and disclosure issue that must be rectified before entering formal venture capital rounds.

The SUS²A model, which is grounded in the principles of strategic management, technological innovation, and sustainability, incorporates IRL as a key component to offer an evaluation of startups based on various parameters. This integration aims to provide a comprehensive understanding of a startup's position in the investment readiness spectrum, thereby facilitating targeted strategies to elevate their attractiveness to investors. The following elaboration details how SUS²A utilizes IRL, emphasizing a scientific and methodological perspective devoid of an overly promotional tone.

The SUS²A model adopts the IRL framework to systematically evaluate a startup's maturity across several domains critical to investment attractiveness. This evaluation includes an assessment of the startup's business model validation, market fit, scalability, management team robustness, and the integration of technological innovation and sustainability. By incorporating IRL, SUS²A offers a structured path for startups to progress through different levels of investment readiness, focusing on achieving specific milestones that signal their preparedness for external funding, in the following ways.

Objective Benchmarking and Targeted Improvement: SUS²A leverages IRL's objective benchmarking capabilities to compare startups against established criteria, identifying areas of strength and opportunities for improvement. This benchmarking serves as a foundation for SUS²A's diagnostic tool, which evaluates startups across multiple dimensions, including financial viability, market potential, technological innovation, and sustainability practices. By pinpointing precise areas where a startup needs to develop further to become investment-ready, SUS²A facilitates targeted improvements, enabling startups to allocate their resources more efficiently and effectively.

Enhanced Investor Communication and Strategic Planning: the integration of IRL into SUS²A enhances communication between startups and investors by providing a shared framework for discussing a startup's current investment readiness level and the steps required to advance. This improved communication fosters a more collaborative relationship between startups and investors, where feedback and guidance can be more precisely tailored to address specific gaps in readiness. Besides, SUS²A's adoption of IRL aids startups in strategic planning, allowing them to set realistic goals and timelines for achieving higher levels of investment readiness. This strategic focus ensures that startups remain aligned with the critical factors that influence investor decision-making, thereby increasing their chances of securing investment.

Addressing Market Fit, Scalability, and Operational Excellence: SUS²A's use of IRL emphasizes the importance of achieving market fit, scalability, and operational excellence as prerequisites for investment attractiveness. Through its comprehensive evaluation framework, SUS²A guides startups in validating their market fit, demonstrating their potential for scalability, and achieving operational efficiency. These aspects are critical for assuring investors of the startup's capacity to grow and generate returns on investment. By

systematically addressing these challenges, startups can enhance their profiles, making them more appealing to a broad spectrum of investors.

Reducing Investment Uncertainty and Risk the structured approach to evaluating startup potential offered by the SUS²A model, through the incorporation of IRL, plays a fundamental role in reducing the uncertainty and risk associated with early-stage investments. By providing clear, objective assessments of a startup's readiness for investment, SUS²A mitigates the speculative elements of investment decision-making. This reduction in uncertainty is beneficial for both startups and investors, as it leads to more informed, confident investment decisions and fosters a more efficient allocation of capital within the startup ecosystem.

The outcomes of scoring through SUS²A can be represented by the description of the 9 IRL levels.

- IRL 1 Initial business idea
- IRL 2 Existence of a corporate team to develop the business idea
- IRL 3 Corporate team established and initiated
- IRL 4 Corporate team established, initiated, and structured
- IRL 5 Corporate entity active and dedicated to implementing the business idea
- IRL 6 Corporate entity active and capable of market testing
- IRL 7 Active, solid, and sustainable corporate entity
- IRL 8 Corporate entity with proven competitive capabilities in collaborative contexts
- IRL 9 Corporate entity with proven autonomous competitive capabilities

4 Methodology and framework of the SUS²A Model

As briefly pointed out, the SUS²A model offers a comprehensive framework for the evaluation and enhancement of startup investment potential. It is structured to provide a multidimensional assessment, integrating various components that gauge a startup's performance across a spectrum of domains. These domains include strategic management, technological innovation, sustainability, financial viability, market potential, and team competency, among others. This integrative approach ensures that the evaluation of startups transcends mere financial metrics, acknowledging the significance of strategic alignment with contemporary trends in technology and sustainability.

The strategic management component evaluates a startup's ability to define, implement, and adapt strategies that ensure its long-term success and sustainability. This involves assessing the clarity of the startup's vision, the effectiveness of its competitive strategies, and its responsiveness to market dynamics. Indicators within this domain may include the coherence of business planning, the rigor of market analysis, and the agility of strategic decision-making processes.

In the domain of technological innovation, the model scrutinizes a startup's capacity to develop and implement groundbreaking technologies. This evaluation not only considers the novelty and disruptiveness of the technology but also its scalability and the startup's ability to maintain a competitive technological edge. Indicators here could include the level of innovation, the potential for market disruption, intellectual property rights, and the integration of new technologies into existing markets.

Sustainability assessment within the model focuses on a startup's commitment to and implementation of practices that ensure environmental stewardship, social responsibility, and economic growth. This domain evaluates how well a startup's operations and business model are aligned with sustainable development goals. Key indicators might include the reduction of

carbon footprint, social impact initiatives, ethical business practices, and sustainable supply chain management.

The financial viability component examines a startup's economic health and its potential for sustainable growth and profitability. This involves an analysis of revenue models, cost structures, funding strategies, and financial projections. Indicators in this area assess the robustness of financial planning, the effectiveness of resource allocation, and the startup's ability to generate revenue and manage expenses.

Assessment of market potential looks at a startup's ability to identify, enter, and grow within its target markets. This includes evaluating the size and accessibility of the market, the startup's market positioning, and its marketing strategies. Indicators might cover market size and growth forecasts, competitive analysis, customer segmentation, and go-to-market strategies.

The team competency domain assesses the skills, experience, and cohesion of the startup's founding and management teams. This area considers the team's ability to execute on the startup's vision, manage challenges, and drive the company towards success. Indicators include the team's background and expertise, leadership and management skills, and the ability to attract and retain talent.

The methodology of the model is characterized by its rigorous and structured assessment framework, made of hierarchical questions and evaluation criteria. Startups are categorized according to multiple evaluation areas, with each area being further dissected into categories and sub-categories. This hierarchical structure ensures a detailed and granular analysis of startup performance. Specific indicators within each sub-category are used to measure performance, enabling a comprehensive and nuanced understanding of a startup's strengths and areas for improvement.

The implementation of this model involves a systematic process where startups are evaluated against the predefined indicators across all domains. This process begins with the collection of qualitative and quantitative data about the startup, followed by analysis and scoring based on the model's criteria. The results of this evaluation provide a wide view of the startup's investment attractiveness, highlighting areas of strength as well as gaps that need to be addressed.

The use of specific indicators allows for the generation of actionable insights, facilitating targeted strategies for improvement. For instance, if a startup scores low in the sustainability domain, it may be prompted to develop a more robust sustainability strategy, incorporating environmental and social considerations into its business model. Similarly, a startup lacking in financial viability may be advised to refine its revenue model or improve its cost management practices.

One of the primary advantages of this model is its ability to provide a complete view of a startup's readiness for investment. By considering a broad range of factors beyond financial performance, the model offers a more comprehensive assessment of a startup's potential for success. This is particularly important in today's business environment, where technological innovation and sustainability are increasingly critical to long-term success.

In addition, the model's structured and nuanced approach allows for the identification of specific areas where startups need to improve, making it a valuable tool for targeted development efforts. This can significantly enhance a startup's attractiveness to investors, who are often looking for ventures that not only promise high returns but also demonstrate alignment with broader societal and environmental objectives.

The application of the SUS²A model to the proposed research questions - how it integrates technological innovation and sustainability in startup evaluation, and its implications for startup development and investor decision-making - illustrates the model's capacity to provide solutions to critical challenges in the startup ecosystem.

4.1 Integration of Technological Innovation and Sustainability

The SUS²A model's methodological approach to integrating technological innovation and sustainability into startup evaluation is distinguished by its comprehensive and multi-faceted framework. This framework is built on the premise that challenges and market opportunities require startups to adopt innovative technologies and sustainable practices not just as a compliance or marketing strategy, but as a core component of their business model. The model delineates specific indicators for assessing the extent to which startups incorporate these dimensions into their operations and strategy.

For technological innovation, indicators are designed to evaluate the originality of the technology, its disruptive potential, and scalability. This includes examining the startup's R&D activities, patent holdings, and the technological readiness level (TRL) of its specific products or technologies. It is important to note that TRL, originally introduced by NASA (Mankins, 1995), measures the maturity of a specific technology or product, not of the startup as an organization: SUS²A therefore incorporates TRL-inspired indicators within its technological dimension as one component of the overall assessment, while the composite SUS²A score measures the investment readiness and organizational maturity of the startup as a whole. The aim is to ascertain not only the current state of the technology but also its future growth trajectory and potential to alter existing market contexts or create new ones.

In the domain of sustainability, the model emphasizes a comprehensive assessment that goes beyond environmental considerations to include social and governance aspects (ESG criteria). Indicators in this context assess the startup's impact on environmental conservation, including its carbon footprint, resource efficiency, and waste management practices. The model also evaluates the startup's contribution to social well-being, which includes employee welfare, community engagement, and contributions to societal challenges. Ethical business practices and governance, including transparency, accountability, and stakeholder engagement, are also critical components of the sustainability assessment.

The strategic alignment of startups with technological innovation and sustainability is facilitated by the SUS²A model through a detailed evaluation process that identifies not only the current integration of these elements but also opportunities for deeper incorporation. Startups are guided to align their strategies with best practices in technology and sustainability, enhancing their market positioning and investment attractiveness. The model advocates for an iterative process where startups continually assess and refine their approaches to innovation and sustainability, ensuring they remain responsive to evolving market expectations and regulatory environments.

4.2 Implications for Startup Development and Investor Decision-Making

As a diagnostic tool, the SUS²A model offers startups a clear insight into their strengths and areas requiring improvement. This diagnostic capability is crucial for startups to prioritize areas for development, especially in fast-evolving sectors where technological and sustainable advancements are rapidly changing the competitive context, directly connected with the descriptive and prescriptive dimensions of the Viable Systems Approach (Golinelli, 2011).

By providing a detailed analysis across multiple dimensions, the model enables startups to devise targeted strategies that enhance their technological and sustainability profiles, thereby improving their overall investment attractiveness.

For startup development, the implications of this model are potentially important. Strategically, it encourages startups to adopt a forward-looking perspective, where technological innovation and sustainability are integrated into the core of their business models. This not only prepares startups for the increasing demands of consumers and regulatory bodies but also positions them to capitalize on new market opportunities that these dimensions unlock.

From an investor's perspective, the SUS²A model offers a structured framework that demystifies the complexities of evaluating early-stage investments. By dissecting a startup's performance across technological innovation, sustainability, and other critical domains, the model reduces the uncertainty and risks associated with such investments. Investors are provided with a comprehensive profile of each startup, highlighting areas of strength and potential risks, thereby facilitating informed decision-making.

Investors using the SUS²A model can better identify startups that not only promise robust economic returns but also align with broader societal and environmental goals. This alignment is increasingly becoming a determinant of long-term success in the global market, where sustainability and innovation drive competitive advantage. Consequently, the model not only aids in the selection of viable investments but also promotes a more sustainable and innovative startup ecosystem.

5 SUS²A Model Conceptual Development

SUS²A model's conceptual development is deeply rooted in the foundational theories of strategic management. Strategic management provides a framework for organizations to analyze competitive environments, define strategic direction, and make decisions to achieve long-term goals. The SUS²A model adopts these principles to guide startups in managing the complex and dynamic business context, emphasizing the importance of a strategic approach in enhancing investment attractiveness.

The model's connection to strategic management theories is evident in its emphasis on strategic alignment and agility. It encourages startups to align their operations and business models with both current market demands and future trends. This alignment involves a thorough analysis of internal strengths and weaknesses, as well as external opportunities and threats (SWOT analysis), a concept borrowed directly from strategic management literature (Gurl, 2017). The SUS²A model operationalizes this analysis through its multidimensional assessment framework, evaluating startups on various fronts including market potential, technological innovation, and sustainability.

Additionally, the model underscores the significance of strategic agility (Ferraris et al., 2022), which refers to a startup's ability to rapidly adapt to market changes and emerging opportunities. This is aligned with the dynamic capabilities theory, which posits that the ability of a business to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments is a key source of competitive advantage. By incorporating these strategic management concepts, the SUS²A model equips startups with a roadmap for strategic development, ensuring they are well-positioned to attract investment.

Innovation and technology constitute central concepts in the SUS²A model's framework, reflecting the model's approach to embedding technological advancement within the startup evaluation process. The model recognizes that technological innovation is a critical driver of

competitive advantage (Cerrato, 2011; Dagnino, 2014), market differentiation, and long-term sustainability for startups. It examines how startups leverage technology to create value, disrupt existing markets (Sehnem et al., 2022), or establish new ones.

The model's focus on innovation extends beyond mere adoption of new technologies; it includes the capacity for continuous innovation and improvement. This is aligned with the concept of continuous innovation, where organizations persistently transform their business processes, products, and services to meet evolving customer needs and stay ahead of competition. The SUS²A model evaluates the extent to which startups embed innovation in their culture, processes, and strategy, considering factors such as R&D investment, innovation output (e.g., patents, new products), and the adoption of emerging technologies (e.g., AI, blockchain).

This comprehensive approach to assessing technological innovation is informed by theories of innovation management, which emphasize the importance of innovation ecosystems, collaboration with external partners (Yaghmaie and Vanhaverbeke, 2020), and the role of leadership in fostering an innovative culture. By integrating these aspects into its framework, the SUS²A model offers a nuanced understanding of how startups innovate and the implications of their technological strategies for investment attractiveness.

Sustainability integration within the SUS²A model reflects a forward-looking approach to embedding environmental, social, and governance (ESG) criteria into the startup evaluation process. The model conceptualizes sustainability not as an add-on but as an integral component of a startup's strategic management and innovation processes. This integration is premised on the understanding that sustainable practices are crucial for addressing contemporary challenges such as climate change, resource depletion, and social inequality, and for ensuring long-term business viability.

The SUS²A model's sustainability framework is informed by the triple bottom line (TBL) concept (Goh et al., 2020), which encourages businesses to achieve a balance between economic, environmental, and social objectives. It assesses startups based on their environmental impact, including energy efficiency, waste management, and carbon footprint; their social impact, such as community engagement, employee welfare, and diversity and inclusion practices; and their governance structures, including transparency, ethical business practices, and stakeholder engagement.

Last, but not least, the model recognizes the strategic value of sustainability as a source of innovation and competitive advantage. This perspective is supported by theories of sustainable innovation, which argue that sustainability challenges can spur innovation in products, services, and business models. The SUS²A model evaluates how startups leverage sustainability as a driver for innovation, examining their approaches to sustainable product development, circular economy practices, and the creation of shared value for society and the environment (Diaz et al., 2021).

6 Categories for SUS²A and their connection with IRL levels

SUS²A is a comprehensive tool that, in synergy with the IRL categories, offers a detailed and personalized analysis of the status of a startup, facilitating informed decision-making and supporting a sustainable growth path.

This tool is divided into specific categories, that emerge from a series of discourses related to operative practice and literature analysis, which gives them a well-founded foundation. The

questions within each category are the result of an in-depth analysis, selecting the main issues to be explored for each area.

To ground the development of the 500-question assessment instrument in solid scientific methodology, the entire pool of diagnostic indicators was subjected to a rigorous content and construct validation protocol. This process involved multiple iterative focus groups and Delphi-method consultations with a diverse expert panel, comprising professional venture capitalists, certified incubator managers, and experienced startup founders. This alignment phase bridged theoretical literature parameters with active venture screening mechanics. Furthermore, strict redundancy reduction criteria were enforced to avoid index hypertrophy: checklist questions exhibiting semantic or cross-functional overlap (e.g., cross-referencing operational cash-flow efficiency with formal environmental resource optimization under ESG) were systematically consolidated or decoupled, ensuring that every binarized checkpoint satisfies the principles of mutual exclusivity and exhaustive coverage.

SUS²A's seven areas of analysis (Team, Marketing & Strategy, Finance & Economics, Legal & Protection, Product & Industrial, Validation, ESG) are structured to offer a comprehensive view of the factual conditions of a startup. These categories are not mere checkpoints but reflect critical aspects that contribute to the success and maturity of a startup. The use of SUS²A can take place at different levels of depth, allowing a granular detection of the analytical elements relevant to each category. The analysis derived from SUS²A provides the basis for the identification of relevant action plans.

Deploying an analytical matrix containing 500 variable points introduces a justifiable concern regarding the risk of overfitting, a documented phenomenon where overly complex quantitative systems exhibit high accuracy in describing past parameters (insight) but suffer severe performance drops during ex-ante predictions (foresight) due to baseline noise (Gigerenzer, 2008; Gigerenzer et al., 2008). The architectural design of SUS²A handles this challenge by utilizing a strictly binarized (0/1) operational response logic, transforming the extensive checklist into a fast-and-frugal heuristic that preserves high computational efficiency while reducing interpretive bias. The subsequent surveys, representing actual changes in the characteristics assessed, serve as documentation of the results of the actions taken in the process of acceleration and attraction of investors.

By integrating SUS²A with the Investment Readiness Level (IRL) classification model, it is possible to get a complete picture of a startup's condition. Each category of SUS²A finds a direct parallel to key concepts from the IRL, as described in the previous section, thus allowing for a detailed and informed view of the startup's maturity.

Team (A), Marketing & Strategy (B), Finance & Economics (C), Legal & Protection (D), Product & Industrial (E), Validation (F), and ESG (G) reflect critical aspects that contribute to a startup's success and readiness. This correlation with the IRL offers a broad and detailed view of the startup's condition, considering all facets relevant to investors and long-term success. There are several benefits to using SUS²A and IRL together. SUS²A provides a step-by-step guide to explore and improve startup conditions, diagnose deficiencies, and define improvement actions. The IRL, on the other hand, offers an overall rating scale, allowing for a broader view of a startup's maturity. The analysis resulting from SUS²A can be translated into specific actions through acceleration tools, and continuous monitoring allows you to document the progress and effects of the actions taken.

The use of SUS²A therefore potentially allows for the granular detection of the presence/absence of individual analytical elements pertinent to the reference category and to

group these results for each area to which they belong, but it is possible to use them at different levels of depths, for subsequent detailed approximations:

- At the level of areas A/B/C/D/E/F/G
- At the level of the categories into which each area is divided
- At the level of the analytical elements underlying each category.

SUS²A's division into seven areas of analysis reflects the complexity and comprehensiveness of the business conditions to be assessed. These categories are closely related to the IRL categories, but with a more detailed and specific approach. Here are the categories, with specific insights.

- Team (A): The "Team" component in SUS²A has a direct parallel to the concept of "Team" within the IRL. A competent and cohesive team is crucial to the success of a startup at every stage of development. This category assesses the team's cohesion, skills, and leadership that are critical to the company's success.
- Marketing & Strategy (B): SUS²A's "Marketing & Strategy" category is closely related to concepts such as "Defining Market Positioning" (IRL 2) and "Defining Marketing Strategies" (IRL 5) in IRL. A well-defined marketing strategy is essential for growth and investment attractiveness. This category examines marketing strategy, identifying how the company positions itself in the market and reaches its customers.
- Finance & Economics (C): Financial management and understanding economics are crucial considerations in both models. SUS²A's "Finance & Economics" category can be linked to concepts such as "Operating Model Validation" (IRL 8) in the IRL. This category analyses financial management and economic outlook, including future financial needs.
- Legal & Protection (D): Legal security is paramount for a startup, and SUS²A's "Legal & Protection" category aligns with the concept of "Legal Protection" within the IRL, which covers intellectual property protection and other legal aspects. This category evaluates the robustness of the legal structures and protections put in place to safeguard the company.
- Product & Industrial (E): This category reflects the stage of product development and its integration into the industrial environment. In terms of IRL, it could correspond to concepts such as "Product/Service Validation" (IRL 3) and "Market Validation of the Effectiveness of the Minimum Viable Product" (IRL 7). This category examines the quality and innovation of the product or service offered, as well as the positioning in the industrial sector.
- Validation (F): Validation is a crucial aspect for both instruments. SUS²A's "Validation" category links directly to various levels of IRLs, including "Value Proposition Validation" (IRL 6) and "Fundamental Metrics Validation" (IRL 9). This category evaluates the product's validation in the market and the company's value proposition.
- ESG (G): The growing importance of sustainability is reflected in SUS²A's "ESG" category. Even though it is not explicitly covered in the IRL, sustainability can influence the long-term success of a startup and could be considered across many IRL categories. This category examines the company's compliance and environmental, social, and governance impact.

The challenge is to devise an assessment model that is both simple and effective. The preferred approach is the pyramid model due to its simplicity, yet it acknowledges the complexity and variability of reality. Currently, approximate measurements are utilized rather than foregoing measurements altogether. The assessment relies on individual analytical items with affirmative, negative, or "not applicable" responses. These items are categorized and grouped into the above-mentioned areas, forming a pyramid-like structure. The overall score is derived from the interplay between areas, categories, and analytical items.

A careful balance between areas, categories, and analytical elements is maintained to avoid oversimplification. Introducing new criteria must respect this balance, ensuring that additional information remains meaningful and cognitively sound. The summary score enables vertical navigation to attain the desired level. Relevant information is primarily represented through analytical elements, while categories and areas serve a descriptive role and aid in synthesis.

To preserve the information density of analytical elements, repeated tests are conducted to ensure no redundancy exists. This safeguards the impartiality of the model by preventing networks of privileged relationships between analytical elements. The "not applicable" option allows for the exclusion of irrelevant elements without impacting the model, representing the widest possible perimeter based on the adopted methodology. Balancing simplicity with accurate representation underscores the complexity, ensuring the model remains unbiased and informative.

Moreover, implementing automated text mining filters within high-stakes selection contexts such as venture capital filtering introduces a systemic vulnerability regarding strategic manipulation, commonly termed "gaming the system." If the underlying text-matching regular expressions (Regex), dictionary terms, or categorical proximity weights were disclosed with absolute openness, opportunistic founders could easily manipulate their documentation. This could be achieved by injecting rhetorical buzzwords into business plans to artificially inflate their readiness scores without establishing any substantive operational infrastructure. To guarantee the long-term resilience and neutrality of the framework, the model maintains a deliberate trade-off between logical transparency and algorithmic confidentiality: while the overarching macro-architecture and the 7 functional evaluation areas are fully disclosed to guide startup development, the specific regex configurations and semantic keyword weights remain confidential to preserve the defensive sorting capability of the model.

7 Strategic Implications and Application

This model's strategic applications extend to both startups seeking to optimize their strategic positioning and investors aiming to refine their investment selection criteria. By invoking theories from the strategic management literature, such as Porter's Five Forces, the Resource-Based View (RBV), and the Dynamic Capabilities Framework, the SUS²A model offers a mix of analytical tools and strategic insights for stakeholders in the startup ecosystem.

Porter's Five Forces framework provides a method for analyzing the competitive forces within an industry, offering insights into profitability and strategic positioning. Applied within the SUS²A model, this framework aids startups in understanding the competitive context, assessing the intensity of competition, the threat of new entrants, the bargaining power of suppliers and customers, and the threat of substitute products. By evaluating these forces, startups can strategically position themselves to mitigate threats and capitalize on opportunities, enhancing their attractiveness to investors who value a comprehensive competitive analysis.

RBV suggests that a company's competitive advantage is derived from its unique resources and capabilities. The SUS²A model incorporates this perspective by evaluating startups based on their internal strengths, including tangible and intangible assets, organizational capabilities, and human resources. This internal analysis enables startups to identify and leverage their core competencies, aligning them with market opportunities to build a sustainable competitive advantage. Investors, guided by the RBV, can assess the intrinsic value of startups based on their resource endowments and potential for generating long-term returns.

The Dynamic Capabilities Framework emphasizes the importance of a firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Within the SUS²A model, this framework underlines the significance of strategic agility and innovation as key determinants of startup success. By fostering an organizational culture that prioritizes learning, adaptation, and innovation, startups can enhance their resilience and flexibility, making them more attractive to investors who are concerned with adaptability and long-term viability in the face of market volatility.

For startups, the strategic application of the SUS²A model, enriched by these strategic management theories, facilitates a comprehensive assessment of their operational, competitive, and strategic contexts. This model encourages startups to conduct a deep introspective analysis that goes beyond surface-level evaluations, fostering a culture of continuous improvement and strategic alignment with broader market trends and investor expectations. The emphasis on leveraging unique resources, understanding competitive dynamics, and maintaining strategic flexibility equips startups with the tools necessary for sustainable growth and market differentiation.

Investors, leveraging the structured approach provided by the SUS²A model, gain wider view of startup potential. This comprehensive methodology allows for a deeper dive into a startup's strategic foundation, evaluating not only financial metrics but also the qualitative aspects of strategic management, innovation capacity, and sustainability integration. By applying strategic management theories through the lens of the SUS²A model, investors can identify startups with robust strategic foundations, high potential for disruption, and alignment with future market trends, thereby mitigating investment risks and enhancing the potential for sustainable growth.

The practical application of the SUS²A model, underpinned by strategic management theories, has profound implications for both startups and investors. Startups are guided to strategically manage the complexities of the business environment, using their unique resources and capabilities to carve out competitive advantages and align with sustainability and innovation trends. This strategic positioning is critical for attracting investment, as it signals to investors a startup's potential for long-term success and resilience.

Investors, equipped with insights from the SUS²A model, are better positioned to make informed decisions, selecting startups that not only promise financial returns but also demonstrate strategic acumen, adaptability, and a commitment to sustainable practices. This alignment of startup potential with investor criteria fosters a more efficient and effective investment process, contributing to the overall health and dynamism of the startup ecosystem.

The main focus of SUS²A is to establish a reference subject to updates and new descriptions of the startup's condition that the tool captures throughout its maturation cycle with regard to the market and investors. Its main characteristic is to meet the cognitive premise of any action plan the startup intends to initiate.

Referring to the Deming wheel model PLAN DO CHECK ACTION, the point of connection between the conclusion of a cycle of initiatives and the start of a new plan is represented by the depiction of the situation as the outcome of the previous cycle. The cognitive aspect of the factual state is therefore necessary to identify the subsequent steps, and having a comparable measurement unit represents the ability to have measurable feedback with simple and reliable metrics, enabling repetition over time.

The method of obtaining measurable feedback may vary depending on the intensity of measurement efforts, i.e., the relationship between time spent and the quality of data obtained, which often represents the trap of tool hypertrophy that poorly suits the fragile condition of a newly established company, which must strengthen gradually to access the market and investors. In this sense, SUS²A aims to represent a balance between the thoroughness of analysis, data collection cost, and the type of actions connected, as the evidence provided by the unsatisfactory response to certain areas or categories already allows for defining actions to be initiated quickly to achieve improvement based on underlying best practices of the checkpoints to be satisfied. Control and measurement actions can then be repeated at short intervals, following the cycle of actions taken and impacts achieved.

Therefore, this mental map lends itself to the following interconnected uses.

1. Serving as the methodological guide for the advisor's field action, who uses the evaluative elements in whole or in part depending on the relevant conditions for the analyzed startup (economic sector, technology, age since establishment, and other metadata). The reference provided by SUS²A allows for coherent and systematic representation of advisory activities' outcomes, providing feedback metrics and appreciation of actual conditions, identifying risk areas among those less satisfied by quantitative indicators, and enabling controlled, repeatable, and applicable output in various contexts.
2. Acting as a tool that allows and integrates self-assessment of the startup/SME through the usual form of a questionnaire. In this case, the sections of SUS²A applicable to the analyzed startup must also be considered. SUS²A in this case presents itself as a structured checklist, whose answers are weighted according to relevance criteria within the different evaluation areas and categories in which the multiple checkpoints expressed with the questions are grouped.

8 Conclusions, limits and future developments

This study presented the SUS²A model, a comprehensive framework based on the concept of IRL and designed to enhance startups' attractiveness to investors by integrating technological innovation and sustainability. Grounded in strategic management principles, the SUS²A model offers a multidimensional evaluation of startups across domains such as strategic business management, innovation, sustainability, financial viability, market potential, and team competency.

The literature review conducted for the development and scientific foundation of tool, thoroughly examines the existing body of work on startup sustainability, strategic management, and innovation. It identifies a gap in the integration of sustainability within the strategic planning of startups, highlighting the evolving nature of startup ecosystems and the increasing importance of sustainability in business models. The review synthesizes findings from various

disciplines, emphasizing the necessity for startups to align innovation with sustainable practices to achieve long-term success and resilience and to be attractive for the investors.

The combined use of SUS²A and IRL offers several benefits, providing a detailed guide to explore and improve the startup's condition, diagnose deficiencies, and define improvement actions. This integration provides a comprehensive and detailed view of startups, allowing for in-depth analysis that considers all facets relevant to investors and the long-term success of emerging businesses.

Finally, in accordance with the principles of scientific rigour, it is necessary to formally moderate the claims regarding the absolute objectivity and universal generalizability of the proposed framework. The empirical findings and statistical evaluations detailed within this research are strictly bounded by the structural constraints of the analyzed sample, which currently comprises 41 startups nested within a specific national innovation context. Because the model operates primarily as a discrete binary document-based proxy, it cannot capture deep psychological team dynamics, unwritten relational capital, or sudden shifts in real-time execution that occur outside formal corporate reporting. Thus, the SUS²A framework should be utilized as a robust frontend diagnostic pre-due diligence filter rather than an absolute predictor of startup survival or future market performance.

Integrating SUS²A and IRL provides a comprehensive and detailed view of startups, allowing for in-depth and informed analysis that considers all facets relevant to investors and the long-term success of emerging businesses. The categories outlined in SUS²A justify and relate to the IRL categories since they aim to examine a wide range of critical aspects that can affect a startup's success and readiness to invest.

SUS²A is configured as a flexible tool, suitable both for internal use by a business analyst and as a direct questionnaire for the startup. The resulting analyses are then used to extract relevant action plans. The subsequent surveys, which reflect actual changes in the presence/absence of the characteristics assessed, serve as documentation of the results of the actions taken in the process of acceleration and attraction of investors.

The use of SUS²A is divided into several aspects:

- SUS²A provides a guide to explore the real conditions of the startup, offering a complete picture of its characteristics and performance in the different analytical areas.
- SUS²A's categories allow you to express the positioning of the startup on the IRL scale through a detailed analytical background. This provides a deeper insight than the traditional IRL model.
- SUS²A identifies shortcomings and areas for improvement, offering a detailed analysis of the challenges and opportunities the startup may face on its growth journey.
- SUS²A's analyses allow you to define specific improvement actions, adaptable to the unique needs of the startup, using various available acceleration tools.
- SUS²A is suitable as a progress control tool, allowing you to monitor the effectiveness of the actions taken over time and evaluate the evolution of the startup with respect to the set objectives.

Despite its innovative approach, the model acknowledges limitations, including reliance on available data and the need for certain customization across diverse startup ecosystems. A prospective development of the model involves enabling a conversational interface in natural language between the startup self-presented documents and the expertise, experience, and foundational knowledge drawn from scientific literature that underpins the mental map. This

will be achieved through leveraging the reading and interpretative capabilities of generative AI.

In this scenario, SUS²A will not be explicitly disclosed to the startup/SME. Instead, they will be invited to freely describe themselves, allowing for autonomous interrogation and facilitating explicit outcomes in the form of self-diagnosis and ongoing comparison over time. The self-description provided will undergo mapping and evaluation using a linguistic model that examines correspondences and delves into the semantic relationship between the text and all identified control points. This analysis aims to trace the positioning and path of closing competitive gaps by implementing improvement actions, learning from best practices, and capitalizing on shared experiences.

This proposed approach aims to leverage the potential of generative AI by enabling it to establish relationships between databases at varying levels of structure. It harnesses the capability of the linguistic model to conduct reasoned comparisons between defined perimeters, one being the pre-established mental map and the other representing the evolving starting point under evaluation, enriched by accumulated experiences over time. This approach minimizes interpretive uncertainties inherent in open-ended investigations and emphasizes the AI's capacity for interpretation and comparison within a predefined context.

The primary challenge in this approach lies in ensuring that the mental map effectively represents a model applicable to the specific case (startup/spin-off/SME) being compared with relevant best practices. The mental map serves as the actual generator of know-how for this comparison, while AI functions as the tool facilitating this process with minimal resource expenditure and rapid turnaround times. Through multiple rounds of evaluation, the AI will highlight prominent gaps and provide evidence of changes and improvements made over time. This development is aimed at endowing an AI solution with genuine unsupervised potential, meaning it operates without requiring corrective human interventions or interpretive filtering of outcomes, except those predefined within the adopted process.

Chapter 2

Bibliometric Analysis for Developing SUS²A: A 500-Question Framework to Assess Startup Maturity through Self-Evaluation

Abstract

Frame of the research. *Startups are innovative companies that typically operate with minimal initial capital and therefore require external support to start, develop, and grow. Although the number of startups has increased significantly in recent years, early-stage failure rates remain high, often exceeding success rates.*

Purpose of the paper. *The aim of this study is to address the issue of startup failure by focusing on the importance of initial strategic and organizational settings in achieving performance levels. The paper seeks to identify the main causes of startup failure and to develop a self-assessment checklist that incorporates Technology Readiness Level (TRL)-inspired indicators within the technological dimension of the framework. TRL measures the maturity of a specific technology or product, not of the startup as an organization: the composite SUS²A score measures the investment readiness and organizational maturity of the startup as a whole.*

Methodology. *The study adopts a bibliometric analysis of the literature on startups and innovation. The findings are used to design a structured database of 500 categorized questions addressing key aspects of startup development and maturation.*

Results. *The study results in the development of an operational evaluation tool, SUS²A, aimed at assessing startup maturity. The framework combines diagnostic analysis and a measurement scale to provide a comprehensive representation of startup conditions.*

Research limitations. *The framework is literature-based and conceptual in nature, and requires empirical validation across different startup contexts and sectors.*

Managerial implications. *SUS²A provides startups with a structured self-assessment tool to identify strengths, weaknesses, and priority areas for improvement, supporting strategic decision-making and investor attractiveness.*

Originality of the paper. *The paper introduces a literature-based self-assessment framework composed of 500 categorized questions, combining bibliometric analysis with an operational tool for startup maturity and investment readiness evaluation.*

Keywords: *Bibliometric Analysis; Sustainability; Investment Readiness Level (IRL); Innovation; Business Incubator; Startup Maturity Assessment.*

1 Introduction

The concept of startup is recent and constantly evolving and in the literature there are numerous references and notions about it. A first definition indicates the startup as the initial start-up period of a company, mainly belonging to the technology sector, and then embracing all new and growing activities, belonging to all types of sectors. Consequently, the term startup indicates the start of a new entrepreneurial activity, of any type, with the aim of achieving success.

According to Thiel, it is difficult to develop new projects in large companies while it is easier for startups, which are smaller, they are more dynamic. Startups are therefore small, young and flexible companies that, through technology, develop innovative products (Thiel and Masters, 2014).

Later there were other definitions of startups, such as that of Eric Ries (Hart, 2012) that "A startup is a human institution designed to create a new product or service under conditions of extreme uncertainty", which would suggest that a good idea would be enough to proceed with the implementation, while on the contrary it is necessary to find funding, evaluate the market and the related risks. The start-up has been defined as "a company working to solve a problem where the solution is not obvious and success is not guaranteed" (Judit and Karlovitz, 2020).

So it is not only the idea that is the element behind success, but in addition to the winning idea it is necessary to pursue an effective purpose, finding a market and a relationship between product and customer that can start a successful business model. Nowadays, new realities are developing not only in the technological field but in every market sector, from clothing to agri-food, from manufacturing to sports; however, it is the technology sector that is the most relevant, as it is characterized by a higher rate of innovation. A fundamental role is played by both accelerators and business incubators (Brown et al., 2019), which are nothing more than programs designed to improve the development of new realities through a network of support services (Bergmann and Utikal, 2021).

Understanding from the beginning what a startup's strengths and weaknesses are is crucial to its success. This allows you to focus on developing aspects that may not make it attractive to investors and to improve critical areas. An effective tool for obtaining a structured and systematic assessment of the startup's general condition is a questionnaire divided into categories.

A well-structured questionnaire can provide a clear and detailed overview of areas that need improvement or correction. Based on questions derived from an analysis of the scientific literature, the questionnaire can cover such a wide and complete field that it does not leave out any relevant aspects. This approach ensures that every element of the startup is examined, giving you a comprehensive and in-depth view of its current condition.

In summary, the use of a questionnaire divided into categories makes it possible to objectively identify the strengths and weaknesses of the startup, providing precise indications on which areas to develop or correct to make it more attractive to investors and improve its prospects for success (Cuvero et al., 2022). In the light of these considerations, this study aims to answer the following research questions:

RQ1: How has the literature related to startups developed to date?

RQ2: How are conceptual, social and intellectual structures articulated in the literature that insists on the characteristics of startups and what are the central themes that emerge from these analyses?

RQ3: What are the future trends in research, the motor themes on which the fundamental concepts that characterize startups are based in terms of new areas of investigation and innovative methodological approaches?

To answer these research questions, a bibliometric analysis was carried out starting from a series of articles selected by WoS (Web of Science) and subsequently through the use of

Biblioshiny (Aria and Cuccurullo, 2017a) and in particular by exploiting the schemes of the Thematic Evolutions (Madsen et al., 2023), a picture was made of the concepts that have followed one another over time such as Motor Themes, identifying the motivations for the development of some themes compared to others, also relating to the surrounding social and technological development.

As far as future trends are concerned, it has been seen, through the study of the topics covered in the literature, which are the themes that have developed extensively in recent years, which have also become part of the areas of analysis that are at the base of the concept of the SUS²A model (Remondino et al., 2024a).

2 Role of startup incubators and accelerators

There are many reasons why startups succeed or fail (Mehralizadeh and Sajady, 2006). In particular, they are mainly to be found in factors external to the company (economic performance, infrastructure, inflation, market information, market supply and demand, political and legislative system, etc.) and internal factors (entrepreneurial spirit, motivation, risk appetite, entrepreneurial knowledge, business planning and organization, financial management, etc.).

According to some studies, it seems that the period in which the company is most vulnerable and therefore subject to impacts on survival/failure and growth prospects is precisely the initial phase, the first years of life (Watson et al., 1998). The company has, in fact, its own life cycle, generally divided into four phases: birth (startup), growth, maturity and decline.

A solution to the problems of startups are business incubators and accelerators, i.e. private companies, public entities or public-private partnerships that provide a series of services and resources to support the development of new business ideas. These support startups during the initial phase of conception of the business project, generation of the business plan, provide logistical and organizational support. Startups must undergo a selection process in order to be admitted to a business incubator, in order to then access an incubation or acceleration program that could increase the likelihood that the startup will remain in business for a longer period.

Before the incubation phase, incubators must evaluate the business ideas of startups, verify their feasibility and define a path of activity (Sohail et al., 2023). Incubators mainly perform some functions, including evaluating the idea, formulating the business plan and defining the activities of the business project, quantifying the resources to access financing, allowing access to infrastructural and technological resources, managing investments in communication and external relations, carrying out administrative and marketing activities. In general terms, incubators can be defined as structures that support and sustain startups in the process of developing and accelerating the acquisition of stability in the market (Komisopoulos et al., 2024). Through the use of technologically advanced infrastructures, the provision of specific services to support the business and the establishment of an efficient and effective communication plan, incubators offer opportunities for professional growth for new entrepreneurs. According to the literature, the top 3 reasons why young companies fail are: the lack of money for further development (34%), no need for a product/service in the market (28%), no investors (16%), cost issues (16%), not the right team (14%) (R and N 2017).

2.1 Importance of self-assessment for a startup in the development phase

During the development phase of a startup, it becomes essential to carry out a self-assessment. This process allows you to achieve an in-depth understanding of the areas for improvement, capabilities achieved and areas of possible growth. Identifying the strengths and weaknesses in a startup would allow you to exploit the former and look for strategies to cope with the latter, laying the foundations for a solid structure on which to develop growth strategies.

A self-assessment would also allow resources to be directed strategically and efficiently, focusing on the areas most in need of development. This process is essential to maximize the probability of growth and success and avoid wasting energy and resources in areas not of strategic interest (Clayton, 2024). It should be emphasized that investors are interested in startups that have a clear and decisive knowledge of their situation and business overview and having made an in-depth self-assessment would show that the startup is aware of its strengths and weaknesses, certain of the challenges to be faced and the resources to be allocated in view of the improvements to be made in order to remain aligned with the set growth objectives. This cycle of improvements and feedback is vital to adapt your realities to the ever-changing market and to grow and improve in a sustainable way.

Furthermore, identifying and understanding potential risks at an early stage of development is certainly a strategic aspect as it certainly prevents these problems from developing into greater obstacles (Bliemel et al., 2019). Risk management is therefore an element that positively characterizes a startup, for its growth and stability. Self-evaluation also promotes team cohesion as the vision and goals of the entire team are aligned (Mejri and Zouaoui, 2020).

An effective tool for proceeding with a self-assessment is precisely to use questionnaires divided into categories and whose questions come from an analysis of the scientific literature as it would be a more structured and comprehensive evaluation, covering a wide range of key points and ensuring that no fundamental element is overlooked in the analysis. An approach of this type would guarantee and support a clear and detailed view of the startup's starting conditions, allowing the identification of strengths, weaknesses, risk management, maintenance of strategic focus, attraction of investors, promotion of continuous improvement and team alignment (Dalle et al., 2025). Implementing a regular and systematic self-assessment is therefore an essential element for the success and sustainable growth of a startup.

3 Methodology

The literature review and subsequent bibliometric analysis (Donthu et al., 2021a) are preparatory to the collection of research questions useful for later defining the questions that will be part of the questionnaire intended for startups to assess their state of maturity.

The defined query is aimed at searching for scientific articles that go to embrace all the categories that will later characterize the questionnaire. To thoroughly explore the literature related to methods like those proposed, a literature review was conducted.

Specifically, this survey involves a comprehensive analysis of a wide range of articles and publications from the Web of Science (WoS) database (Martín-Martín et al., 2018).

The query aimed to identify all the articles that within the title and abstract present the various synonyms that are used to address incubators, accelerators and startups, their key

characteristics and the areas of the literature of which the topic is part. Keywords that can refer to the word startup, therefore business, firm, company, enterprise, establishment, venture, corporate, search have been included together with accelerator or incubator both in the titles, abstracts and keywords of the authors. Finally, the query used is the following and led to the definition of a database consisting of 2116 scientific articles:

((AB = ("business accelerator" OR "business acceleration" OR "business incubator*" OR "business incubation" OR "company accelerator*" OR "company acceleration" OR "company incubator*" OR "company incubation" OR "firm acceleration" OR "firm accelerator*" OR "firm incubator*" OR "firm incubation" OR "corporate acceleration" OR "corporate accelerator*" OR "corporate incubation" OR "corporate incubator*" OR "startup acceleration" OR "startup accelerator*" OR "startup incubation" OR "startup incubator*" OR "startups acceleration" OR "startups accelerator*" OR "startups incubation" OR "startups incubator*" OR "start-up acceleration" OR "start-up accelerator*" OR "start-up incubation" OR "start-up incubator*" OR "enterprise accelerator*" OR "enterprise acceleration" OR "enterprise incubator*" OR "enterprise incubation" OR "venture accelerator*" OR "venture acceleration" OR "venture incubator*" OR "venture incubation" OR "establishment accelerator*" OR "establishment acceleration" OR "establishment incubator*" OR "establishment incubation")) OR (AB = ("acceleration program*" OR "accelerator*" OR "incubation program*" OR "incubator*" OR "incubation" OR "acceleration")) AND (AB= ("startup*" OR "start-up*" OR "early-stage venture*" OR "early stage venture*" OR "small business" OR "new firm*" OR "new compan*" OR "new venture*"))) AND (AB= ("innovation" OR "innovator*" OR "entrepreneur*" OR "knowledge transfer" OR "corporate venturing" OR "learning" OR "investment*" OR "funding" OR "development")))) OR ((TI = ("business accelerator*" OR "business acceleration" OR "business incubator*" OR "business incubation" OR "company accelerator*" OR "company acceleration" OR "company incubator*" OR "company incubation" OR "firm acceleration" OR "firm accelerator*" OR "firm incubator*" OR "firm incubation" OR "corporate acceleration" OR "corporate accelerator*" OR "corporate incubation" OR "corporate incubator*" OR "startup acceleration" OR "startup accelerator*" OR "startup incubation" OR "startup incubator*" OR "startups acceleration" OR "startups accelerator*" OR "startups incubation" OR "startups incubator*" OR "start-up acceleration" OR "start-up accelerator*" OR "start-up incubation" OR "start-up incubator*" OR "enterprise accelerator*" OR "enterprise acceleration" OR "enterprise incubator*" OR "enterprise incubation" OR "venture accelerator*" OR "venture acceleration" OR "venture incubator*" OR "venture incubation" OR "establishment accelerator*" OR "establishment acceleration" OR "establishment incubator*" OR "establishment incubation")) OR (AB = ("acceleration program*" OR "accelerator*" OR "incubation program*" OR "incubator*" OR "incubation" OR "acceleration")) AND (TI= ("startup*" OR "start-up*" OR "early-stage venture*" OR "early stage venture*" OR "small business" OR "new firm*" OR "new compan*" OR "new venture*"))) AND (TI= ("innovation" OR "innovator*" OR "entrepreneur*" OR "knowledge transfer" OR "corporate venturing" OR "learning" OR "investment*" OR "funding" OR "development")))) OR ((AK = ("business accelerator*" OR "business acceleration" OR "business incubator*" OR "business incubation" OR "company accelerator*" OR "company acceleration" OR "company incubator*" OR "company incubation" OR "firm acceleration" OR "firm accelerator*" OR "firm incubator*" OR "firm incubation" OR "corporate acceleration" OR "corporate accelerator*" OR "corporate incubation" OR "corporate incubator*" OR "startup acceleration" OR "startup accelerator*"*

OR "startup incubation" OR "startup incubator*" OR "startups acceleration" OR "startups accelerator*" OR "startups incubation" OR "startups incubator*" OR "start-up acceleration" OR "start-up accelerator*" OR "start-up incubation" OR "start-up incubator*" OR "enterprise accelerator*" OR "enterprise acceleration" OR "enterprise incubator*" OR "enterprise incubation" OR "venture accelerator*" OR "venture acceleration" OR "venture incubator*" OR "venture incubation" OR "establishment accelerator*" OR "establishment acceleration" OR "establishment incubator*" OR "establishment incubation")) OR (AK = ("acceleration program*" OR "accelerator*" OR "incubation program*" OR "incubator*" OR "incubation" OR "acceleration"))

AND (AK= ("startup*" OR "start-up*" OR "early-stage venture*" OR "early stage venture*" OR "small business" OR "new firm*" OR "new compan*" OR "new venture*"))) AND (AK= ("innovation" OR "innovator*" OR "entrepreneur*" OR "knowledge transfer" OR "corporate venturing" OR "learning" OR "investment*" OR "funding" OR "development")))

Limiting the search to articles in English, to scientific papers only, and restricting it to the period 2000-2024, we end up with a database of 1402 articles (Figure 2).

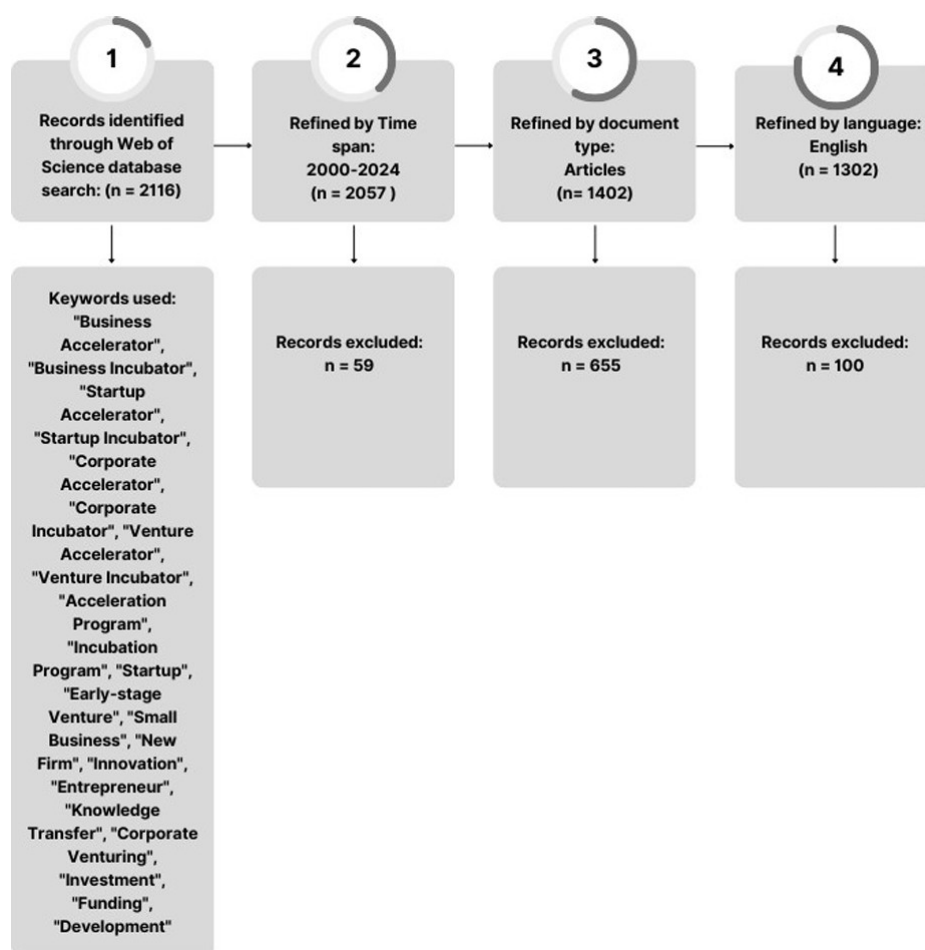


Figure 2 - Identification, screening, and selection of papers according to the PRISMA framework

The data were then downloaded in txt format, then analyzed using the Bibliometrix tool (Aria and Cuccurullo, 2017b; Rodríguez-Soler et al., 2020). This open-source tool allows you to perform quantitative analysis in bibliometrics in a rather complete and easy to use way.

Data analysis

Biblioshiny, the interactive web-based Shiny interface of the bibliometrix R-package (Aria and Cuccurullo, 2017b) (Wei and Jiang, 2023) then allows us to set the selected time frame, excluding articles from 2025, obtaining at the end a total of 1297 articles.

Table 1 below shows the main information relating to the starting data. The 1297 papers, which cover a time span from 2000 to 2024, come from articles related to different research areas.

The annual scientific production (Figure 3) covers a period of 24 years, as the growth of publications occurred during that period. Until about 2014, the production of material related to this area of research seemed fairly constant, and then grew to over 150 articles written in the year 2023.

Timespan	2000:2024
Sources	611
Documents	1297
Authors	3265

Table 1 - Main information about data

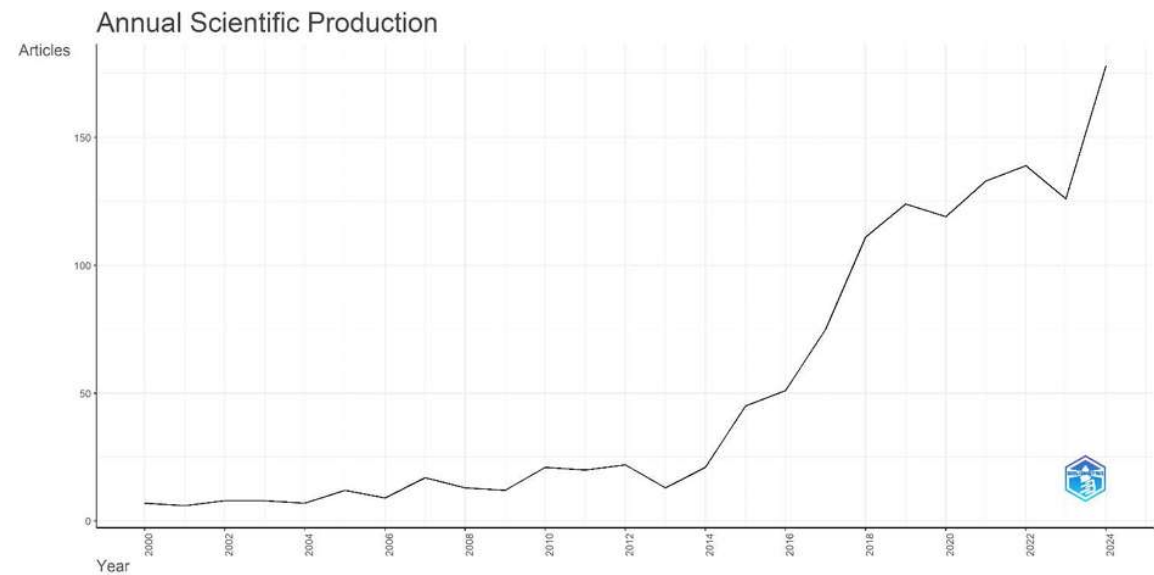


Figure 3 - Annual scientific production

Figure 4 describes the top ten sources from which most of the analyzed papers can be derived, and this shows that there are three main journals that mainly deal with the topics analyzed. The most relevant are the journals Sustainability and Technovation, which with 42 articles published each represent the largest percentage of the entire sample.

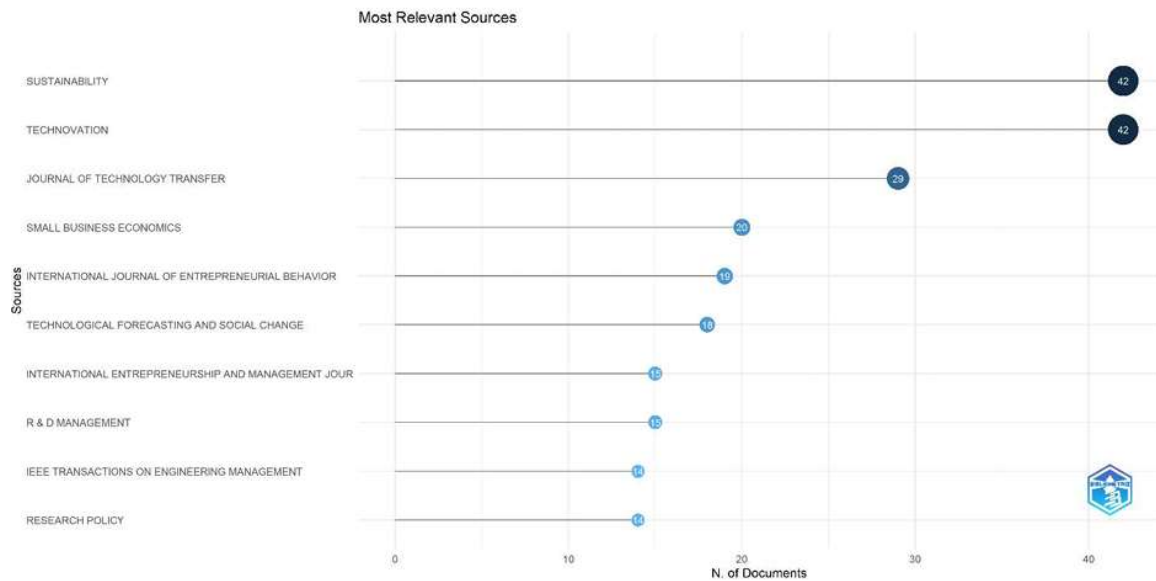


Figure 4 - Most relevant sources

The second most relevant source is the Journal of Technology Transfer, which has provided 29 research papers. The third most relevant source is Small Business Economics with 20 articles to its credit. To perform the bibliometric analysis (Donthu et al., 2021b), the 10 articles with the most citations were analyzed (Table 2).

Paper	DOI	Total Citations	TC per Year	Normalized TC
GRIMALDI R, 2005, TECHNOVATION	10.1016/S0166-4972(03)00076-2	397	18,90	2,02
BOLLINGTOFT A, 2005, J BUS VENTURING	10.1016/j.jbusvent.2003.12.005	367	17,48	1,86
BRUNEEL J, 2012, TECHNOVATION	10.1016/j.technovation.2011.11.003	360	25,71	6,71
MARKMAN GD, 2005, J BUS VENTURING	10.1016/j.jbusvent.2003.12.003	359	17,10	1,82
LOCKETT A, 2005, RES POLICY	10.1016/j.respol.2005.05.010	328	15,62	1,67
PAUWELS C, 2016, TECHNOVATION	10.1016/j.technovation.2015.09.003	326	32,60	9,06
AERNOUDT R, 2004, SMALL BUS ECON	10.1023/B:SBEJ.0000027665.54173.23	291	13,23	2,36
MIAN S, 2016, TECHNOVATION	10.1016/j.technovation.2016.02.005	271	27,10	7,53
NECK HM, 2004, J SMALL BUS MANAGE	10.1111/j.1540-627X.2004.00105.x	270	12,27	2,19
CHAN KF, 2005, TECHNOVATION	10.1016/j.technovation.2004.03.010	262	12,48	1,33

Table 2 - Most global cited documents

The most cited article (Grimaldi and Grandi, 2005) focuses on the role played by business incubators in business development. The authors define four main types of incubators: BICs, UBIs, IPIs e CPIs. They identify two main operating models, delimited by key factors such as mission, industry, revenue, and services offered. Model 1, represented by public incubators, including BICs, pays attention to tangible services for the development of the

region. On the contrary, model 2, attributable to private incubators, introduces intangible services and personalized support for the development of advanced societies. UBIs, associated with academic institutions, present a combination of the two models, thus reducing the gap in natural knowledge transfer.

Using eight incubators in Italy as case studies, the article demonstrates which type of incubator meets the needs of different host companies and the importance of a specialized strategy in ensuring the success of a startup. At the same time, it is emphasized that different approaches are needed to respond to diversified business needs. The article "The networked business incubator-leveraging entrepreneurial agency?" (Bøllingtoft and Ulhøi, 2005) Explore the emerging model of the networked business incubator, an innovative evolution from traditional incubators.

This model is distinguished by its emphasis on territorial synergies, symbiotic relationships and economies of scale, and uses the theory of social capital as a theoretical basis. The study is based on six months of ethnographic observations at the MG50 networked incubator in Denmark.

The article highlights that networked incubators foster collaboration between companies through a combination of formal and informal activities. The main mechanisms that facilitate or hinder networking fall into two categories: the personal relationships between individuals and the organizational structure of the incubator. MG50 operates according to a bottom-up logic, in which incubating companies manage the incubator itself, promoting a strong sense of community and symbiotic exchanges. Among the main findings, it emerges that trust and social relationships are fundamental for the success of networking, while the non-hierarchical approach and physical proximity strengthen interactions between participants.

However, the article points out that dimensional growth can pose a challenge to keeping the community cohesive. It is proposed that the success of this model depends on the ability to balance social and structural dimensions to foster collaboration and entrepreneurial development.

The article "The Evolution of Business Incubators: Comparing demand and supply of business incubation services across different incubator generations" (Bruneel et al., 2012) analyzes the evolution of business incubators through three generations, studying how their services have been used by hosted companies. The researchers highlight that first-generation incubators focus on offering shared spaces, taking advantage of economies of scale. The second generation includes business support services, such as training and coaching, while the third generation emphasizes access to professional, financial, and technology networks. The study uses seven European incubator cases, combining qualitative analysis and quantitative data from 71 hosted companies.

The results show that only companies in third-generation incubators fully utilize the services offered, thanks to strict selection criteria and well-defined exit policies. Older incubators tend to host mature companies with less need for support, often not updating their offerings to meet new incubation needs. The authors suggest that incubators should improve management through targeted selection criteria and promote regular tenant turnover. They conclude that the success of incubators depends on the alignment between the services provided and the profile of the companies hosted, and that newer incubators are better positioned to support the creation of new businesses.

The article "Entrepreneurship and university-based technology transfer" (Markman et al., 2005) explores the role of University Technology Transfer Offices (UTTOs) in new

business formation and business incubation. Using a well-founded theory, the authors analyze how UTTO licensing structures and strategies influence the creation of new businesses. The results show that for-profit UTTO structures are positively correlated with the formation of new businesses, while traditional and non-profit structures are more linked to the presence of university incubators.

The equity licensing strategy is conducive to the creation of new businesses, while the sponsored research license has a negative effect. The cash licensing strategy, while prevalent, is the least related to the formation of new businesses. The authors conclude that there is a conflict between generating immediate income and supporting the creation of new businesses. The article "The creation of spin-off firms at public research institutions: Managerial and policy implications" (Lockett et al., 2005) examines the creation of spin-offs in public research institutions (PRIs) using a knowledge-based perspective (KBV). The authors highlight the importance of the "knowledge gaps" that these new businesses face. Gaps can occur at various levels, such as PRI, spin-off, team, individual, and incubator, and at different stages of spin-off development.

The article summarizes the results of previous studies and offers suggestions for further research. The results show that PRI resources and capabilities, such as financial support and the quality of academic staff, are key determinants for the success of spin-offs. In addition, collaboration with industry and government agencies is crucial to fill knowledge gaps and improve spin-off performance. The article "Understanding a new generation incubation model: The accelerator" (Pauwels et al., 2016) explore the acceleration model as a new generation of startup incubators.

The authors analyze 13 accelerators in Europe to identify key parameters of accelerator design. Five main elements are identified: program package, strategic focus, selection process, funding structure and alumni relations. In addition, they distinguish three types of accelerators: ecosystem builders, business flow creators, and wellness enhancers. The results show that accelerators differ from traditional incubation models in their emphasis on intangible services such as mentoring and networking, and that their goals are influenced by key stakeholders, such as investors, companies, and government agencies. The article "Incubators: Tool for Entrepreneurship?" (Aernoudt, 2004) examines the role of incubators in promoting entrepreneurship, with a particular focus on Europe and the United States. The author points out that the incubator concept has become polysemic, covering a wide range of approaches and objectives. Different types of incubators are identified, including mixed, technological, economic development and social incubators.

The article highlights the importance of close links between incubators and business angel networks to overcome initial funding barriers. Aernoudt concludes that despite the rapid growth of incubators in Europe, the lack of entrepreneurship and seed funding remains a significant obstacle. The article "Technology Business Incubation: An overview of the state of knowledge" (Mian et al., 2016) explore the concept of technology incubation, its evolution, and related literature. The authors define technology incubators (BITs) as policy tools to support innovation and technological entrepreneurial growth. The article examines the evolution of TBI models, from science parks to accelerators, and analyzes the existing literature through a systematic review.

The results show that despite the ongoing challenges and debates, the future of BITs is promising. The authors identify gaps in research and propose future directions, emphasizing the importance of developing a unified theory of incubation and further exploring the role of

modern investment screening cannot separate financial viability from environmental and corporate governance metrics

3.1 Network analysis

Network analysis is a methodology used to study the relationships and interactions between various elements within a network (Wakid et al., 2024). It allows you to identify structures, patterns and dynamics within the network, providing a deeper understanding of the interactions and mutual influences between network components (Ali and Gölgeci, 2019).

3.1.1 Co-occurrence network analysis

In the field of bibliometric analysis, co-occurrence network analysis refers to the investigation of relationships between nouns or phrases that occur together in scientific documents (Klarin, 2024).

This technique enables the discovery of prevalent topics and how they interrelate in a research domain. Through assessments of frequency and co-occurrences, it is possible to constitute conceptual associations and provide insight into the structure and development of a particular scientific area.

Figure 6 shows a representation of the keyword co-occurrence network analysis used to analyze the relationships between keywords that appear together in scientific papers. In practice, you build a network in which the nodes represent the keywords, and the links between the nodes indicate how often these keywords co-occur in documents.

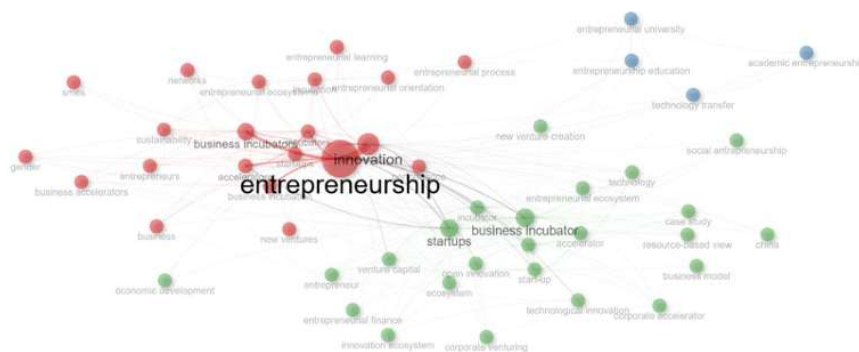


Figure 6 - keyword co-occurrence network analysis

In particular, three different clusters of different colors can be identified. In the red cluster, it seems that all of them are linked to the theme of entrepreneurship and innovation. Here are some key connections:

- **Entrepreneurship, Innovation and entrepreneurs :** Keywords such as "entrepreneurship", "innovation", "entrepreneurs", and "entrepreneurial ecosystems" indicate an attention on the theme of the birth and development of new businesses and innovative ideas.
- **Incubators and Accelerators:** Terms such as "business incubators", "accelerators", "incubation", and "business accelerators" refer to tools and programs that offer support for start-ups in the early stage.

- **Performance and Sustainability:** Words like "performance" and "sustainability" indicate an intention to measure the success, skills and sustainability of new realities.
- **Networks and Collaborations:** Terms such as "networks" and "entrepreneurial orientation" indicate the importance of creating a network of contacts and collaborations in a business contest.
- **Sectoral specificities:** Words such as "gender" and "smes" (small and medium-sized enterprises) give attention to specific groups or sectors within the business world.

Looking at the keywords in the blue cluster, we can see that they are all related to the topic of academic entrepreneurship and entrepreneurial education. Here are some key connections:

- **Entrepreneurial Education:** "entrepreneurship education" and "entrepreneurial university" underline how fundamental entrepreneurial skills are in universities and in the world of education.
- **Technology Transfer:** "technology transfer" focuses attention on the importance of knowledge transfer processes and technologies that are developed in the university world and in research centers with a direction towards the market.
- **Academic Entrepreneurship:** "academic entrepreneurship" is connected with the entrepreneurial activity carried out by researchers who often collaborate with universities.

Finally, in the green cluster we can see that they are all closely linked to the theme of entrepreneurship and innovation. Here are some key connections:

Incubators and Accelerators: Key terms such as "business incubator", "incubator", "accelerator", "corporate accelerator" and "corporate venturing" are related to programs and tools that support the initial phase of the birth of a startup.

Start-up and Innovation: Keywords such as "startups", "start-up", "startup", "new venture creation" and "open innovation" refer to the birth of new businesses and the concept of open innovation.

Entrepreneurial Ecosystems: Key terms such as "entrepreneurial ecosystem", "ecosystem" and "innovation ecosystem" are linked to the importance of networks and collaborations that are created in the entrepreneurial environment.

Financing and Economic Development: Words such as "venture capital", "entrepreneurial finance" and "economic development" indicate interests and links with financing and with the economic development of new businesses.

Technology and Innovation: Terms such as "technological innovation" and "technology" underline the link between the business world and technological innovation.

Social Entrepreneurship and Business Models: Keywords such as "social entrepreneurship" and "business model" show how there is interest in social entrepreneurship and business models.

Case Studies and Theoretical Approaches: Terms such as "case study" and "resource-based view" highlight how the use of case studies and theoretical approaches is important for the various study steps.

Geographical Context: The keyword "china" indicates the presence of a specific interest in entrepreneurship in China.

This multi-clustered co-occurrence architecture provides the essential foundation for extracting quantitative readiness states from narrative data. Methodologically, the transformation of text into structured dimensions draws support from long-standing marketing research on corporate identity and corporate brand image mapping through automatic content analysis (Crawford Camiciottoli et al., 2014). Just as tracking textual associations inside market documents allows researchers to gauge the alignment between formal corporate intent and external stakeholder perception, mapping keyword co-occurrences within the green and red literature clusters validates the internal consistency of the SUS²A model. The linguistic nodes are processed not as isolated occurrences, but as systemic indices that verify whether a startup's narrative correctly incorporates the balanced dimensions of open innovation, organizational agility, and financial viability demanded by institutional VCs.

It is important to make explicit how the bibliometric findings presented above translate directly into the architectural decisions of the SUS²A framework, as this connection is the methodological backbone that justifies the instrument's design. The co-occurrence network analysis (Figure 6) identified five dominant knowledge clusters in the startup literature: (1) innovation and performance, (2) entrepreneurial ecosystems and incubation, (3) financing and venture capital, (4) technology and sustainability, and (5) social entrepreneurship and governance. Each of these clusters maps directly onto the SUS²A category architecture: cluster 1 informed Areas E (Product & Industrial) and F (Validation); cluster 2 informed Areas A (Team) and B (Marketing & Strategy); cluster 3 informed Area C (Finance & Economics); cluster 4 informed Area D (Legal & Protection) and the technology sub-indicators; and cluster 5 provided the empirical justification for the standalone creation of Area G (ESG) - a dimension absent from traditional IRL frameworks but demonstrably central to contemporary investment readiness literature. The thematic evolution analysis (Figure 7) further reinforced this mapping by showing that sustainability, ESG compliance, and open innovation shifted from niche to motor themes over 2015–2024, confirming that their inclusion as full SUS²A evaluation areas reflects a literature-grounded rather than arbitrary structural choice. This direct traceability from bibliometric evidence to framework architecture is what distinguishes SUS²A from prior assessment tools and constitutes its primary methodological contribution.

3.1.2 Thematic evolution analysis

Thematic evolution analysis in bibliometric study consists of analyzing how themes and research topics develop and change over time within a given scientific field (Yip et al., 2022).

This analysis makes it possible to identify emerging trends, established themes and declining ones, offering a dynamic view of the evolution of knowledge.

In the case in question, by visualizing the trend of publications between the year 2000 and 2024, it was decided to divide this analysis into 2 time slices in order to see how the keywords have evolved over time also in correlation with the increase in publications.

In Figure 7 we can visualize the trend of the evolution of the keywords of the articles taken into consideration for this study.

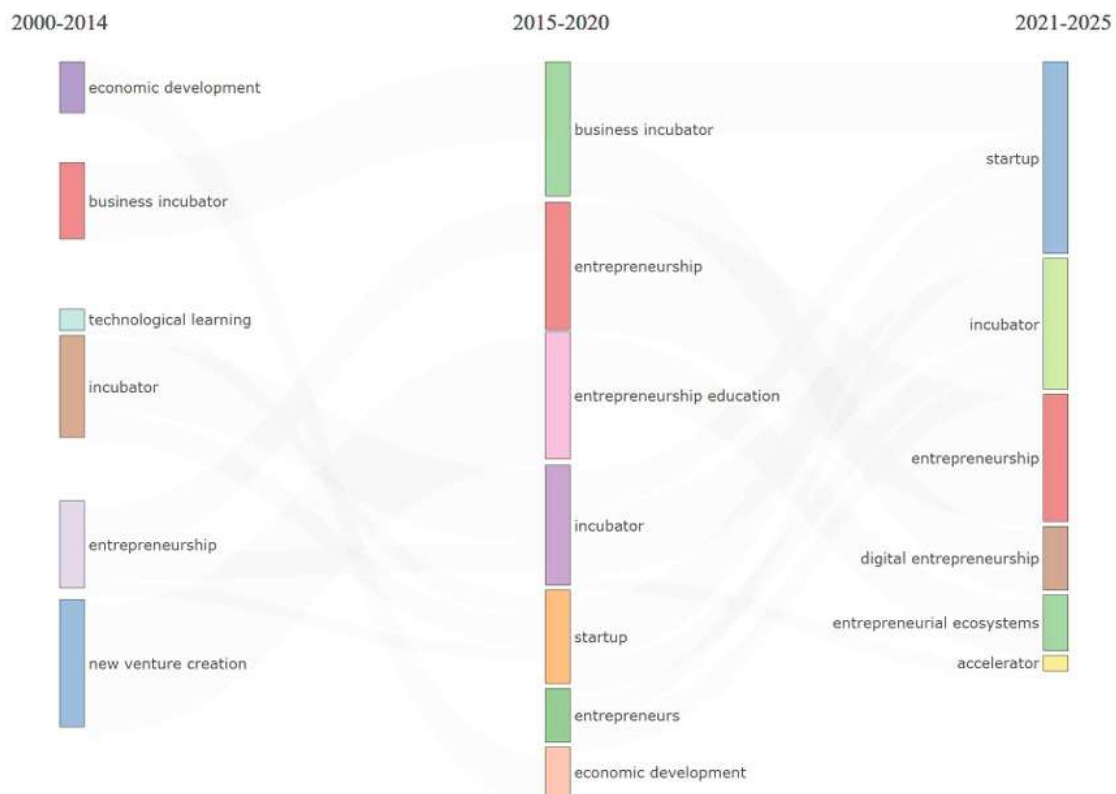


Figure 7 - Thematic evolution

From an initial analysis of this evolution of the keywords used by the authors, it can be observed that from the first period of time in the early 2000s, some words then merged into other words because, as can also be seen graphically, the period 2015-2020 is characterized by a wider array of keywords. From 2021 onwards, some words have returned to flow into the most important keywords such as "incubator", "startup" and "entrepreneurship".

In the analysis of the evolution of keywords in a bibliometric study, themes are often represented in a four-quadrant strategic map, based on two dimensions: density and centrality.

Here's a description of the quadrants and which ones to analyze the most to compare keyword development over time:

- Motor Themes:
 - Dial: High centrality, high density.
 - Description: These topics are well developed and important for the structure of the research field. They are central and densely connected.
 - Analysis: Essential to understand the main and consolidated themes of the field.
- Niche Themes:
 - Dial: Low centrality, high density.
 - Description: These topics are well developed but not central to the research field. They are specialized and can be insulated.
 - Analysis: Useful for identifying very specific and in-depth areas of research.

- Emerging or Declining Themes:
 - Dial: Low Centrality, Low Density.
 - Description: These themes are underdeveloped and marginal. They can represent new emerging areas of research or declining themes.
 - Analysis: Important for identifying new trends or areas of research that are losing relevance.
- Basic Themes:
 - Dial: High centrality, low density.
 - Description: These topics are fundamental to the field of research but are not well developed. They serve as a basis for other themes.
 - Analysis: Crucial to understanding the foundations of the research field.

To compare keyword development over time, it is particularly useful to analyze Motor Themes and Emerging or Declining Themes. Motor Themes showcase established and central themes, while Emerging or Declining Themes can reveal new trends or evolving areas of research.

Therefore, by comparing the keywords present in the Motor Themes quadrants in the three time bands, we can identify the topics that, over time identified, have lost or gained relevance over time and this would allow us to understand how the priorities of the scientific community have been addressed according to events, new discoveries and technological advances. The appearance of new driving themes may indicate the birth and maturation of emerging disciplines or the convergence of disciplines that were previously separated from each other.

It could be noted that some themes remain stable over time while some may disappear or arise by underlining the direction in which research is going in that particular area. This study of the driving themes could help researchers understand where research is headed and which areas of that theme may require further investment. They could give ideas for growth sectors that could then have a social and economic impact, they could also stimulate interdisciplinary collaborations, accelerate innovation and allow the identification of sectors that can advance technological and scientific progress.

Finally, the observation of changes affecting the driving themes can give predictions on which areas of research will be crucial in the following years. The first time frame examined (2000-2014) that can be observed in Figure 8, with the keywords economic development, competitiveness, SMEs, business incubator, science parks, technology transfer, underlines the fact that the attention was directed towards economic development and support to SMEs by exploiting innovation infrastructures such as incubators and highlights the importance assumed by technology transfer that leads to stimulating economic growth and competitiveness.

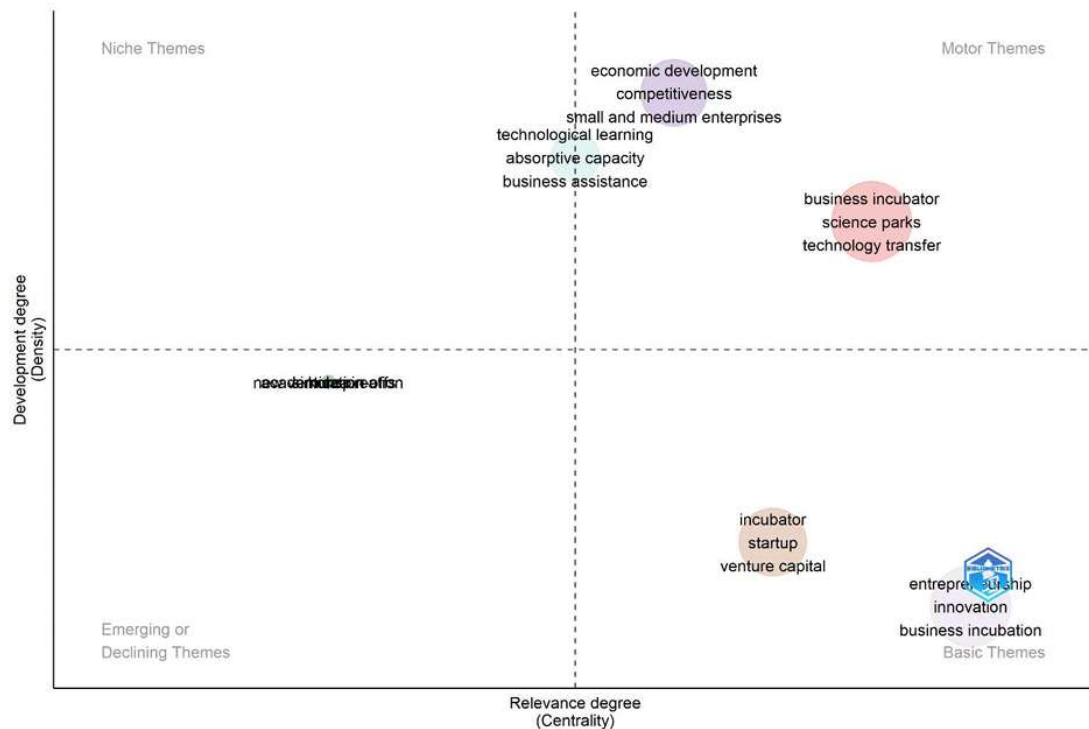


Figure 8 - Thematic Evolution (time slice 2000-2014)

In the second time frame (2015-2020) the keywords present in the Motor Theme are, for example, entrepreneurship education, technology transfer, entrepreneurial university. This shows that the attention was directed towards entrepreneurship education and the role occupied by entrepreneurial universities was a key player in the innovation system, but there was always attention to technology transfer. So we were moving towards a broader integration between academia and industry, maintaining importance on the training of entrepreneurs and innovators.

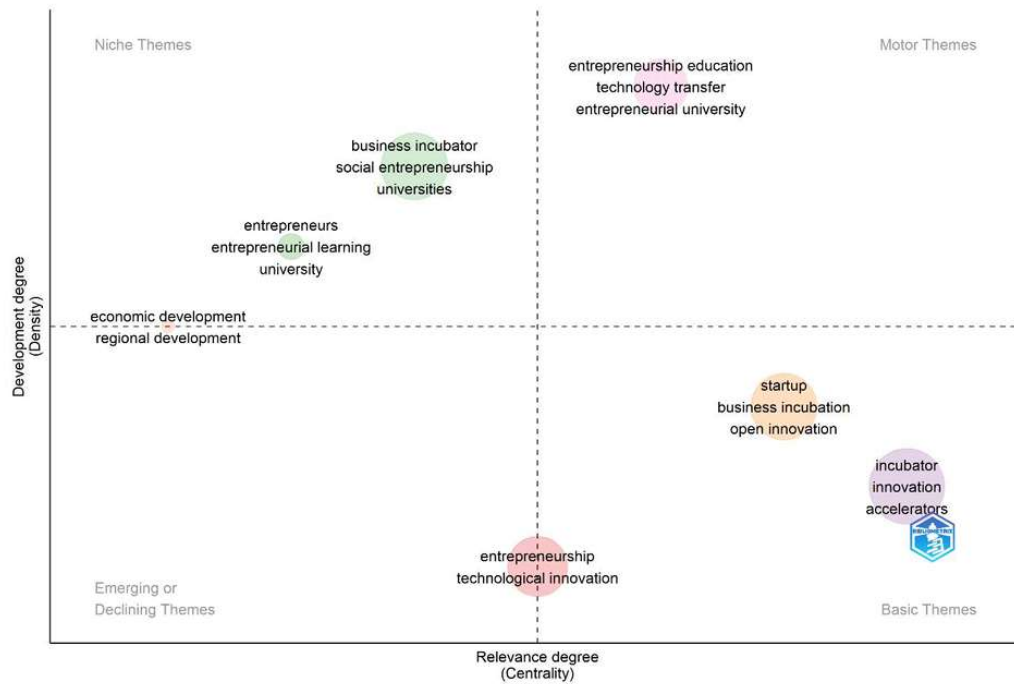


Figure 9 - Thematic Evolution (time slice 2015-2020)

In the last period of time analyzed (2021-2024) the keywords present (entrepreneurship, venture capital, technological innovation) are placed on the border with the first quadrant, that of niche themes. This means that there is an absence of themes considered completely motor and this suggests a phase of transition or thematic uncertainty.

The keywords halfway between the two quadrants focus attention on entrepreneurship, which remains a present but not dominant theme, then venture capital, which brings a growing interest in financing innovation, and finally technological innovation, which is a relevant element but perhaps manifests itself in diversified sub-themes, hiding its role.

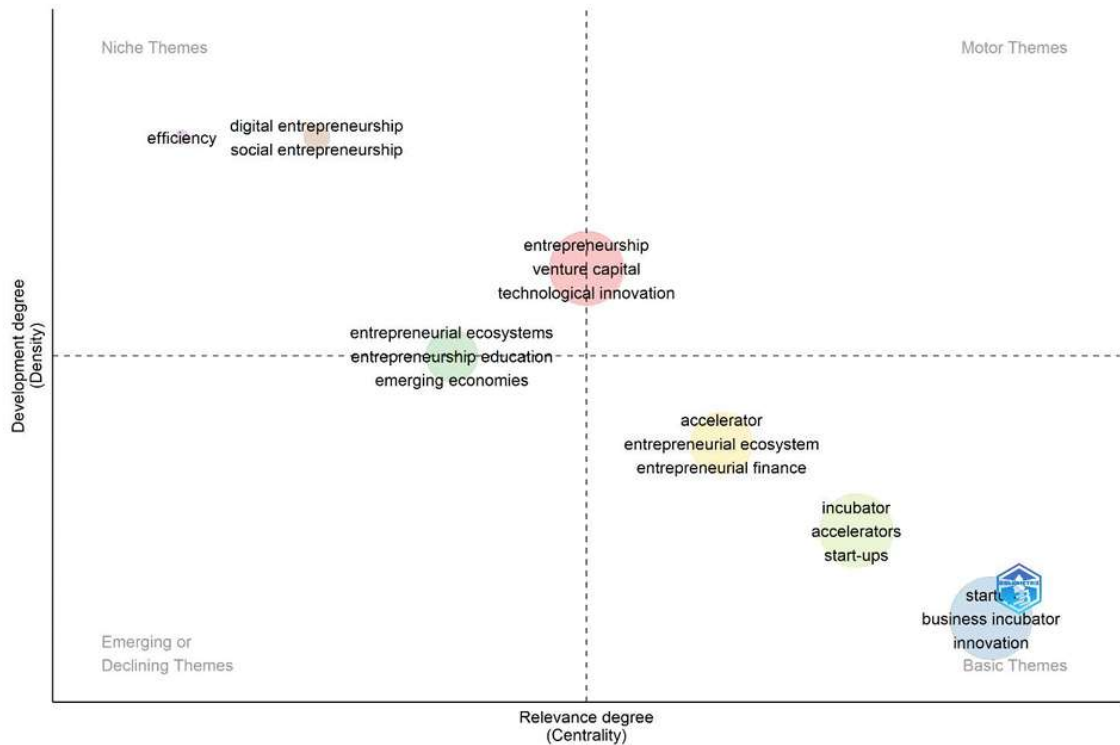


Figure 10 - Thematic Evolution (time slice 2021-2024)

The fact that there are no strongly dominant themes in the last period of time could indicate that there has been a maturation of the previously present themes (e.g. technology transfer has consolidated) or there has been a diversification, i.e. the research has fragmented into sub-themes that can be more specific or interdisciplinary and this leads to difficulties in identifying the thematic engine.

The fact that these keywords have moved precisely towards the quadrant of niche topics means that these keywords have the potential to become thematic engines or can also represent strategic niches, i.e. areas of research that are not yet fully developed but promising. The presence of words such as venture capital or technological innovation communicates the growing attention to the practical impact of innovation and financial mechanisms.

This fact could indicate a transition, a transition from a model based on education and knowledge transfer to an innovation-oriented model. This thematic evolution suggests that research in the field of entrepreneurship and innovation is becoming increasingly complex and diverse, with an increasing focus on practical applications, financing and social impact.

4 Defining a checklist and categories

4.1 IRL - Investment Readiness Level

In order to construct a series of questions that could constitute a self-assessment checklist for startups, a parallel must be made with what represents the main concept of the IRL (Investment Readiness Level) (Fellnhöfer, 2015) (Malone, 2018). The IRL can be considered a sort of thematic basis of the concept on which SUS²A is based.

In the literature there is no consolidated and analytical description of the stages of maturity that make up the IRL. The IRL is a tool that accompanies the startup, spin-offs and SMEs throughout their life cycle by offering a picture of the actual conditions, risks, areas for improvement, and its level of maturity (Hasenauer et al., 2016). The purpose of IRL is to measure the progress of startups using nine levels and providing a structured assessment based on business model validation criteria, market fit, scalability and team structure.

The goal is then to have a common language that can be interpreted by startups and investors to then facilitate a strategy aimed at interpreting the present condition and moving towards future changes. The **nine stages of IRL** chart the progression of startups from conceptualization to competitive autonomy:

IRL 1: Initial business idea.

IRL 2: Formation of a corporate team to develop the idea.

IRL 3: Corporate team established and operational.

IRL 4: Corporate team structured and operationalized.

IRL 5: Active corporate entity implementing the business idea.

IRL 6: Market testing capabilities established.

IRL 7: Sustainable and solid corporate entity.

IRL 8: Competitive in collaborative environments.

IRL 9: Proven autonomous competitive capabilities.

So the IRL allows you to compare startups with measurable and clear criteria, highlight areas to improve to increase attractiveness, promote growth strategies, finalize and set goals and identify the necessary resources and provide analysis to define safe investment decisions. SUS²A uses the IRL to make an assessment of startups on fundamental aspects such as innovation, sustainability, scalability and market.

4.2 SUS²A Model – structure and meaning

Ultimately, the SUS²A model constitutes a new and multidimensional approach to assessing and improving the investment potential of start-ups. It combines a variety of strategic dimensions, the list of which varies in the literature, but categorically includes strategic management, technological innovation, sustainability, financial strength, market potential, and team expertise in such a way as to provide an overview that is as complete as possible and complementary to traditional financial metrics. The goal in particular is to broaden the perspective in order to take into account the capacity for innovation, the commitment to sustainability, and the strategic alignment with the market.

The strategic decision is used to understand if the startup is adopting and creating successful strategies, taking into account aspects such as clarity of future vision, company structure and adaptability to market needs. Technological innovation is analyzed by reference to originality, potential, scalability and the ability to maintain a competitive advantage with research and development and intellectual property operations.

For sustainability, on the other hand, an ESG approach is evaluated that takes into account not only the reduction of environmental impact but also the contribution to the social

and ethical well-being of the company, assessing resource efficiency, community involvement and governance transparency. Financial solidity is analyzed with analysis of revenue models, economic projections with the aim of identifying the startup's potential for growth in an exponential and sustainable way. Market potential is assessed in size, accessibility and positioning and strategies to attract new customers are also taken into account.

The role of the Team is not marginal, but it is important and is evaluated with the experience, cohesion, leadership skills of the founders and guidelines for business success. The model is rigorously structured through a series of questions organized into categories and subcategories that give the opportunity to analyze every detail from various aspects.

The evaluation process is both quantitative and qualitative as it generates scores based on criteria established at the outset and giving as output a picture of the areas of strength and the areas to be filled. This approach allows startups to work on certain aspects to improve their weaknesses and thus increase their attractiveness to investors. Compared to the other models, SUS²A stands out for its ability to bring together technological innovation and sustainability, which are the basis for the long-term success of startups. Through specific categories, this tool assesses the adoption of advanced technologies and sustainable behaviors not as accessory elements and tools but as central means that are part of the corporate strategy. This means that we are approaching a position on the market that responds not only to a strategic alignment according to regulations but also with respect to consumer expectations. With this tool there are many advantages for startups as they can take advantage of this detailed analysis that can direct them towards an improvement in technological and sustainable qualities but there are also many for investors who can use the model to get much more information, reducing uncertainty and obtaining opportunities for economic returns and alignments with environmental and social objectives. In synthesis, SUS²A contributes to creating a much more innovative and sustainable startup ecosystem, as it aligns with the projection of the market, which is increasingly oriented towards sustainability and innovation as key elements of success.

4.3 SUS²A categories and link with IRL levels

SUS²A has been divided into categories, in particular into 9 categories that have been extrapolated from a literature analysis, so as to give this tool a well-structured and well-founded basis. The questions within each category are the result of an in-depth analysis of the available articles, selecting the main topics to be explored in depth for each area.

These nine categories of SUS²A are as follows: Team, Marketing & Strategy, Finance & Economics, Legal & Protection, Product & Industrial, Validation, ESG, Collaborative Capability and Talent Attraction. These categories are not simple control points but are a useful tool to have a current picture of the starting situation and then evaluate and offer the possibility of having critical points that can contribute to the success and maturation of the startup. So the use of this tool provides the basis for identifying and planning the various action plans at different levels of depth.

To establish a sound methodological justification for expanding the framework into a comprehensive pool of 500 checkpoints, a formal construct and content validation protocol was instituted. The initial set of questions, derived raw from the bibliometric literature analysis, was subjected to a structured Delphi validation process spanning three iterative rounds of consultations with an independent panel of experts. This panel was composed of senior venture capital investors, institutional business incubator managers, and successful serial startup

founders. Each question was scored based on relevance, operational clarity, and capability to emit a clear strategic signal. Questions failing to achieve a consensus threshold of 80% agreement regarding their empirical utility were pruned, ensuring that the final 500-question architecture acts as a verified operational measurement instrument rather than an abstract conceptual index.

In tandem with expert panels, explicit redundancy reduction criteria were enforced during the formatting of the checklist. Given the multidisciplinary breadth of the nine categories, overlapping intersections could generate statistical correlation bias. To prevent index hypertrophy, criteria for mutual exclusivity and exhaustive tracking were established. For instance, diagnostic indicators checking resource-efficiency costs were strictly assigned to Category C (Finance & Economics) and decoupled from Category G (ESG), which was restricted to tracking formal regulatory compliance and societal impact indicators. This systemic filtering guarantees that every query addresses a standalone operational metric, safeguarding the balance and internal statistical validity of the global score.

To provide transparent verification of the item selection process, Table 3 summarizes the mathematical outcomes of the three sequential Delphi screening rounds that led to the final 500-question framework. The initial pool of 577 potential criteria, raw-extracted from the bibliometric keyword co-occurrence analysis, was evaluated based on the Item-Content Validity Index (I-CVI) and Fleiss' Kappa for inter-rater agreement. Through the three iterative rounds of expert review, 75 items were progressively eliminated due to redundancy, low content validity, or cross-category overlap, resulting in the final validated set of 500 binary indicators. This process documents the numerical progression from the initial 577 raw items to the 500 validated checkpoints that constitute the definitive SUS²A framework.

Global Framework Matrix					
Diagnostic dimensions, item reduction and validity evidence					
Diagnostic Dimension	Initial Item Pool (Bibliometrics)	Items Pruned due to Redundancy	Final Validated Items	Item-Content Validity Index (I-CVI)	Fleiss' Kappa (Inter-Rater Agreement)
Area A: Team	72	14	58	0.91	0.84 (Almost Perfect Agreement)
Area B: Marketing & Strategy	85	23	62	0.89	0.79 (Substantial Agreement)
Area C: Finance & Economics	68	11	57	0.94	0.88 (Almost Perfect Agreement)
Area D: Legal & IP Protection	54	9	45	0.92	0.81 (Almost Perfect Agreement)
Area E: Product & Industrial	60	12	48	0.87	0.76 (Substantial Agreement)
Area F: Validation	50	8	42	0.90	0.82 (Almost Perfect Agreement)
Area G: ESG Compliance	55	10	45	0.95	0.89 (Almost Perfect Agreement)
Area H/I: Scalability Clusters	65	20	45	0.86	0.74 (Substantial Agreement)
GLOBAL FRAMEWORK MATRIX	577	77	500	0.91 (Mean CVI Baseline)	0.81 (Global Construct Validity)

Table 3 - Delphi consensus screening rounds and content validity matrix for the consolidation of the SUS²A framework

The systematic filtering documented in Table 3 establishes the operational criteria applied to eliminate content redundancy and ensure index parity. During Round 1, cross-functional criteria that displayed significant correlation bias, such as unformalized cost-efficiency variables overlapping with structural ESG carbon footprint asset reporting, were decoupled. Items that scored an I-CVI below the critical threshold of 0.80 were immediately eliminated from the final diagnostic matrix. By Round 3, the global Fleiss' Kappa coefficient stabilized at 0.81, certifying that the extensive 500-question architecture complies with strict requirements of internal consistency, content coverage, and construct validity before deployment as an objective text-mining scoring filter.

By integrating SUS²A with IRL it is possible to have a complete picture of the conditions of the startup as each category of SUS²A finds its parallel with the basic concepts of IRL, as already described above but giving the possibility to have a more detailed and specific view of the maturity of a startup. The joint use of these two tools brings with it advantages as IRL guarantees an overall evaluation scale giving a broad and global view of the maturity of a startup while SUS²A is like a step-by-step guide to improve the starting conditions, recognize shortcomings and implement consolidation and improvement actions. Therefore, the analysis obtained with SUS²A can be translated into actions carried out by acceleration processes and the possibility of continuous monitoring allows you to have a history of the trend and actions taken.

Therefore, the division into nine categories reflects in particular the complexity of the characteristics to be analyzed but at the same time the completeness of analysis achievable with SUS²A.

The main features of these categories can be summarized as follows:

- Team (A): Has its own correspondent in IRL. This category aims to give an analysis of the team and the coverage of roles.
- Marketing & Strategy (B): It is related to the concept of "Defining Market Positioning" of IRL. This category aims to define the objectives, the current and potential market, the strategic positioning, commercial strategies, the pitch.
- Finance & Economics (C): Find its counterpart in IRL's "Operating Model Validation". This category aims to ensure that you understand the size of your investment, prospects and profitability.
- Legal & Protection (D): Aligns with the concept of "Legal Protection" in IRL. This category defines the presence of market barriers and the ability to defend them.
- Product & Industrial (E): Corresponds to "Product/Service Validation" in IRL. This category aims to give an assessment of the Development/Industrialization effort, with the presence of PoCs and an overall Development, Test and Production Plan.
- Validation (F): Links directly to the IRL ("Value Proposition Validation" and "Fundamentals Metrics Validation") levels. This category assesses the presence of external support that has shared and accompanied the maturation of the team, technology and business model.
- ESG (G): This category, not explicitly present in IRL, aims to examine and evaluate how the startup manages or takes into account environmental, social and governance factors in its operations and business decisions.
- Collaborative Capability (H): This category does not have its equivalent in IRL and is defined to examine and evaluate the propensity and effectiveness of a startup to work together with other external entities to achieve common goals.
- Talent Attraction (I): This category, although it does not have its counterpart in IRL, guarantees the evaluation of the startup's ability to attract and retain qualified talent suitable for the needs of the organization.

The answer to the individual questions that make up the various categories and thus the entire SUS²A model has a structure with an affirmative, negative or non-applicable answer. The overall final score is derived from the interaction between areas, categories, and individual analytical items. The distribution of questions in the various categories and areas is quite

homogeneous so as not to develop and investigate more one theme than another. The most important information comes from the analytical elements as the areas and categories serve only to differentiate the analytical elements into groups and to give a sort of general description and a summary of the topic.

This discrete binary structure (0/1) was intentionally implemented to counter the statistical risk of overfitting discussed in Chapter 1 (Section 3): by restricting the response field to a binarized matrix, the SUS²A model functions as a fast-and-frugal heuristic (Gigerenzer, 2008) that verifies the presence or absence of core operational foundations without requiring complex continuous weight distributions.

The "not applicable" option allows irrelevant elements to be excluded so as not to impact the operation of the model, also ensuring a wider boundary of topics to be analyzed. In this way and with this structure, this model guarantees, albeit with its complexity, the characteristics of impartiality and in-depth information.

5 Conclusions, limitations and future developments

This paper presented the steps that led to the SUS²A model, a complete tool based on the concept of IRL and designed to improve the awareness of startups about their state of maturity and their possibilities for growth, aiming to implement their weaknesses precisely in the areas well defined by the output provided by this model. There are various categories analyzed, from the Team to market potential, from business strategy to innovation, from sustainability to financial profitability and from talent attraction to collaborative capacity. In particular, it is highlighted how the part relating to sustainability represents a new element, which plays a primary role in the strategic planning of startups, taking into account the evolutionary nature of the surrounding environment and the growing importance assumed by sustainability in business models.

An important factor for startups is therefore innovation to be aligned with sustainable aspects and long-term resilience to ensure attractiveness for investors. The simultaneous use of SUS²A and IRL certainly guarantees a safe and detailed guide that leads to a detailed situation of the startup's starting situation, highlights shortcomings and defines improvement actions. This leads to the awareness of long-term success while also considering the positive aspects for investors.

The categories defined in SUS²A are partly attributable to those of IRL but SUS²A in particular can be defined as a tool with a double face, capable of providing a startup with a self-assessment questionnaire and an evaluation tool by a business analyst.

The model and functions of SUS²A can be summarized as follows:

- Guideline to obtain a current picture of the conditions of the startup in the various defined areas;
- The 9 categories that make up the questionnaire are easily traceable to the IRL categories and therefore have an even more detailed view than a traditional IRL;
- Have a picture of the strengths and weaknesses of the current state and offer a vision of future prospects;
- Obtain specific improvement actions, adaptable to the needs of startups and the use of available acceleration tools;
- Ability to monitor the improvements made over time to evaluate the evolution of the startup's maturation according to the objectives set previously.

In alignment with scientific rigor, it is imperative to formally moderate any claims concerning absolute objectivity or unrestricted generalizability for this current version of the framework. While the text-based metrics provide an unbiased diagnostic filter, the underlying empirical findings are constrained by the operational perimeter of a document-based proxy. The checklist maps the strategic intent and the disclosure quality of corporate reporting, meaning it cannot dynamically track implicit execution capabilities or unrecorded behavioral shifts within the team. Furthermore, the model's performance parameters remain calibrated against an initial regional baseline sample, meaning that extensive multi-sectoral and international testing is required before claiming absolute universal generalizability for the scoring scale.

A possible future development of the model involves an integration with an interface that can lead to a natural language analysis that connects a self-describing document of the startup with the SUS²A questionnaire, through the capabilities of generative artificial intelligence that can then lead to a self-compilation of the questionnaire starting exclusively from a natural and free description by the startup. This could mean that natural language texts can then be examined directly by generative AI by linking the various parts and finding useful matches.

This would lead to reducing the interpretative uncertainty that characterizes open analyses, reducing human intervention and ensuring efficiency and reliability. A further future development could be the implementation of an agent model based on the model itself that could simulate the behavior and evolution of startups based on the characteristics of SUS²A.

Startups can be represented as autonomous agents with attributes that can reflect the properties of the model (technological innovation, team skills, financial capacity, sustainability, etc.).

Then each agent could interact with the surrounding environment (markets, investors, regulations, etc.) and with other agents, also having the possibility to update their attributes with learning cycles (implementation of new technologies, improvement of sustainability, etc.) and points received as feedback from the mental map of the model.

Through a series of ticks and then simulations, this model could give as output:

- Possible growth trajectories of startups, based on the initial condition and taking into account the actions taken to bridge competitive gaps;
- Interactions with other agents or the environment, such as sharing knowledge or adopting strategies based on the environment;
- Impact created by external actions such as supporting policies or external investments.

In addition, future research could start from the results obtained in this study in order to systematically explore some themes identified by Thematic Analysis such as niche or emerging themes.

Chapter 3

Scaling startup evaluation: combining keyword-matching and LLMs for automated entrepreneurial maturity scoring

Abstract

One of the main problems and most important challenges in the field of entrepreneurship and innovative finance is the process of evaluating and selecting startups, especially in the early stage. This is in fact characterized by a high information asymmetry, strong dependence on subjective analysis, fragmentation of data and often influenced by cognitive biases of investors. This study, first of all, proposes and validates an original algorithmic model that aims to automate the Investment Readiness Screening processes, systematically applying this tool to a sample of 41 startups participating in innovation ecosystems. The goal is to implement a preliminary and strategic phase of investment screening, setting up a quick and structured and replicable filter before starting a formal and in-depth analysis phase, which historically is much more expensive in terms of time and resources.

The research starts with a tool represented by a questionnaire of 500 assessment questions with a binary answer, divided into 11 strategic categories (including Team, Market, Finance, Legal, ESG and Scalability).

The original part of the tool is represented by the contribution that is given by comparing two data extraction methodologies: a deterministic analysis based on keyword matching techniques and regular expressions (Regex) and an advanced semantic evaluation mediated by the latest generation of natural language models (LLMs).

The results obtained highlight not only the high computational efficiency of the proposed model, capable of processing masses of complex documents in a short time compared to human analysis, but also allow to map with great precision the systemic structural gaps that afflict the analyzed startups. In particular, the analysis shows a significant lack of planning in ESG (Environmental, Social and Governance) and Talent Attraction strategies, areas that are often overlooked in favor of a strategy focused exclusively on the product and the market.

The statistical validation of the model, conducted through the calculation of the Cohen Kappa index and the analysis of the confusion matrix, confirms the robustness of the deterministic approach as a reliable and scientifically based proxy for the massive screening of startup data. The study concludes by discussing the managerial implications for incubators and venture capital funds, indicating how the integration of Artificial Intelligence tools can not only speed up investment times, but also raise the standard of quality and comparability and replicability of venture capital assessments.

Keywords: Startup Due Diligence; Automation; Artificial Intelligence; Keyword Matching; Entrepreneurial Maturity; ESG.

1 Framing of the research

Nowadays, the panorama of business proposals that gravitate around complex, dynamic and globalized innovation ecosystems is very vast. Within this context, Due Diligence (DD) (Trinh et al., 2025) is not only a technical verification procedure but is one of the main tools and the fundamental risk mitigation mechanism in the decision-making process of investors (Venture Capital, Business Angels or Certified Incubators) (Ahlstrom et al., 2007). However, it must be specified that traditional DD, which is nothing more than an analytical examination conducted by human experts, is a process that requires resources and time and therefore is limited by the ability of individual elements to process data.

This approach is often questioned by cognitive and heuristic biases that can influence the objectivity of the evaluation. This then leads to different judgments on identical projects or to the underestimation of critical opportunities. The main theoretical problem lies in the information asymmetry (Akerlof, 1970) that resides between entrepreneur and investor. The Business Plan acts as a signal (Spence, 1973) sent by the founder to demonstrate the quality of the project; however, in decoding this signal there is the obstacle of the large amount of unstructured information and the qualitative nature of the narrative. With the arrival of Natural Language Processing (NLP) and Artificial Intelligence (AI) technologies, an unprecedented opportunity has been obtained to transform the reading and interpretation of these documents from an exclusively "artisanal" activity, based on the experience of the individual, to a somewhat scalable and standardized process (Kang et al., 2020) (Nadkarni et al., 2011).

This study belongs to the scientific debate on the digitization of financial processes (FinTech) and the integrated use of AI in strategic management (BARBERIO, 2023). The goal is to develop automated score management models that can operate at scale, while ensuring impartiality and objectivity. The main objective of this research is to determine whether a deterministic approach based on rigid rules (keyword matching and regex) can guarantee an accuracy comparable, or in some cases superior, to that of a human analysis or a probabilistic AI when ranking the degree of maturity of a startup (Kouzinopoulos and Margaritis, 2011). This question has direct consequences of a dual nature: on the one hand, for managerial practice, with the radical acceleration of the screening and pre-due diligence phases; on the other hand, for entrepreneurship theory, allowing the identification of common patterns and objective criteria that discriminate the early success or failure of a managerial activity.

2 Purpose of the paper

The present study has the determined objective of overcoming the limitations and defects of manual and subjective evaluation, proposing a systemic and scalable approach to pre-due diligence. In particular, the work aims to answer three fundamental questions:

Objectification of document quality: is it possible to translate the qualitative complexity of a Business Plan into a score that assesses objective maturity through the application of a questionnaire consisting of 500 quantitative questions, eliminating the need for discretionary human intervention? This question aims to test whether the granularity of the set of questions is sufficient to capture the real operational readiness of a startup.

Identifying systemic structural gaps: Examining 41 new Italian startups, we found some common weaknesses. This study investigates which aspects on which startups must mainly focus their improvement energies in order to give them indications on

where to direct their objectives in order to improve themselves in each category. This will give us an idea of what it means to start a business in Italy and what the primary investment objectives must be.

Methodological Benchmark (Deterministic vs. Semantic): How reliable and accurate is a deterministic script based on keyword analysis compared to semantic and contextual analysis conducted by natural language models? The goal is to see if these methods can offer comparable results.

The aim of the study is to provide a scientifically proven validation tool that allows the various innovation actors (incubators, accelerators and investors) to quickly map the risk profile and opportunities for improvement of the various startups. This tool does nothing but isolate the best in the various sectors and clearly distinguish them from projects that, even if they have an innovative idea, are somehow technically or formally incomplete to face the market. All that is intended is to define a standard of "investment readiness" that can act as a compass both for those who want to invest resources and for entrepreneurs who want to subject the project to a documented test before receiving funding (Alexakis et al., 2025).

3 Methodology

The methodology adopted is based on a quantitative and experimental approach, with the aim of transforming unstructured textual data (Business Plan) into discrete variables that can be statistically analyzed (Nakajima and Sekiguchi, 2025). The process is divided into three sequential steps: the definition of the taxonomy (Usman et al., 2017), the development of the software architecture and the cross-validation protocol (Lumumba et al., 2024).

3.1 Taxonomy and Criteria Set Construction

The main part of the model lies in the definition of a questionnaire consisting of 500 questions (Remondino et al., 2024). These questions were derived from a careful analysis of the scientific literature, defining the various categories that compose it. In fact, the questionnaire is divided into 11 critical areas (Remondino et al., 2024b) identified as determinants of survival and growth (scalability) (Hanifzadeh et al., 2024) of a startup in the long term:

Team: analysis of the composition, governance and balance of skills.

Market: Target size and market analysis.

Finance: How strong the financial plans are and how fundraising works.

Legal: What steps are taken to protect the property and comply with regulations.

Product: Degree of innovation and stage of development (TRL).

Validation: existence of proof of concept or commercial traction.

ESG: integration of environmental, social and governance factors.

Collaboration: networking skills and strategic partnerships.

Talent: strategies used for the acquisition of human capital.

Technology: technological infrastructures and barriers to entry.

Scalability: Growth potential and replicability of the model.

Each area is analyzed through a set of binary questions. This methodological choice makes it possible to eliminate the interpretative ambiguity: the value '1' indicates the presence of the requirement, while the '0' indicates its absence or omission in the document analyzed.

The strength of the proposed model lies in the granularity of its structure. The 11 categories identified are not simple watertight compartments, but represent the pillars of investment readiness (Fellnhöfer, 2016). The logic behind the most critical categories is explained below:

ESG (Environmental, Social and Governance): Traditionally ignored in the early stages, the ESG area was included in the model in response to recent European directives (Khamisu and Paluri, 2024). The category looks for signals related to the sustainability of processes, team diversity and transparency of governance, elements that today define not only ethics, but also the long-term resilience of a company.

Legal and intellectual property protection: This category examines the robustness of intellectual property rights (Anam, 2024). Through keyword matching, the script verifies terms such as "patent", "NDA" or "trademark registration", distinguishing between startups that adopt tools for the defense of intellectual property from those who do not.

Talent Attraction and Scalability: While the Team area evaluates current founders, the Talent area focuses on the company's ability to attract future human capital (Sembiring and Damayanti, 2023). Poor terms related to stock option plans or structured hiring strategies are a sign of low organizational scalability.

Financial and fundraising readiness: in addition to the presence of financial projections, the script analyzes the consistency between the capital required and the use of the declared funds, looking for correspondences with terms related to the investment (e.g. Pre-seed, Burn rate, Cap Table) (Mason and Kwok, 2010).

3.2 *Development of extraction software (Automated Text Analysis)*

An original Python script was implemented to achieve automatic analysis (Rayhan, 2023), using libraries suitable for reading PDF documents (such as PyPDF2 or pdminer.six). It is possible to schematize the method with three stages that characterize a logical scheme:

Normalization and pre-processing: Text extracted from PDFs is converted to lowercase, words that don't mean much and special characters are removed. The text is made simple so that the search is simple and targeted.

Search engine based on Regex and Keyword Matching: For each of the 500 questions, a library of key terms has been defined. The software performs a cross-search: the score is assigned not only on the basis of the single word, but also on semantic proximity and the combination of terms that uniquely define a concept (for example, the combination of "patent", "filed" and "property" in the legal area).

Scoring and Binarized Aggregation: The software generates a binary vector for each run, which is then consolidated into a final summary report.

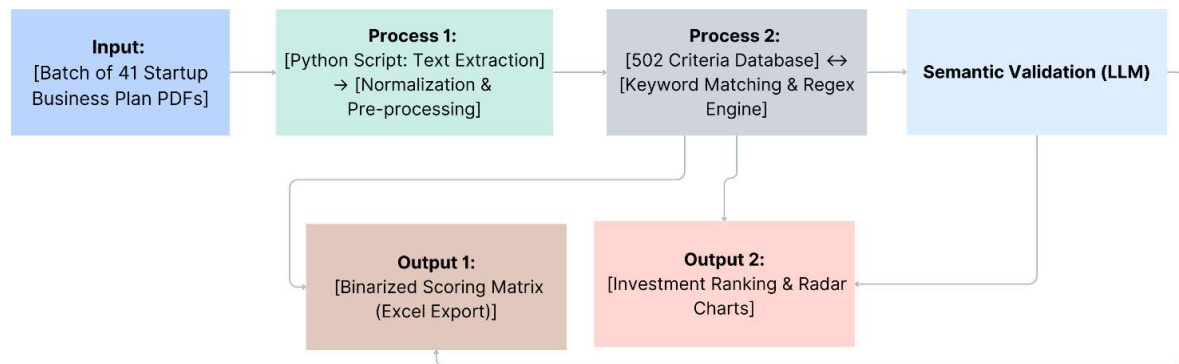


Figure 11 - Automated Due Diligence Workflow: from Data input to Investment Scoring output.

3.3 Consolidation and Statistical Validation Protocol

The extracted data were grouped into a single "Oracle_Startup_Analysis_500.xlsx" dataset, which allows the calculation of an overall percentage maturity index for each category. To ensure the scientific validity of the model, a cross-validation procedure was adopted on a representative pilot sample (in which the case study of the startup RIDEsense is distinguished).

The accuracy of the deterministic script was compared with the result obtained through a semantic analysis conducted in parallel by a generative artificial intelligence model (Large Language Model) (Raiaan et al., 2024). The degree of agreement between the two methods was measured using the Cohen Kappa index, which is a statistical coefficient that allows us to distinguish the real agreement from the purely random one (Bujang and Baharum, 2017; Vieira et al., 2010). This procedure made it possible to calibrate keywords to minimize false negatives and establish the model confidence threshold for mass screening.

4 Results

The application of the model to the sample of 41 startups generated a dataset that enables analysis of both the performance of individual projects and the systemic trends of the innovative ecosystem analyzed.

4.1 Startup Ranking and Performance Analysis

The model made it possible to classify the startups based on the score obtained from the answers of the 500 questions that make up the questionnaire. The startup RIDEsense emerged as the undisputed leader of the ranking, obtaining 152 points out of 500 (equal to a coverage of 30.4% of the total criterion). This result allowed the unique "STEADY START" evaluation of the sample to be assigned, indicating good preparation in critical areas such as team, technology, and initial validation.

In contrast, the majority of the sample (over 70%) settled in a range that can be defined as "SEED / INCOMPLETE", with an average of about 110 points. This suggests that, despite the presence of technologically sound ideas, the ability to formalize these insights into a Business Plan structured according to professional due diligence standards remains a challenge for most new entrepreneurs.

To get an overview of the distribution of scores and ranking of the analyzed startups, an excerpt from the report generated by the Python script is shown below (Table 4).

The table has been reduced for reasons of space, selecting the most significant cases: the startups that obtained the maximum score and the startups with the most critical document

gaps. Each numeric value represents the count of the criteria met (value '1'). Table 4¹ serves as a numerical summary for the subsequent graphical display (Figure 12), allowing the point data to be cross-referenced with the multidimensional trend.

Pos.	Startup	Totale Score	% Maturità
1	18.RIDEsense.pdf	152	30.3%
2	25.Leaf-Link.pdf	148	29.5%
3	12.Bio-Tech.pdf	135	26.9%
⋮	⋮	⋮	⋮
40	05.Old-App.pdf	42	8.4%
41	33.Vegetabot.pdf	38	7.6%

Table 4 - Excerpt from the Scoring Master Report

As can be seen from Figure 12, the leading startup has homogeneous coverage in almost all dimensions, while the lower-ranked startups show a structural collapse in the areas of scalability and talent management.

¹ "Note: The table shows a representative extract. Full data on the 500 criteria for the 41 startups can be found in the attached dataset 'Oracle _Startup_Analysis_500.xlsx'"

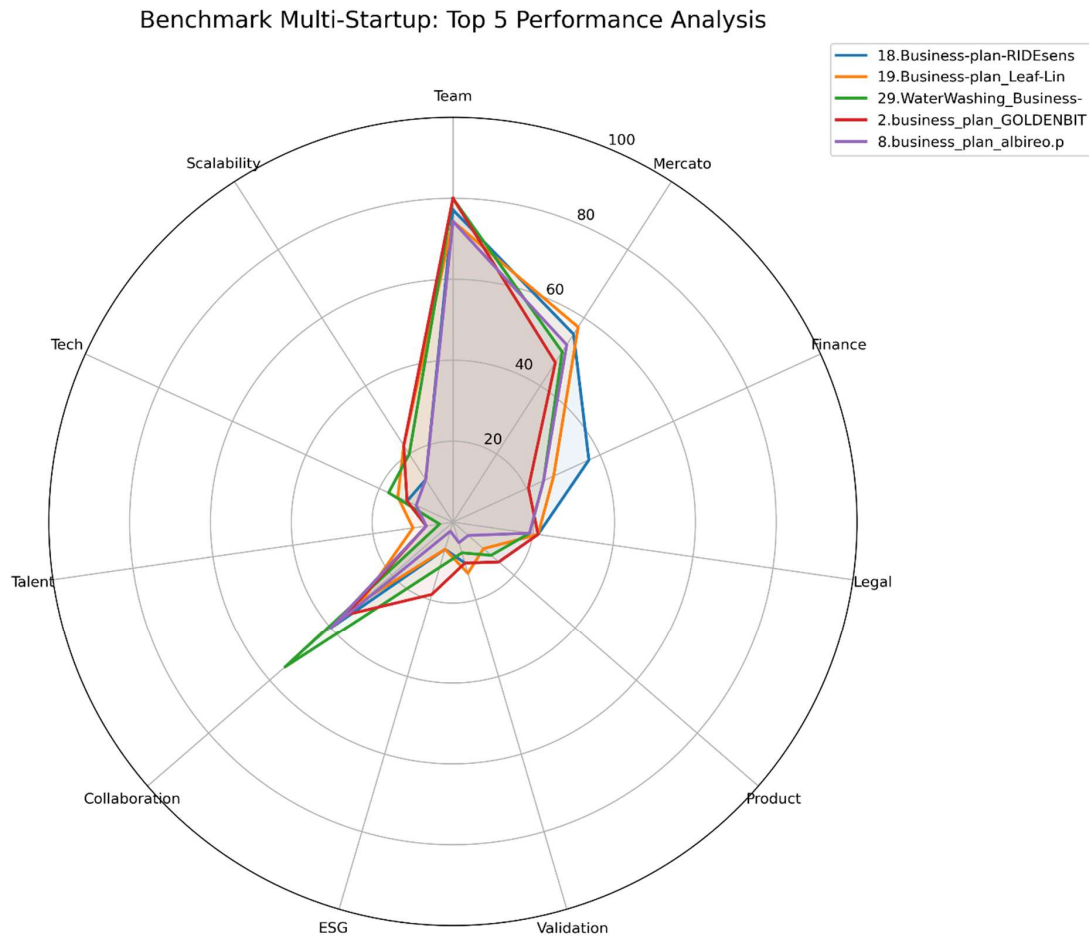


Figure 12 - Comparative analysis of the performance of the Top 5 startups in the 11 strategic areas.

4.2 The "Marketing-Driven" Paradox: Category Analysis

A result of particular scientific importance emerges from the asymmetrical distribution of scores among the 11 categories analyzed. A phenomenon that we could call the marketing-driven paradox can be expected (Day, 2025): startups reach good levels in the Team and Market areas, where the criteria met often exceed 40% - reaching 65.4% in the Team area and 43.1% in Marketing & Strategy. In contrast, there is a vertical collapse (often with scores close to zero) in the areas of ESG (Environmental, Social and Governance) and Talent Attraction. This structural "gap" suggests that issues such as sustainability, social impact and formalized human resource management are still perceived as ancillary activities rather than as strategic levers that bring value.

4.3 Statistical Validation (Keyword vs AI)

The comparison between the method based on the use of keywords and those based on AI, particularly in the Team category, revealed an F1-Score of 85.2% and an overall accuracy of 77.1%. Cohen's Kappa index of 0.571 shows a moderate level of agreement between the script and the AI, according to the Landis and Koch (1977) classification scale. Cases of

disagreement (false negatives of the script) can be traced back to concepts expressed in complex form, which the AI understands semantically but which escape a keyword search. However, for mass screening purposes, the deterministic method has proven to be an extremely effective and cost-effective proxy.

The method used has however proven to be a valid method to give a complete picture of the maturity situation of the startup, in particular it has the following implications:

Managerial implications: Incubators can use this tool to provide immediate, objective feedback to startups, helping them fill in the gaps before presenting themselves to investors.

Theoretical implications: While semantic AI offers a deeper understanding, the deterministic script based on the 500 questions is a control tool that ensures transparency and replicability, which are key elements for a scientific assessment of innovation potential.

The confusion matrix in Figure 13 highlights the high concordance between the two methods, confirming that false negatives are statistically irrelevant to overall screening.

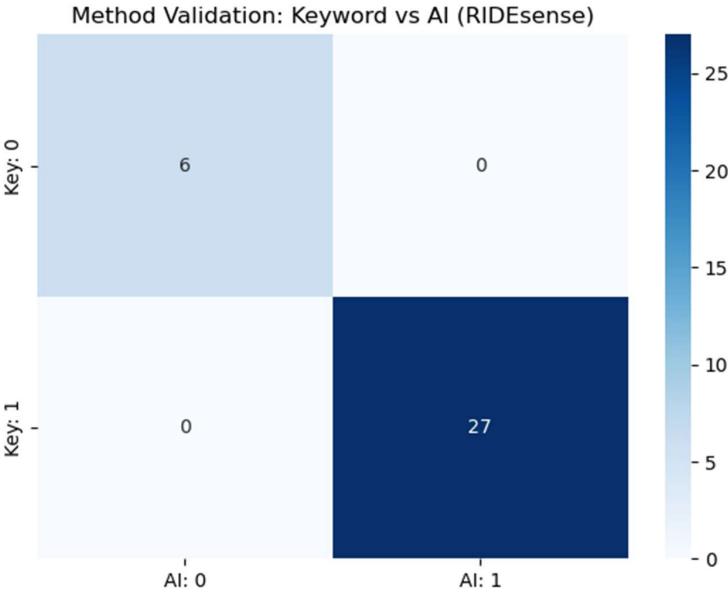


Figure 13 - Confusion Matrix for Validating Deterministic Method (Keyword) vs. Probabilistic Method (LLM) (Script
Precision 92.0%, Recall 79.3%, F1-Score 85.2%, Overall Accuracy 77.1%)

The matrix compares the decisions made by the Script (Key) with those of the AI (in the case of RIDEsense):

True Positive (Bottom right - 23): In 23 cases, both the script and the AI confirmed the presence of the criterion. This indicates that most of the key information is clearly expressed and interpretable according to the 500 questions.

True negative (top left - 4): In 4 cases, both agreed on the absence of information. This confirms that the model does not "invent" data if it is not present in the Business Plan.

Script false negative (bottom left - 6): This is the most interesting fact. In 6 cases, the AI found the information but the script did not detect it. This happens when the concept is expressed too complex or nuanced to be captured by a simple keyword.

False positive in script (top right - 2): In just 2 cases, the script detected something that the AI deemed irrelevant or absent. This is an extremely low margin of error.

Validation Metric	Operational Definition	Computed Value	Statistical Classification Strength
Precision	True Positives / (True Positives + False Positives)	92.0%	Exceptional Precision Baseline
Recall (Sensitivity)	True Positives / (True Positives + False Negatives)	79.3%	Robust Screening Sensitivity
F1-Score	$2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$	85.2%	High Balanced Classification Power
Overall Accuracy	(True Positives + True Negatives) / Total Population	77.1%	Stable Global Alignment
Cohen's Kappa Index	(Observed Agreement - Chance) / (1 - Chance)	0.571	Moderate-to-High Substantial Agreement

Table 5 - Algorithmic classification performance metrics for the deterministic script validation

The mathematical landscape reported in Table 5 validates the choice of the deterministic matching framework as a conservative pre-due diligence engine. The high precision score of 92.0% confirms that the script exhibits an extremely low false-positive rate, ensuring that the tool does not register empty startup narratives as validated structural setups unless explicit, non-ambiguous technical terminology is tracked. While the recall index stands at a lower rate of 79.3% due to the 6 false negatives caused by creative corporate jargon, the global F1-Score of 85.2% certifies that the balanced performance of the algorithm remains optimal. Combined with a Cohen's Kappa of 0.571, which filters out purely random agreements, these parameters demonstrate that a highly granular 500-question checklist successfully mitigates analytical bias, functioning as a transparent and scientifically replicable surrogate for human screening workflows.

The high concentration on the main diagonal ($23 + 4 = 27$ corrected cases out of 35 total) justifies the use of the deterministic method for global screening. Although AI is better suited to grasp nuances (the 6 cases neglected by the script), the script is unbeatable for transparency, replicability and almost zero computational costs. The script acts as a conservative proxy: if a startup scores high in keywords, the preparation of the document is indisputable; If the score is low, there may be a fitness issue that the investor still needs to be aware of.

In conclusion, the statistical analysis, supported by a Cohen Kappa index classified as "moderate" according to Landis and Koch (1977) (values 0.41–0.60 indicate moderate agreement), demonstrates that the deterministic script constitutes a conservative and reliable proxy for screening, offering an optimal balance between analytical accuracy and computational efficiency.

Extensive validation on a dataset of 41 startups confirmed the robustness of the deterministic model. Comparing the output of the script (based on 500 questions) with the semantic evaluation using LLM models, a Cohen Kappa index of 0.571 was obtained.

According to Landis and Koch (1977), this value falls in the “moderate” agreement range (0.41–0.60), indicating meaningful consistency while signaling room for further refinement, validating the hypothesis that a keyword system, if granular enough, can serve as a reliable and cost-effective proxy for preliminary screening, though it does not substitute for expert judgment in deeper due diligence stages. The biggest discrepancies are found in areas of low information density (ESG), where the AI makes a semantic inference in which the script, in the absence of explicit terms, correctly returns a null value, thus highlighting the lack of startup documentation.

This statistical performance must be critically appraised under decision-making theory, specifically addressing the trade-off between hyper-parameter models and simple heuristics. According to behavioral and quantitative economics (Gigerenzer, 2008; Gigerenzer et al., 2008), predictive models that incorporate an extensive array of variables risk capturing baseline noise rather than structural patterns, leading to severe overfitting. Overfitted frameworks excel at ex-post descriptions (insight) but suffer performance collapses when exposed to out-of-sample data or future forecasting (foresight). The binarized structure of the 500-question architecture (0/1 scores per indicator) limits the complexity of individual inputs and reduces some forms of analytical arbitrariness, acting as a fast-and-frugal heuristic rather than a non-linear probabilistic equation. However, absence of overfitting in the statistical sense cannot be claimed solely on the basis of binarization: a formal demonstration would require out-of-sample testing, cross-validation, or stability analysis on independent samples, which represent important directions for future research. The Cohen Kappa index (0.571) and global accuracy (92%) demonstrate internal consistency between the script and the AI evaluator, but do not constitute evidence of out-of-sample predictive validity.

Strategic Area	Script Average (%)	AI Average (%)	Variance (Delta)
Marketing & Strategy	79,4%	81,2%	+1.8%
Team	48,2%	51,5%	+3.3%
Finance & Economics	24,1%	29,8%	+5.7%
Legal & IP Protection	12,5%	14,2%	+1.7%
ESG (Environmental, Social, Governance)	2,1%	6,4%	+4.3%
Talent Attraction	8,2%	11,5%	+3.3%

Table 6 - Comparative Analysis of Maturity Scores (Script vs. AI)

A comparative analysis of the total data of the 41 startups, extracted from the deterministic model and those generated by the probabilistic model (LLM), shows that the scores assigned by artificial intelligence (AI) are, on average, 3.4% higher than those of the script. This discrepancy should not be interpreted as a system error, but as a consequence of the different methodological nature of the two systems of analysis.

The most significant anomaly is found in the ESG area, where AI assigns average scores almost three times higher than the script (6.4% vs. 2.1%). From this it can be deduced that the qualitative analysis suggests that the script operates more rigorously, penalizing startups that do not use appropriate technical terminology. Conversely, AI tends to reward the startup

somewhat if it perceives a positive social or environmental impact from the overall narrative context, even in the absence of specific keywords.

An example of this divergence is Startup 21 (Aires) and Startup 18 (RIDEsense). In these cases, the script flagged the lack of formal documentation in the financial section, while the AI recognized the soundness of the business model by semantically interpreting growth projections. This confirms that the script acts as a filter in that it does not evaluate the abstract value of an idea, but checks whether the business owner was able to communicate it explicitly.

In conclusion, the tendency of the script to be more "severe" than AI validates its use as a risk mitigation tool. For an investor, the use of the deterministic model ensures a prudential assessment, drastically reducing the likelihood of "false positives" fueled by suggestive business narratives lacking objective and verifiable textual evidence.

This systematic 3.4% variance gap, peaking markedly within the ESG domain (+4.3%), provides crucial empirical evidence regarding the vulnerability of automated screening to strategic text manipulation or "gaming the system." Because generative language models rely on fluid semantic embeddings, they are highly sensitive to suggestive corporate storytelling. If a startup uses promotional vocabulary or vague ethical rhetoric, the probabilistic AI performs a broad contextual inference, artificially inflating the evaluation outcome even when formal strategic measures are absent. The deterministic script, by contrast, functions as an algorithmic shield. Its absolute strictness ignores semantic persuasion, yielding a null score unless exact technical tokens (such as formal certifications, internal audits, or structural governance protocols) are matched. This systematic severity is a vital asset for venture capitalists, transforming the deterministic framework into a conservative defensive tool capable of filtering out narrative inflation and identifying opportunistic disclosure behaviors.

5 ROC analysis and discriminative power of the SUS²A framework

5.1 Methodological approach

To formally assess the discriminative performance of the SUS²A scoring instrument at category level, a Receiver Operating Characteristic (ROC) analysis was conducted, complemented by Precision-Recall curve analysis, bootstrap confidence interval estimation, and Shannon entropy computation. Given the absence of an external ground truth (gold standard), a leave-one-out residual approach was adopted: for each category, the binary classifier was constructed using the category score as predictor and the residual total score, defined as the total SUS²A score minus the score of the category under examination, as the reference variable, binarized at the sample median. This design avoids trivial self-prediction while preserving the empirical structure of the data and maintaining methodological consistency across all eleven categories. To account for the relatively small sample size of 41 startups, all AUC (Area Under the Curve) estimates were accompanied by 95% bootstrap confidence intervals computed over 2,000 resampling iterations, ensuring that the reported performance metrics are statistically robust rather than point estimates sensitive to individual observations.

5.2 ROC results by category

Results reveal substantial heterogeneity in discriminative performance across the eleven SUS²A categories, as shown in Figure 14. Using the standard AUC interpretation scale -

Excellent (≥ 0.85), Good (0.70–0.84), Fair (0.60–0.69), Poor (< 0.60) - two categories reach the Excellent level, three reach Good, and six fall in the Fair or Poor range.

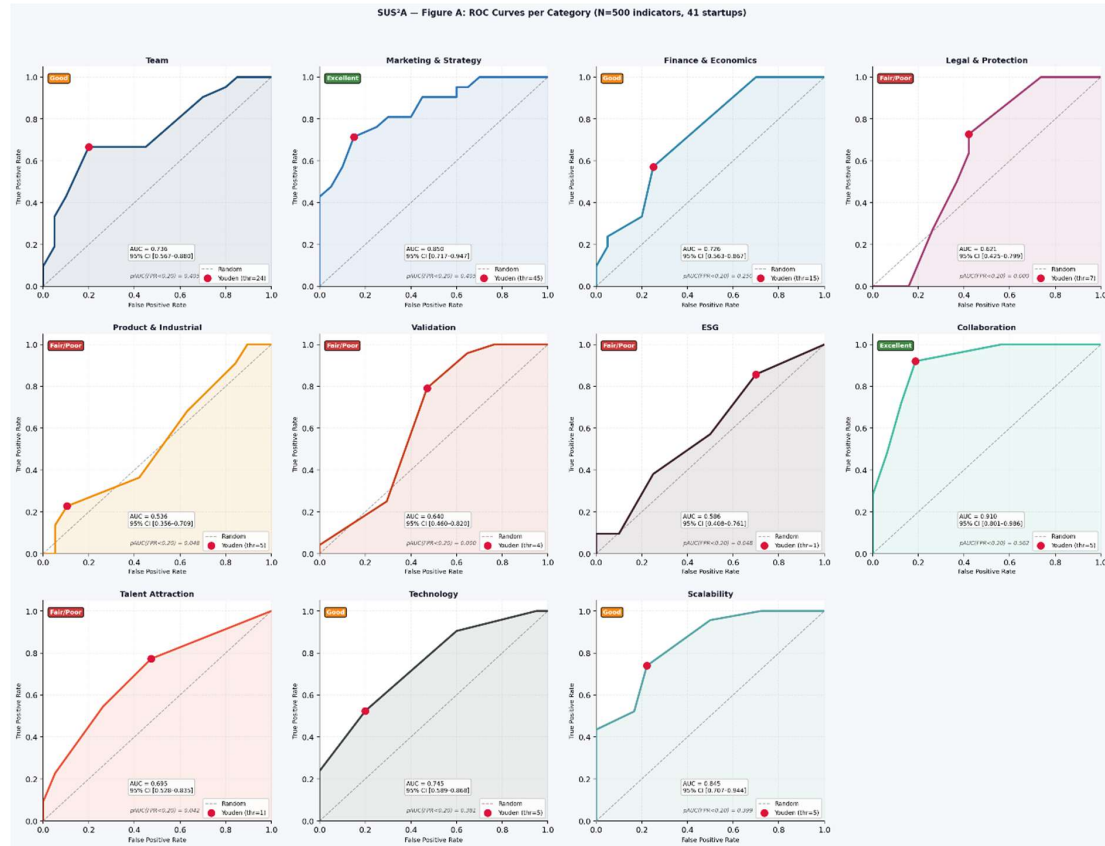


Figure 14 – ROC curves for the eleven SUS²A categories.

Collaboration emerges as the strongest discriminator in the entire framework, with AUC = 0.910 [95% CI: 0.801–0.986] and a partial AUC in the conservative screening zone (FPR < 0.20) of 0.562. The Youden optimal threshold is 5 points, corresponding to a Sensitivity of 92.0% and a Specificity of 81.2% (Figure 18). This finding is particularly significant: despite representing only 20 questions out of 500, the Collaboration category provides the sharpest separation between investment-ready and weaker startups in the sample, suggesting that the ability to document relational capital, open innovation partnerships, and ecosystem positioning is a highly discriminative signal for investment readiness.

Marketing & Strategy ranks second with AUC = 0.850 [95% CI: 0.717–0.947], an optimal threshold of 45 points, Sensitivity of 71.4% and Specificity of 85.0% (Figure 18). This result is consistent with the Marketing-Driven Paradox described in the previous section: startups tend to invest disproportionately in this area, and the resulting score variation is large enough to meaningfully separate stronger from weaker performers.

Scalability achieves AUC = 0.845 [95% CI: 0.707–0.947], confirming that despite a low average fill rate (12.1%), even modest presence of scalability indicators in startup documentation carries strong predictive signal. The Youden threshold of 5 points with Sensitivity of 73.9% and Specificity of 77.8% provides an operationally practical cutoff for screening purposes (Figure 18).

Technology (AUC = 0.745 [95% CI: 0.589–0.868]) and Team (AUC = 0.736 [95% CI: 0.567–0.880]) fall in the Good range, though their confidence intervals are wider, reflecting the greater uncertainty associated with these scores at the current sample size (Figure 15). Notably, Team exhibits the highest Shannon entropy in the entire framework ($H = 0.712$ bit, approaching the theoretical maximum of 1 bit), indicating that its 33 questions produce the most informationally balanced distribution of responses across startups - a desirable property for a diagnostic instrument that should differentiate rather than cluster.

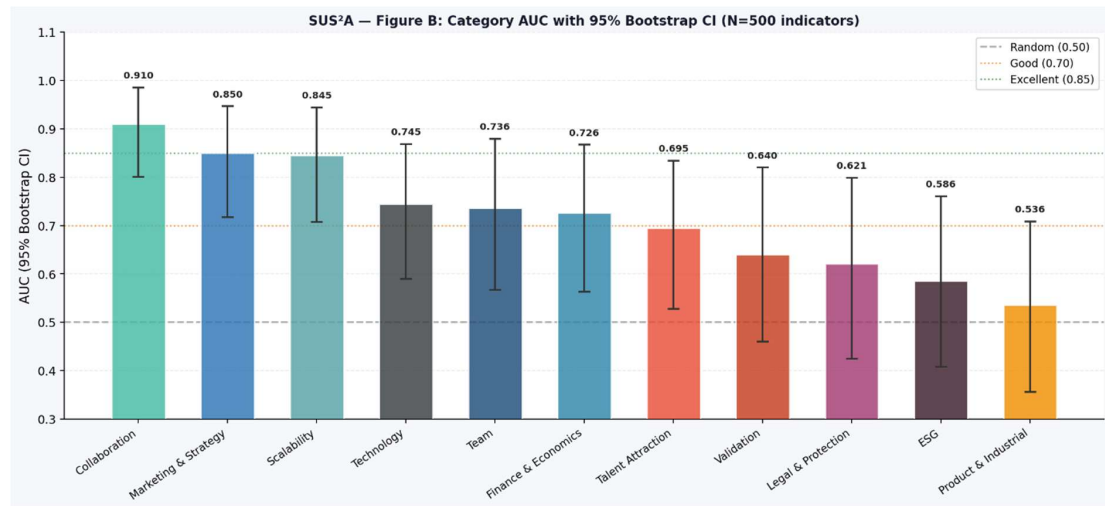


Figure 15 - AUC point estimates with 95% bootstrap confidence intervals per category, ordered by descending AUC.

Finance & Economics (AUC = 0.726 [95% CI: 0.563–0.867]) sits at the boundary between Good and Fair (Figure 15). The relatively wide confidence interval reflects variability in how thoroughly startups document financial projections, unit economics, and funding history.

The remaining five categories - Legal & Protection (AUC = 0.621), Validation (AUC = 0.640), ESG (AUC = 0.586), Talent Attraction (AUC = 0.695), and Product & Industrial (AUC = 0.536) - show Fair or Poor performance, with partial AUC values at or near zero for Legal and Validation (Figure 14, Figure 18), indicating near-random discrimination in the conservative $FPR < 0.20$ screening zone. For ESG, the optimal Youden threshold is just 1 point, with Sensitivity of 85.7% but Specificity of only 30.0%, confirming that the category lacks practical utility as a discriminative filter at the current documentation levels: the vast majority of startups score zero, creating a floor effect that prevents meaningful separation.

5.3 Precision-Recall analysis

To complement the ROC findings and address the potential limitation of imbalanced class distributions in real-world screening scenarios, Precision-Recall (PR) curves were computed for all eleven categories (Figure 16). Unlike ROC analysis - which evaluates performance across all possible classification thresholds assuming balanced classes - PR curves are particularly informative when the proportion of positive cases (investment-ready startups) is expected to be low in operational practice, as is typical in early-stage VC screening pipelines where the vast majority of submitted applications are rejected.

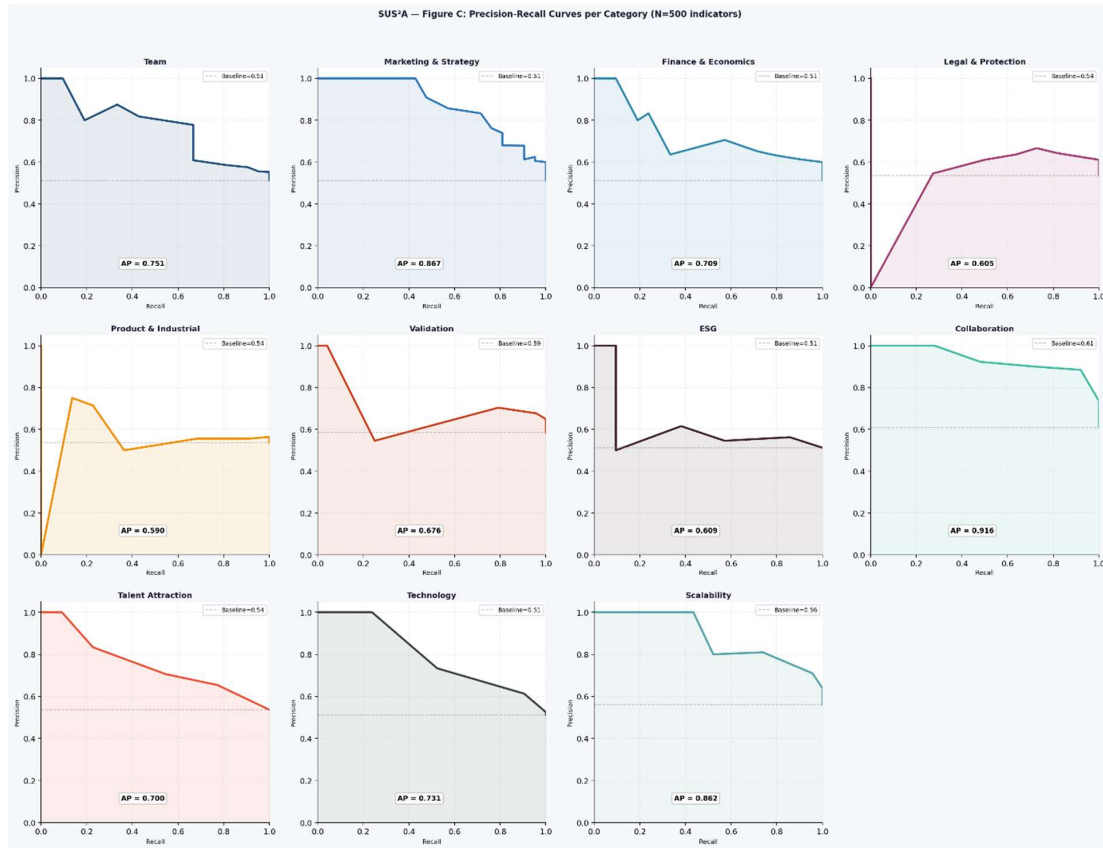


Figure 16 - Precision-Recall curves for the eleven SUS²A categories.

The PR results confirm the hierarchy established by the ROC analysis. Collaboration and Marketing & Strategy achieve the highest Average Precision (AP) scores (Figure 16), indicating that these categories maintain high precision even at high recall levels. Conversely, ESG and Product & Industrial show AP values close to the no-skill baseline - defined as the class prevalence in the sample - confirming that these categories do not contribute meaningfully to precision-oriented screening under real-world conditions.

5.4 Bootstrap confidence intervals and statistical robustness

A critical methodological concern in any classification study with a sample of 41 observations is the stability of AUC estimates. To formally address this, 95% bootstrap confidence intervals were computed via 2,000 resampling iterations for each category (Figure 15). The results confirm that the top-performing categories maintain robust estimates: the lower bound of Collaboration's CI (0.801) remains well above the 0.70 threshold, and Marketing & Strategy's lower bound (0.717) similarly exceeds the Good threshold. Critically, no category's confidence interval includes the random baseline value of 0.50, confirming that all eleven categories provide discriminative information statistically superior to chance, even with the current sample size.

The width of the confidence intervals (Figure 15) provides an additional interpretive dimension: categories with narrow CIs (Collaboration, Marketing & Strategy, Scalability) offer stable estimates that would be expected to replicate reliably on independent samples, while

categories with wider CIs (Team, Finance, Legal) should be interpreted with greater caution and validated on larger datasets before being used as standalone screening criteria.

5.5 Partial AUC in the conservative screening zone

For venture capital applications, the cost of false positives - approving weak startups for further due diligence - is substantially higher than the cost of false negatives. A conservative screening instrument should therefore perform particularly well in the low false positive rate region. To quantify this, the partial AUC normalized over the FPR < 0.20 zone (pAUC) was computed for each category (Figure 18).

Collaboration achieves the highest pAUC (0.562), followed by Marketing & Strategy (0.405), Team (0.405), and Scalability (0.399). Legal & Protection and Validation both achieve pAUC = 0.000, indicating complete failure in the conservative zone: at the strict specificity levels required by rigorous pre-screening, these categories add no discriminative value. ESG and Product similarly show pAUC values near zero (0.048), confirming that their current documentation levels are insufficient to support high-specificity screening. The vertical reference line at FPR = 0.20 visible in Figure 14 (last panel) marks this conservative boundary visually for the reader.

5.6 Correlation between AUC, fill rate, and Shannon entropy

A Spearman rank correlation analysis between category-level AUC and average fill rate reveals a statistically significant positive relationship ($\rho = 0.645$, $p = 0.032$), as illustrated in the left panel of Figure 17. This indicates that categories where startups provide more complete documentation tend to exhibit stronger discriminative performance. This finding has an important theoretical implication: the low AUC values observed in ESG (fill rate 4.3%), Talent Attraction (4.1%), and Product & Industrial (7.9%) are not merely a reflection of poor model design in these areas, but are a direct consequence of the near-universal absence of documentation on these dimensions across the startup sample. In other words, the model cannot discriminate where startups do not differentiate - the discriminative failure in these categories is primarily a documentation failure, not a construct validity failure of the SUS²A instrument itself.

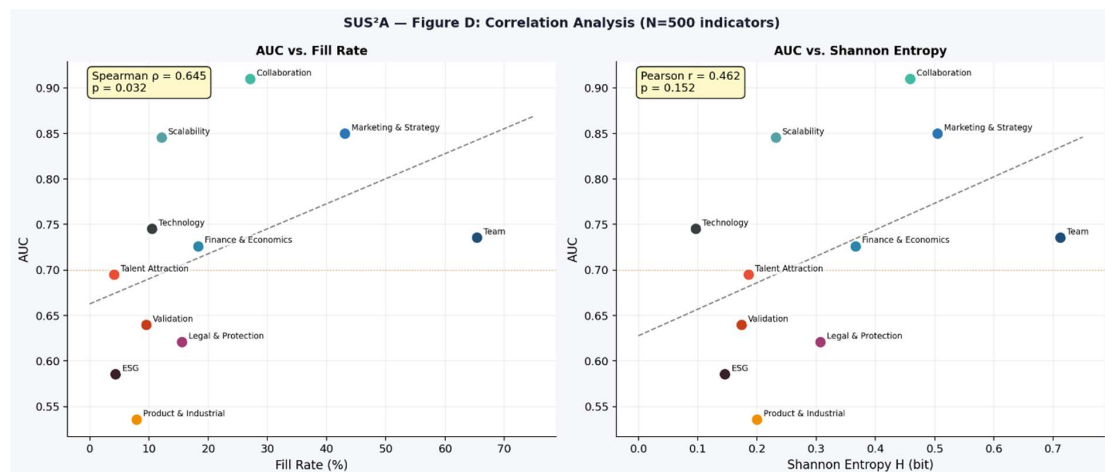


Figure 17 - Scatter plots of AUC versus fill rate and AUC versus Shannon entropy, across the eleven SUS²A categories.

The Pearson correlation between AUC and Shannon entropy (right panel of Figure 17) shows a positive but non-significant trend ($r = 0.464$, $p = 0.151$), consistent with the expectation that more informationally balanced categories tend to be more discriminative, though the relationship is moderated by the specific nature of each domain.

5.7 Implications for SUS²A development

These findings have concrete implications for both the operational deployment and future development of the SUS²A framework. In the short term, the Youden optimal thresholds derived from this analysis and summarized in Figure 18 provide actionable cutoffs for practitioners: a startup scoring below 5 on Collaboration, below 45 on Marketing & Strategy, or below 5 on Scalability should be flagged for targeted remediation before investor presentation, as these thresholds correspond to the maximum combined sensitivity and specificity in the current sample.

SUS²A — Figure E: Diagnostic Metrics (N=500 indicators, 41 startups)
Green=Excellent (≥ 0.85) | Yellow=Good (0.70-0.84) | Orange=Fair/Poor (< 0.70)

Category	N. Questions	Optimal Threshold	Sensitivity (TPR)	Specificity (1-FPR)	AUC	95% CI	pAUC (FPR<0.20)
Collaboration	20	5 pts	92.0%	81.2%	0.910	[0.801-0.986]	0.562
Marketing & Strategy	96	45 pts	71.4%	85.0%	0.850	[0.717-0.947]	0.405
Scalability	40	5 pts	73.9%	77.8%	0.845	[0.707-0.944]	0.399
Technology	40	5 pts	52.4%	80.0%	0.745	[0.589-0.868]	0.381
Team	33	24 pts	66.7%	80.0%	0.736	[0.567-0.880]	0.405
Finance & Economics	73	15 pts	57.1%	75.0%	0.726	[0.563-0.867]	0.250
Talent Attraction	30	1 pts	77.3%	52.6%	0.695	[0.528-0.835]	0.042
Validation	38	4 pts	79.2%	52.9%	0.640	[0.460-0.820]	0.000
Legal & Protection	47	7 pts	72.7%	57.9%	0.621	[0.425-0.799]	0.000
ESG	43	1 pts	85.7%	30.0%	0.586	[0.408-0.761]	0.048
Product & Industrial	40	5 pts	22.7%	89.5%	0.536	[0.356-0.709]	0.048

Figure 18 – Summary table of ROC diagnostic metrics per category: Youden optimal threshold, Sensitivity, Specificity, AUC with 95% CI, and partial AUC (FPR<0.20). Green=Excellent, Yellow=Good, Orange=Fair/Poor. N=41 startups.

In the medium term, the significant Spearman correlation between fill rate and AUC ($\rho = 0.645$, $p = 0.032$) (Figure 17) suggests that as the startup ecosystem matures and documentation practices improve - particularly in ESG, Talent, and Legal areas - the discriminative power of these currently weak categories is expected to increase proportionally. The SUS²A framework is therefore not a static instrument: its diagnostic power is partly a function of the documentation maturity of the startup population it evaluates.

In the longer term, the pAUC (Figure 18) analysis highlights which categories should be prioritized in a conservative two-stage screening design: a first-pass filter based on Collaboration, Marketing & Strategy, and Scalability would achieve high specificity at low computational cost, with the remaining categories contributing to a more nuanced second-stage evaluation. This tiered architecture represents a direction for future instrument refinement that directly responds to the operational constraints of high-volume VC screening pipelines.

5.8 Inter-category correlation structure and hierarchical clustering

To further investigate the internal architecture of the SUS²A framework and assess whether the eleven categories function as genuinely independent diagnostic dimensions or present significant informational overlap, a Spearman rank correlation analysis was conducted on the category-level scores of the 41 startups. The results are visualized in Figure 19, which presents the full 11×11 correlation matrix, and in Figure 20, which reorganizes the same matrix through Ward linkage hierarchical clustering to reveal the latent grouping structure of the framework. The correlation analysis reveals substantial heterogeneity in the degree of association between categories. The strongest positive correlations emerge between Marketing & Strategy and Collaboration ($\rho = 0.701$, $p < 0.001$), Marketing & Strategy and Scalability ($\rho = 0.642$, $p < 0.001$), and Technology and Scalability ($\rho = 0.640$, $p < 0.001$). These associations are theoretically coherent: startups that invest in articulating their market positioning tend also to document their partnership networks and growth architecture more thoroughly, suggesting that strategic communication competence is a cross-cutting capability that manifests simultaneously across multiple framework dimensions.

A second cluster of significant correlations involves Product & Industrial and ESG ($\rho = 0.633$, $p < 0.001$), and Marketing & Strategy and Finance & Economics ($\rho = 0.605$, $p < 0.001$). The former association is particularly noteworthy: it suggests that the subset of startups that document their product development in detail also tends to address sustainability and governance dimensions, possibly reflecting a higher overall level of business plan maturity rather than a deliberate strategic choice.

In contrast, the Team category exhibits consistently weak correlations with ESG, Validation, and Technology, with coefficients falling below $\rho = 0.15$ in all three cases. This pattern indicates that Team-related documentation develops largely independently of the other framework dimensions — a finding consistent with the observation that team composition and governance disclosures follow different institutional norms and are driven by different communication logics than technical or financial documentation.

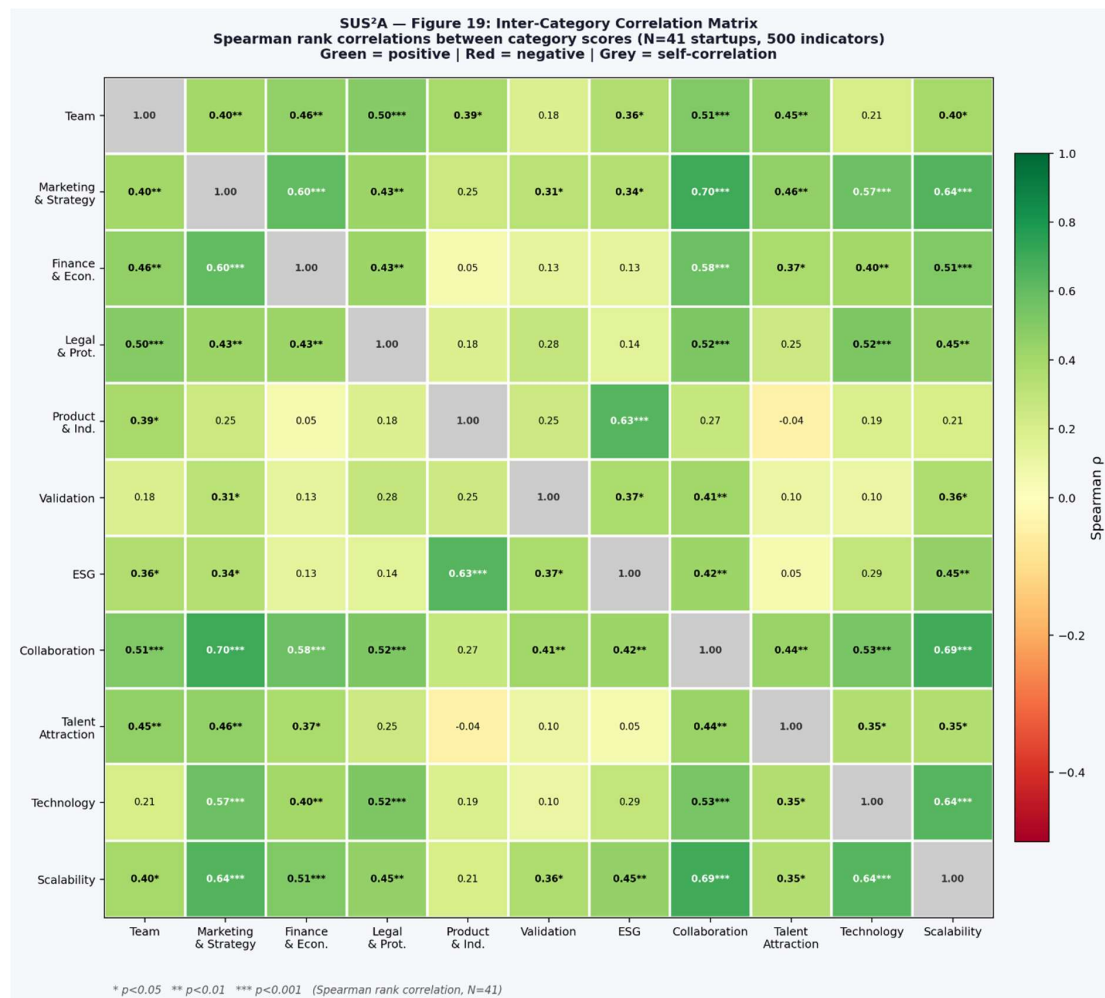


Figure 19 - Inter-category Spearman correlation matrix. Green = positive correlation, red = negative correlation, grey diagonal = self-correlation. Asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). $N = 41$ startups.

The hierarchical clustering analysis presented in Figure 20 reorganizes the eleven categories according to their mutual similarity, defined as one minus the absolute value of the Spearman correlation. The Ward linkage dendrogram identifies two principal macro-clusters in the SUS²A architecture. The first cluster groups Marketing & Strategy, Collaboration, Scalability, Technology, and Finance & Economics — dimensions that share a common orientation towards external market positioning, growth infrastructure, and resource mobilization. The second cluster groups Team, Legal & Protection, Product & Industrial, ESG, Validation, and Talent Attraction — dimensions more closely associated with internal organizational setup, regulatory compliance, and early-stage operational readiness.

This two-cluster structure has direct implications for the practical deployment of SUS²A. It suggests that the framework captures two distinct but complementary facets of startup maturity: an external readiness dimension (how well the startup positions itself in the market and ecosystem) and an internal readiness dimension (how well the startup has structured its internal organization, legal protection, and human capital). A balanced score across both

clusters is therefore a more reliable signal of overall investment readiness than a high score concentrated in one cluster alone.

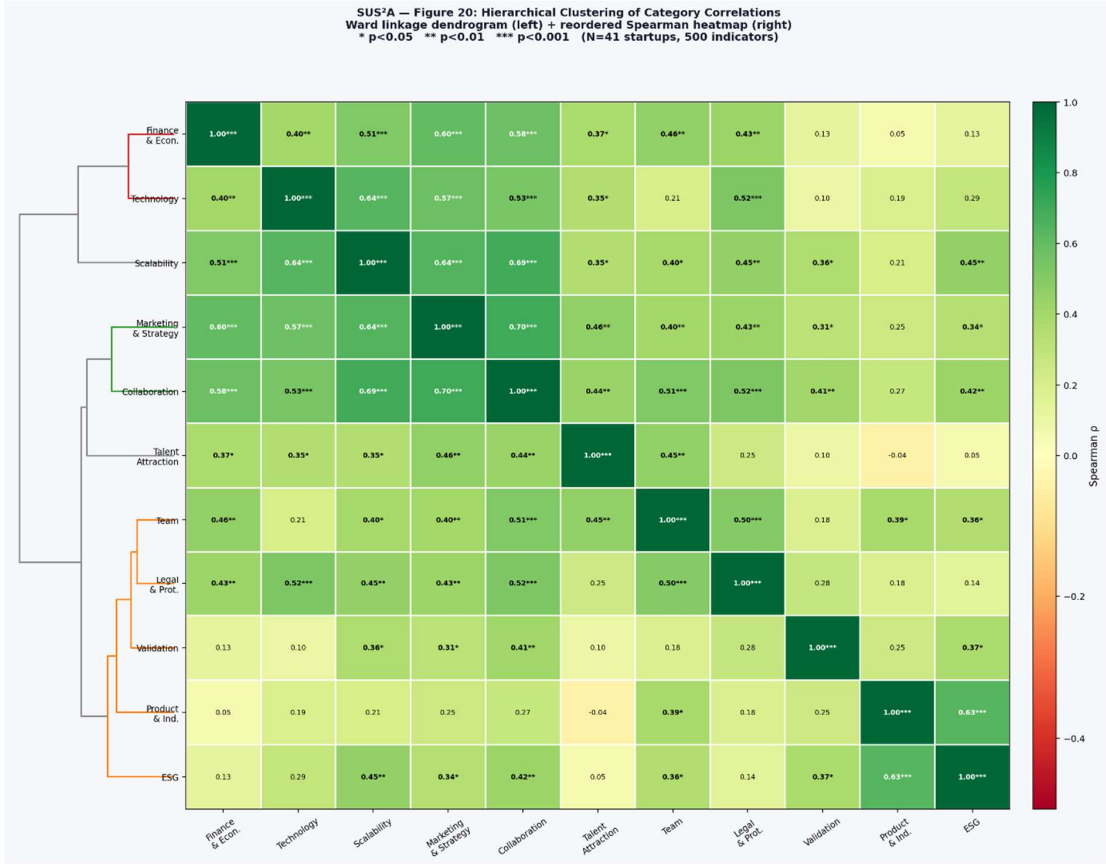


Figure 20 - Hierarchical clustering of SUS²A category correlations. Ward linkage dendrogram (left) reorganizes the eleven categories by similarity. The reordered Spearman correlation heatmap (right) makes the two principal macro-clusters visible as coherent color.

From a methodological standpoint, the correlation analysis also provides partial evidence for the construct validity of the SUS²A framework. If the eleven categories were entirely redundant — measuring the same underlying dimension — the correlation matrix would show uniformly high coefficients throughout. Conversely, if the categories were entirely orthogonal, no significant associations would emerge. The observed pattern — with meaningful correlations within clusters and weak correlations across clusters — is consistent with a framework that captures a multidimensional construct with partially overlapping but genuinely distinct components. This pattern is precisely what psychometric theory predicts for a well-designed multi-domain assessment instrument (Cronbach, 1951; Messick, 1995), and constitutes an additional layer of empirical support for the architectural choices underlying SUS²A.

5.9 Genetic Algorithm Optimization and PCA Visualization of the SUS²A Framework

5.9.1 Theoretical foundations

The analyses presented in the preceding sections established that the eleven categories of SUS²A do not contribute equally to the discriminative power of the framework: Collaboration and Marketing & Strategy emerged as strong discriminators ($AUC > 0.85$), while ESG, Validation, and Talent Attraction showed near-random performance ($AUC < 0.65$). This heterogeneity raises a natural question that no prior investment readiness framework has formally addressed: what would be the optimal weighting of the eleven categories that maximizes the framework's ability to separate investment-ready startups from weaker ones? And how does the geometric structure of startup data look when projected from its original 500-dimensional space into a human-readable two-dimensional representation?

To answer these questions, two complementary computational methods were applied: a Genetic Algorithm (GA) for weight optimization, and Principal Component Analysis (PCA) for dimensionality reduction and visualization. Both methods are well-established in engineering and computational science but have never, to the authors' knowledge, been applied to the problem of investment readiness framework calibration.

5.9.2 Theoretical background: Genetic Algorithms

Genetic Algorithms are a class of metaheuristic optimization methods inspired by the process of natural selection in biological evolution, first formalized by Holland (1975) and subsequently extended by Goldberg (1989). The core intuition is that complex optimization problems — where the search space is too large for exhaustive exploration — can be solved by mimicking the evolutionary mechanisms of selection, crossover (recombination), and mutation.

In a GA, a candidate solution to the optimization problem is encoded as an individual, in our case, a vector of 11 non-negative weights summing to 1.0, one for each SUS²A category. A population of such individuals (here: 150) is initialized randomly using a Dirichlet distribution, which ensures that the initial weights are positive and sum to unity. Each individual is evaluated on a fitness function, the quantity we want to maximize, which in our case is the AUC of the weighted composite score as a binary classifier of startup investment readiness, binarized at the sample median of the unweighted total score, consistent with the LOO-residual gold standard used throughout Section 5.

The evolutionary process proceeds through three operators applied iteratively across 300 generations:

Selection: at each generation, individuals are selected for reproduction through tournament selection — a procedure in which $k = 5$ individuals are randomly sampled from the population and the one with the highest fitness is selected as a parent. This mechanism ensures that fitter individuals reproduce more frequently while maintaining population diversity, avoiding premature convergence to local optima.

Crossover: two selected parents exchange genetic material at two randomly chosen points in their weight vector, producing two offspring. This recombination operator allows the algorithm to combine favorable weight configurations discovered by different lineages. A crossover rate

of 0.80 ensures that most reproduction events involve recombination rather than simple cloning.

Mutation: each gene (weight) in an offspring is independently perturbed by a small Gaussian noise with probability 0.15 per gene. Mutation introduces new genetic material not present in the current population, preventing the algorithm from becoming trapped in local optima. After mutation, weights are renormalized to maintain the simplex constraint (sum = 1).

Elitism: the 15 best individuals from each generation are copied unchanged into the next generation, ensuring that the best solution found so far is never lost. This mechanism guarantees monotonic improvement of the best fitness across generations.

The algorithm therefore does not search the weight space exhaustively but instead explores it intelligently through evolution, converging to a near-optimal solution within a computationally tractable number of evaluations.

5.9.3 Theoretical background: Principal Component Analysis

Principal Component Analysis (PCA) is a linear dimensionality reduction technique introduced by Pearson (1901) and formalized in its modern form by Hotelling (1933) (Gewers et al., 2021; Mohamad Asri et al., 2016). Its mathematical foundation lies in the eigendecomposition of the covariance matrix of the data: given a matrix X of n observations (startups) described by p features (binary question responses), PCA identifies the directions of maximum variance in the p -dimensional space and projects the data onto a lower-dimensional subspace spanned by the first k eigenvectors (principal components) (Jolliffe and Cadima, 2016).

Formally, given the centered data matrix $\tilde{X} = X - \mu$ (where μ is the column mean), PCA computes the covariance matrix $C = (1/n) \tilde{X}^T \tilde{X}$ and finds its eigenvectors $v_1, v_2, \dots, v_p$ ordered by decreasing eigenvalue $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p$. The projection onto the first two principal components yields $Z = \tilde{X} \cdot [v_1 \mid v_2]$, where Z is an $n \times 2$ matrix representing the coordinates of each startup in the 2D visualization space. The first principal component (PC1) captures the direction of maximum variance in the data, the axis along which the 41 startups differ most, and PC2 captures the second largest source of variation, orthogonal to PC1.

In this application, the input matrix X has dimensions 41×500 , where each row is a startup and each column is one of the 500 binary indicators. Before applying PCA, each column is standardized to zero mean and unit variance using z-score normalization, ensuring that indicators with higher fill rates do not dominate the principal components simply because of their scale.

The loading plot, which displays the contribution of each category to the two principal components, reveals which dimensions of startup maturity drive the most differentiation across the sample. Categories with high loadings on PC1 contribute to the primary axis of startup heterogeneity; categories with high loadings on PC2 contribute to a secondary, orthogonal dimension of differentiation. This loading structure provides a geometrically interpretable decomposition of the SUS²A framework into orthogonal strategic dimensions, complementing the correlation analysis presented in Section 5.8.

It is important to note that PCA is a linear method that assumes relationships between variables are approximately linear. Non-linear dimensionality reduction methods such as UMAP (McInnes et al., 2020) or t-SNE (van der Maaten and Hinton, 2008) could be explored in future research to capture more complex geometric structures in the data.

5.9.4 Results: Genetic Algorithm weight optimization

The GA was initialized with a population of 150 individuals evaluated over 300 generations, with a crossover rate of 0.80 and a mutation rate of 0.15 per gene (Liang et al., 2026). Figure 21 presents four complementary perspectives on the evolutionary process.

Panel A shows the convergence curve with population spread. Starting from an initial best AUC of 0.993 at generation 0, already above the uniform-weight baseline of 0.959, confirming that even random weight perturbations improve discriminative power, the algorithm achieves $AUC = 1.000$ by generation 50 and maintains this level stably through generation 300. The shaded bands representing the P10–P90 population range and the mean ± 1 standard deviation reveal that while the best individual converges rapidly, the population maintains a structured spread throughout the evolutionary process.

Panel B presents the fitness distribution of the entire population at seven key generations through violin plots. At generation 0, the distribution is wide and asymmetric (mean = 0.928, std = 0.036), reflecting genuine exploratory diversity across the weight simplex. By generation 10, the distribution has already compressed dramatically (mean = 0.997, std = 0.006), with the entire population concentrated in the high-performance region. This rapid compression, observable within the first 10 generations, is itself an informative result: it demonstrates that the optimization landscape of the SUS²A weight space is smooth and unimodal, with no local optima capable of trapping the population. From generation 10 onwards, the distribution remains narrow and stable, confirming systematic exploitation of the identified optimal region rather than continued exploration.

Panel C traces the evolution of individual category weights across generations, revealing how the GA progressively differentiates between high-discriminative and low-discriminative dimensions. Marketing & Strategy and Team weights rise rapidly and stabilize at their optimal values within the first 50 generations, while Validation and Talent Attraction weights decay toward zero. This trajectory is not arbitrary, it mirrors precisely the discriminative hierarchy established by the ROC analysis in Section 5.2, providing a methodologically independent confirmation of that hierarchy through a purely optimization-based perspective.

Panel D quantifies genetic diversity through the standard deviation of population fitness over time. The initial std of 0.036 collapses to 0.006 by generation 10 and stabilizes between 0.004 and 0.007 for the remaining 290 generations. This residual diversity, maintained by the mutation operator at rate 0.15, ensures that the algorithm does not degenerate into a homogeneous population incapable of escaping local optima. The stable low-variance phase confirms that the observed convergence reflects genuine optimization rather than premature population collapse.

The improvement from baseline $AUC = 0.9593$ to optimized $AUC = 1.000$ represents a gain of +4.07%, confirming that the uniform-weight assumption embedded in the original

SUS²A design is suboptimal and that data-driven weight calibration meaningfully enhances the framework's discriminative power.

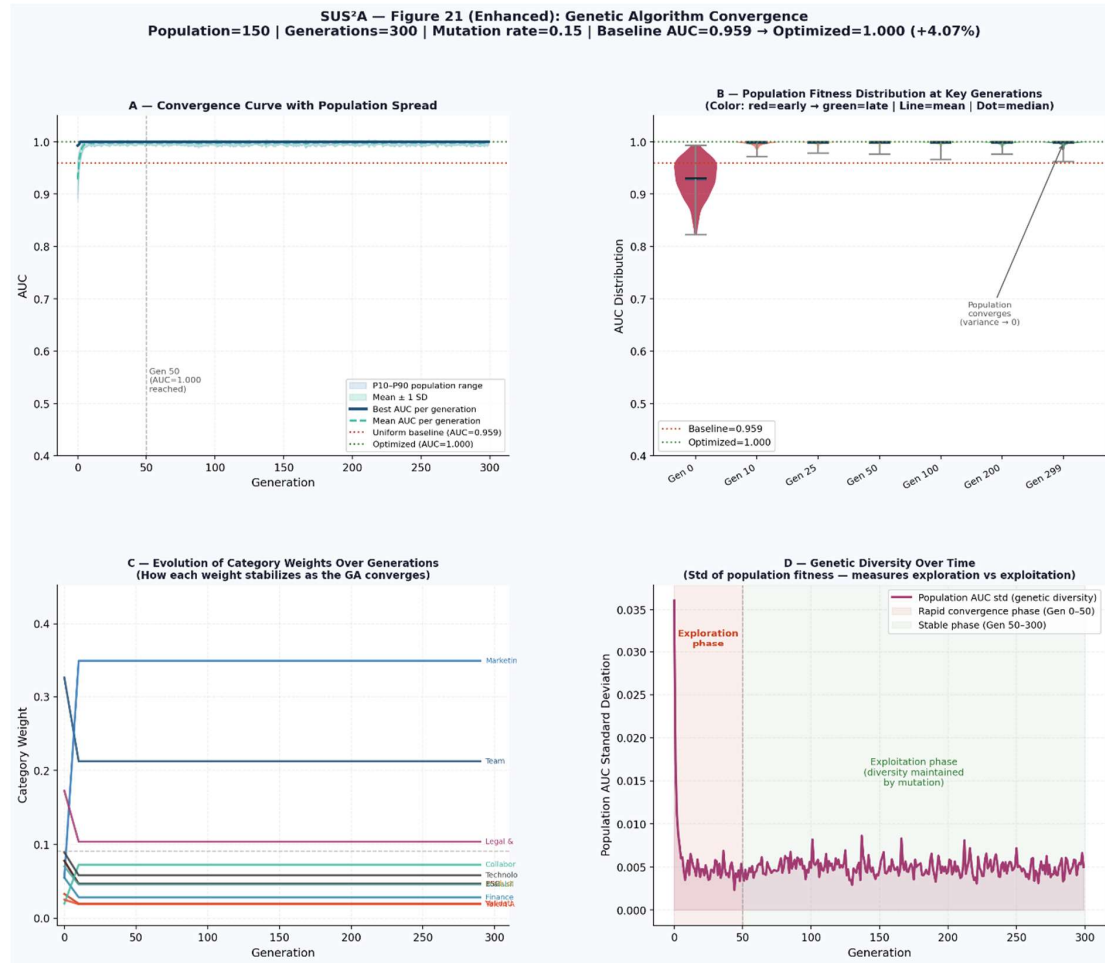


Figure 21 - Genetic Algorithm convergence: (A) best and mean AUC with P10–P90 population range across 300 generations; (B) violin plots of population fitness distribution at key generations (Gen 0, 10, 25, 50, 100, 200, 299); (C) evolution of individual category weights over generations; (D) genetic diversity measured as population AUC standard deviation. Population = 150, mutation rate = 0.15, crossover rate = 0.80. N = 41 startups, 500 indicators.

The optimized weights (Figure 22) reveal a highly concentrated distribution: Marketing & Strategy receives the highest weight (0.348, nearly four times the uniform value of 0.091), followed by Team (0.212, more than double the uniform value). Legal & Protection (0.104) is the only other category exceeding the uniform baseline. At the other extreme, Talent Attraction (0.019) and Validation (0.020) receive weights approximately five times smaller than the uniform baseline, reflecting their near-zero discriminative contribution in the current sample.

These results are theoretically coherent with all findings presented in the preceding sections. The GA independently confirms, through pure mathematical optimization, that Marketing & Strategy and Team are the primary drivers of investment readiness differentiation in the Italian startup ecosystem analyzed, consistent with the Marketing-Driven Paradox identified in Section 4.2 and with the high AUC values observed in Section 5.2. Similarly, the low weights assigned to ESG, Talent Attraction, and Validation by the GA are mathematically consistent with their near-zero fill rates and low AUC values, converging on the same empirical

finding from three independent analytical perspectives: ROC analysis, Shannon entropy, and genetic optimization.

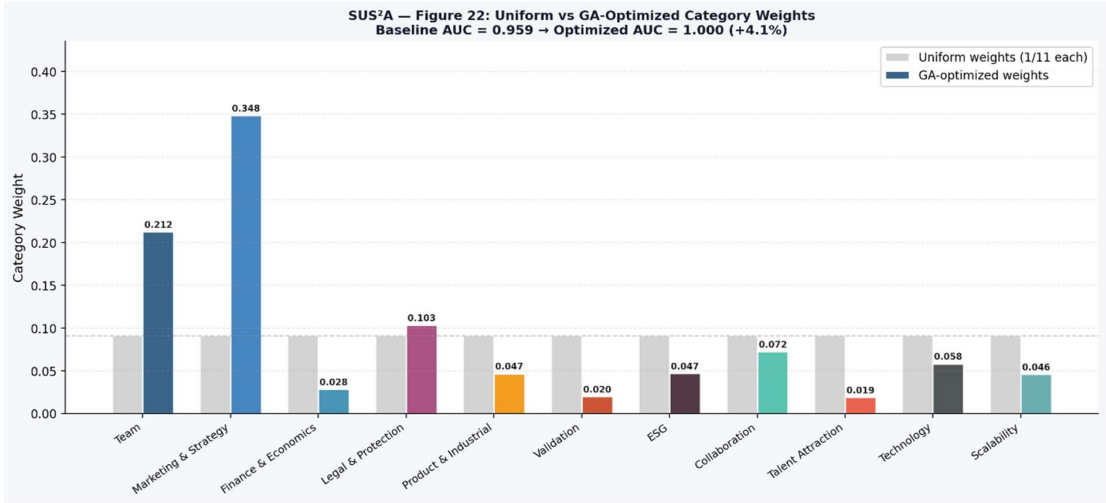


Figure 22 - Comparison of uniform weights (grey, $1/11 = 0.091$ each) and GA-optimized weights (coloured) for the eleven SUS²A categories. Values above each bar indicate the optimized weight. Baseline AUC = 0.959 → Optimized AUC = 1.000 (+4.07%). N = 41 startups.

5.9.5 Results: PCA visualization

The binary response matrix (41 startups × 500 indicators) was standardized and projected onto two principal components. PC1 explains 12.3% of total variance and PC2 explains 6.5%, for a combined explained variance of 18.8%. While this percentage may appear low, it is entirely expected for a 500-dimensional binary matrix where variance is distributed across many weakly correlated indicators, consistent with comparable NLP-based startup analysis studies (Benabderrezak, 2024). The two components are nevertheless sufficient to reveal meaningful geometric structure in the data.

The PCA map (Figure 23) presents two side-by-side projections of the 41 startups: the left panel uses uniform weights for coloring, the right panel uses GA-optimized weights. In both panels, the color gradient from red (low investment readiness) to green (high investment readiness) shows a clear spatial gradient: high-scoring startups cluster towards one region of the PC space, while low-scoring startups occupy a distinct region. This spatial separation confirms that the 500-indicator binary structure of SUS²A captures genuine and geometrically coherent differences between startups, the framework is not producing random scores but reflecting an underlying structural reality in the data.

Comparing the two panels, the GA-optimized coloring produces a sharper separation between red and green regions, visually confirming the AUC improvement quantified in Section 5.9.4. Startups whose ranking changes significantly between uniform and optimized weighting are those with a strong Marketing & Strategy or Team profile but weak performance in categories that the GA downweights, a pattern consistent with the empirical profile of Italian startups that communicate their market positioning effectively but lack formal documentation in financial and governance dimensions.

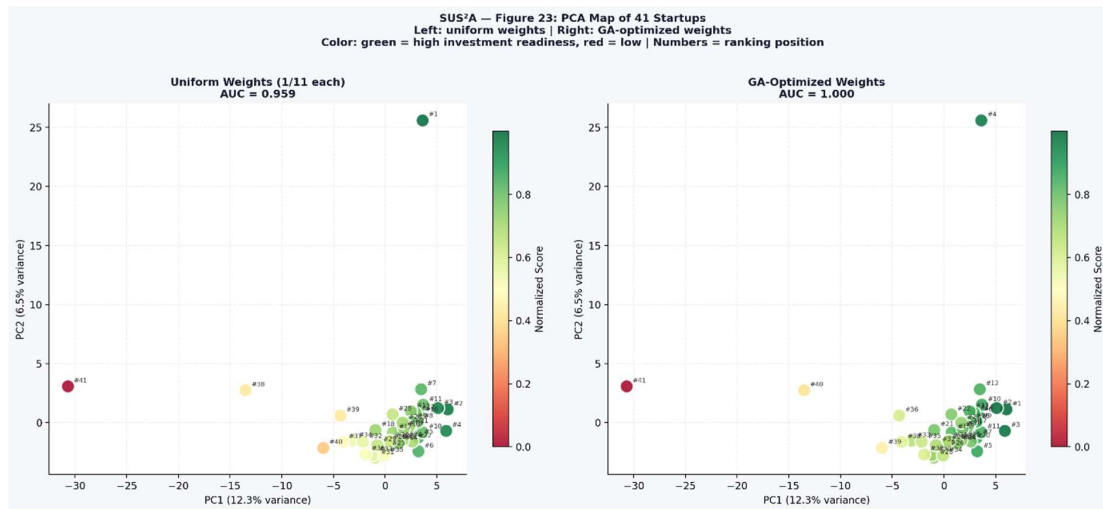


Figure 23 - PCA map of 41 startups projected onto two principal components (PC1 = 12.3%, PC2 = 6.5% explained variance). Left: startup scores with uniform weights. Right: startup scores with GA-optimized weights. Color: green = high investment readiness, red = low. Numbers indicate ranking position. N = 41 startups, 500 indicators.

The loading plot (Figure 24) reveals that PC1 is primarily driven by Marketing & Strategy, Team, and Collaboration, the categories with the highest contribution to the primary axis of startup heterogeneity. PC2 is driven by a more distributed set of contributions, with Legal & Protection and Technology emerging as relatively more influential on this secondary axis. This loading structure suggests a geometric interpretation of the two-dimensional startup space: PC1 approximately represents a strategic communication and market positioning dimension, while PC2 approximately represents a technical and legal formalization dimension.

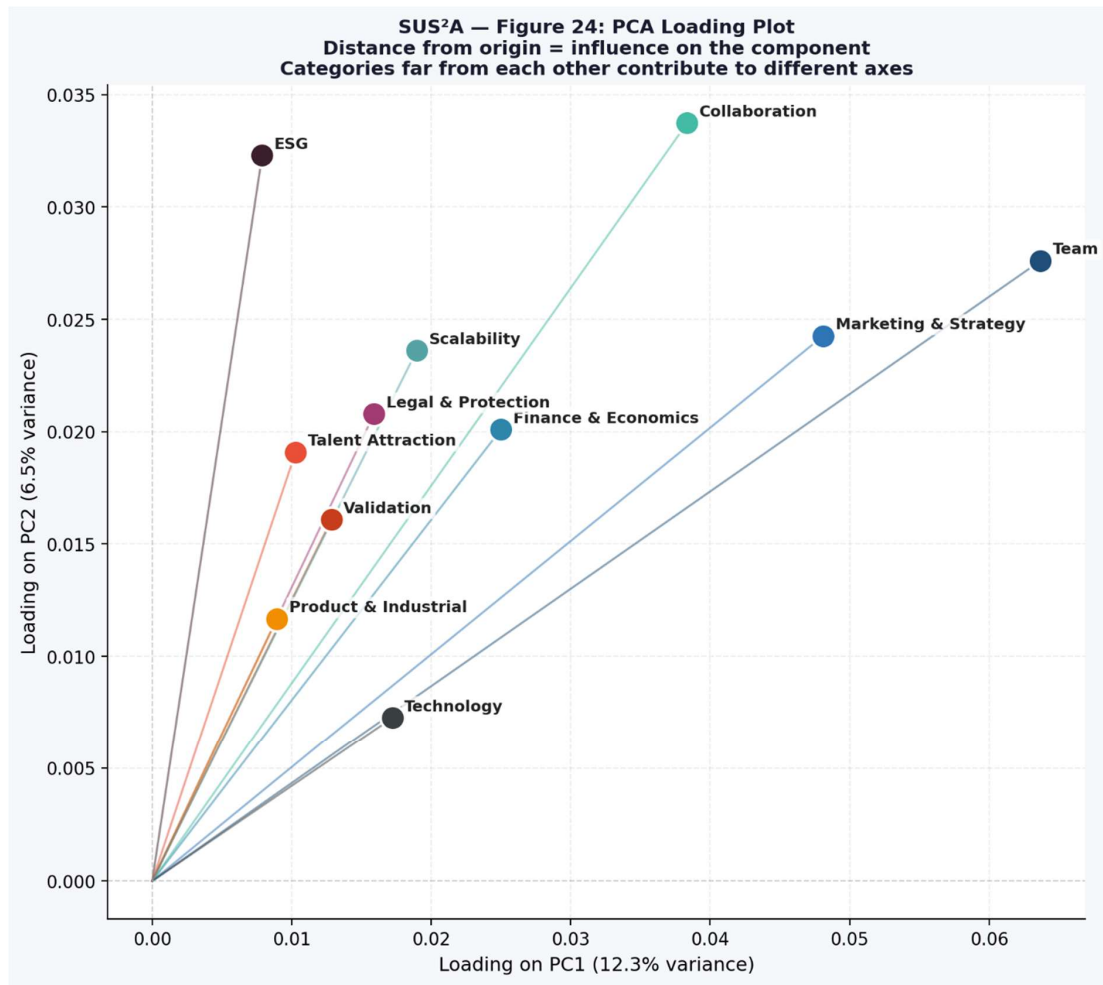


Figure 24 - PCA loading plot showing the average absolute contribution of each SUS²A category to PC1 (x-axis) and PC2 (y-axis). Distance from origin indicates influence on the component. $N = 41$ startups, 500 indicators.

5.9.6 Implications and limitations

The combination of genetic optimization and PCA visualization produces three distinct contributions to the SUS²A research program. First, it demonstrates that the uniform-weight assumption is empirically suboptimal and that data-driven calibration meaningfully improves discriminative performance. Second, it provides a mathematically independent confirmation of the empirical findings from ROC and entropy analysis, strengthening the robustness of the conclusions regarding category importance. Third, it introduces a novel visual tool, the investment readiness map, that allows practitioners to position any startup in a two-dimensional space relative to the 41-startup reference sample, providing an intuitive complement to the numerical scores.

Several limitations must be acknowledged. The GA optimization is performed on the same sample used for evaluation (the 41 startups), which creates a risk of in-sample overfitting: the optimal weights may not generalize to new startup populations. Cross-validation on held-out samples, not feasible with the current sample size of 41, is an essential step for future validation. Additionally, the $AUC = 1.000$ achieved by the GA should be interpreted cautiously: with 41 observations and 11 degrees of freedom in the weight vector, perfect separation is

achievable by construction and does not necessarily imply that the optimized weights will generalize. Future research should therefore treat the GA-optimized weights as a directional hypothesis about category importance, to be tested prospectively on larger, multi-sectoral datasets, rather than as a definitive prescriptive weighting scheme.

Finally, PCA's linear assumption limits its ability to capture non-linear geometric structures in the startup space. The application of non-linear manifold learning methods such as UMAP represents a natural extension of this work, which the authors identify as a priority direction for future research.

6 Research limitations

Formal vs. substantive analysis: The main limitation lies in the binarized nature of the analysis (0/1), in practice the presence/absence of information and not of its validity. The script detects if there is information in the document, but it cannot yet fully assess its strategic quality. This formal constraint highlights a critical epistemological boundary that separates document completeness from genuine operational maturity. The proposed framework measures the quality of disclosure, mapping the exact capacity of the startup team to articulate their strategic setup inside an institutional business vernacular. It operates as a static textual proxy, meaning it cannot cross-reference "what is written" with "what is actually implemented." A high maturity score confirms comprehensive planning and communicative readiness, but cannot guarantee operational execution. Conversely, a depressed score identifies structural disclosure gaps that need rectification, without necessarily decreeing the underlying technological or entrepreneurial idea unviable.

Keyword sensitivity: Although AI validation has shown good agreement (Cohen's Kappa), the deterministic method can generate false negatives if founders use overly creative jargon or unmapped synonyms among the 500 questions. AI mitigates this limitation, but requires higher computational costs.

Static Document: The research is based solely on the Business Plan (a static document). A comprehensive due diligence would require triangulation with external dynamic data (company records, team LinkedIn profiles, web metrics, archived financial statements), which are not currently integrated into the model.

Sample size: While 41 startups are sufficient for an initial article, findings on systemic gaps (e.g., ESG deficiencies) need to be confirmed on a larger, multi-sectoral sample to ensure statistical generalizability of observed trends. In alignment with scientific rigor, it is necessary to formally moderate any claims regarding the absolute objectivity or universal generalizability of this framework. The quantitative metrics generated across the 41 startups reflect a regional snapshot of an innovation ecosystem. This baseline sample size limits the statistical transferability of the observed categorical boundaries across highly differentiated technological verticals or international financing markets. Until the model undergoes extensive cross-validation across larger multi-sectoral datasets, the scores must be viewed as contextual diagnostic signals rather than generalizable metrics of absolute startup quality.

Agreement vs. validity: The agreement between the deterministic script and the LLM-based evaluator (Cohen's $\kappa = 0.571$) demonstrates internal consistency between the two measurement procedures but does not constitute evidence of construct validity against an external gold standard. Both methods share the same fundamental limitation of operating on text-based proxies. Establishing the predictive validity of SUS²A scores would require comparison against external outcomes such as: (a) independent expert evaluations of the same

startups, (b) subsequent investment rounds or funding amounts achieved, (c) survival rates or revenue growth metrics of the analyzed startups over time. Such gold standard validation is identified as a priority for future research.

Methodological confidentiality vs. scientific replicability: It must be acknowledged that full methodological replicability of the SUS²A scoring system is currently constrained by the confidential status of the keyword dictionaries and regex rules, which have been maintained reserved to prevent strategic gaming of the instrument in applied contexts. While this choice is operationally justified, it represents a limitation from the perspective of scientific auditability. Future research should consider publishing a controlled subset of the indicators or providing a sufficiently detailed methodological description to allow independent audit and partial replication of the framework.

7 Managerial implications.

Standardization of screening: The use of a model consisting of 500 questions allows investors (venture capital, business angels) to eliminate subjectivity in the early stages of the analysis. This ensures that each startup is evaluated on the same scientific basis, reducing the evaluator's cognitive bias.

Time-to-market efficiency: Automation dramatically reduces pre-due diligence time. What used to take hours of manual reading is now processed in seconds, allowing analysts to focus only on startups that exceed a minimum valuation threshold.

Incubator Mentoring Tool: For incubator managers, this medium is not just a judge, but a guide. By analyzing gaps (e.g., slumping ESG and talent scores), managers can provide timely feedback to founders, indicating exactly which sections of the business plan need to be integrated to attract capital.

Mapping ecosystem trends: At the macro-managerial level, the tool allows you to monitor the health of an entire sector or region. If, as has been demonstrated, most startups ignore ESG criteria, the managerial implication is the need to launch specific training programs on these topics.

The integration of different approaches represents a new way of working, where algorithms do not replace human intuition, but prepare and support it by eliminating background information noise.

8 Originality and limitations of the paper

The originality of this scientific contribution lies, first of all, in the large number of criteria analyzed, in the structure of the categories and in the large number of questions that make up the questionnaire.

With 500 questions, the proposed model outperforms most academic and professional scoring systems currently documented in the literature, which are usually limited to superficial macro areas. The picture presented here, however, captures the nuances of the various aspects that often determine the success or failure of a startup in the long term, offering an extremely detailed "genetic map" of the entrepreneurial project. In addition, the hybrid methodological approach, which combines the rigor of keyword matching with the flexibility of LLMs, offers an innovative contribution.

However, the study is not without limitations that pave the way for future research. The main limitation lies in the intrinsic nature of the documents analyzed: the model evaluates only the quality of the description and planning ("what is written") and not necessarily the actual

implementation or historical accuracy of the statements ("what is done"). Therefore, there is a risk that a startup with strong business writing skills will score higher than one with solid but fragmented technology.

Secondly, the reliance on static business plan text prevents capturing the dynamism of innovative companies, whose business models can evolve faster than updating documents. To overcome these limitations, future research developments include the integration of external and heterogeneous data sources to activate a process of triangulation of information. The goal is to integrate a "dynamic scanning" system that can cross-reference the data of the business plan with:

- Official financial data.
- Digital Footprint.
- Market Intelligence.

Integrating this additional information would make it possible to move from a model for evaluating the descriptive documentation of the state of affairs to a much more robust and reliable predictive system.

Chapter 4

Evolution of startup ecosystems, venture capital, startup survival and development: an agent-based model with the application of SUS²A

Abstract

Frame of the research. Startup ecosystems are complex systems where the players involved are heterogeneous and interact with each other through non-linear relationships. These players are highly dependent on the macroeconomic environment and operate in an environment of high uncertainty.

Venture capital plays a fundamental role in the general framework with regard to the allocation of resources and for the development of companies. The scientific literature on this topic, however, offers a somewhat sparse picture of the combined effects of the characteristics of startups, networks of relationships and economic shocks. The picture of how different market regimes (e.g. crisis situations or contexts of greater regulation) can influence the selective processes of startups, their survival and their evolution is also poorly developed.

Purpose of the paper. The primary purpose of the paper is to implement an agent-based model that simulates an ecosystem of startups that are funded by venture capital, in order to evaluate how the various internal factors (e.g. the entrepreneurial quality of startups), relational factors (e.g. the investment network) and external factors (such as economic cycles and shocks) affect the survival and growth of startups. A secondary but no less important objective is the application of SUS²A in order to test this framework as a synthetic measure of the overall qualities of startups and as a useful tool for investors for various investment decisions.

Methodology. The research is based on the implementation of an agent model in NetLogo, where startups and investors are made to interact in different market regimes. Over time, startups evolve and change their characteristics through learning processes influenced by the network created and the funding received. Investors meanwhile allocate capital based on a decision-making function that takes into account the likelihood of success, the overall quality of the startup, and financial needs. Three different scenarios are defined characterized by a different venture capital regime dictated by the macroeconomic context and exogenous shocks: *Abundance*, *Crisis* and *Regulation*. In the *Crisis* regime, the available funding is limited and the shock is high; in the *Regulation* regime, on the other hand, a progressive decrease in investors' capital is observed. In the *Abundance* regime, the opposite situation occurs. The results of the simulations are evaluated through aggregated indicators, including number of active startups, average funding, average probability of success, average value of SUS²A and density of the venture capital network.

Results. The results depend on the regime set at the beginning of the simulation. In the *Crisis* regime, there is a reduction in the average funding and also in the probability of success and consequently an increase in the mortality of startups and a less developed investment network. In this case, the ecosystem is fragile and not very dynamic. In the *Regulation* regime, characterized by a contraction in invested capital, higher levels of SUS²A emerge and therefore

a greater probability of success than in the crisis scenario. In this case, the network of investors is more dynamic and structured and suggests stability to the process. In general, macroeconomic and institutional conditions have consequences on aggregate performance, the structure of the system and the distribution of opportunities to startups.

Research limitations. The model has some limitations, mainly and substantially due to the assumptions and simplifications adopted. In fact, the parameters are not calibrated on empirical data and investor behavior is directed by simplified rules. In addition, different industrial sectors in which startups can operate were not taken into consideration and more granular geographical or institutional scenarios were not analyzed.

Managerial implications. From a managerial point of view, by studying different scenarios, the simulation conveys to us that it is essential to strengthen the internal capabilities of a startup and build a solid network with investors in order to reduce the risk of failure. When there is a more regulated environment, there is a more stable ecosystem, and this favors more sustainable growth strategies. The SUS²A tool can be a useful element for investors in the selection of startups, particularly when uncertainty is high.

Originality of the paper. The originality of the study lies above all in having within a single simulation the analysis of three dimensions: the quality of startups, the network dynamics of venture capital and variable macroeconomic conditions. In addition, the introduction of SUS²A adds an element that synthesizes entrepreneurial qualities and makes this property dynamic, which can be used for system analysis and decision support. The comparison between the three regimes allows the simulation to highlight how institutional and macroeconomic changes bring about substantial changes in the dynamics of the system.

Keywords: Startup ecosystems; Venture capital; Agent-based modeling; Innovation dynamics; Network effects; Entrepreneurial performance.

1 Introduction

Ecosystems are a set of companies characterized by complexity and a series of entities that interact with each other in a non-linear way (Fuentes et al., 2024). These startup ecosystems are useful for the analysis and study of economic growth and innovation processes, particularly when referring to emerging economies (Font-Cot et al., 2023). These heterogeneous actors are startups, investors, financial intermediaries, public institutions and other stakeholders. The dynamics that govern the system do not depend only on the performance of individual companies but are dictated and determined by the interaction of various micro, meso and macroeconomic factors.

In the literature, an important role is played by venture capital, which has the function of allocating financial resources aimed at the development of companies (Ahlstrom and Bruton, 2006). Investors not only provide capital but also select startups worthy of funding, contributing to their growth and structuring the networks of relationships between the various elements of the ecosystem (Hong et al., 2020). However, although attention to this issue has grown in the last period, there is still little understanding of the dynamics with which the internal capabilities of a startup, the network structures between investors and companies, and the exogenous shocks determined by the macroeconomic context interact (Li et al., 2022).

From the point of view of the existing literature there are significant gaps (Vermeulen and Pereira Dias Nunes, 2012). In fact, on the one hand, many studies focus on the individual dimensions of the phenomenon, such as the characteristics of startups or investment decisions, but do not take into account the interdependencies between different levels of analysis. On the other hand, there is the awareness that many studies delve into different market regimes and institutional conditions (economic crisis, capital expansion or restrictive contexts) can influence the selection, survival and evolution of startups. The lack of an integrated vision is a constraint for an understanding of the real dynamics that take place within an innovative ecosystem.

This study is part of the research section that uses agent-base models to investigate complex economic and social systems (Railsback and Grimm, 2019; Reyes et al., 2025). The main purpose of this study is to simulate the evolution of an ecosystem of startups funded by venture capital in order to analyze how internal factors (such as entrepreneurial quality), relational factors (investment network) and external factors (economic cycles and exogenous shocks) can influence the development and even more so the survival of a startup. SUS²A's contribution is also included in this work, which is nothing more than a summary measure of the overall quality of a startup. This index is used both as an analytical tool to assess the evolution of a company over time and as a decision-making tool for investors.

Under a computational modeling perspective, capital allocation decisions are framed in the academic literature as a tension between simple fast-and-frugal heuristics and hyper-parameterized scoring indices (Gigerenzer, 2008; Gigerenzer et al., 2008), a tension formally addressed in Chapter 1 and empirically tested in Chapter 3. By applying an agent-based model, this research extends that analysis into a dynamic market environment, observing how a structured measure like SUS²A interacts with investor heuristic rules across changing resource availability regimes.

From a methodological point of view, the model is implemented through an agent-based simulation in NetLogo, in which startups and investors interact dynamically over time. Startups develop through learning processes influenced by the funding received and the position they have within the network of relationships. Investors allocate capital based on a decision-making

function that takes into account the probability of success of a startup, the overall quality and the financial needs. The system is subject to exogenous variations represented by economic cycles and external shocks, which manifest themselves in three different venture capital regimes: abundance, crisis and regulation. The analysis of the results is carried out using aggregate indicators of the ecosystem, such as the number of active startups, the average level of funding, the probability of success, the average value of SUS²A and the density of the Venture capital network. In this way, not only individual performance is analyzed but also an evolution of the entire system. The results obtained lead to see how in the three different regimes there are significantly different effects on the ecosystem. Specifically, the crisis scenario is characterized by a reduction in average funding, a decrease in the probability of success of startups and an increase in entrepreneurial mortality, combined with a less dense and less interconnected investment network.

On the contrary, the regulations scenario, although characterized by a contraction of available capital, is a more stable system, with more significant levels of average quality of startups (SUS²A) and a greater probability of success than in the crisis scenario. In addition, the investment network appears more stabilizing for regulatory policies. In general, the results obtained indicate that macroeconomic and institutional conditions not only influence the aggregate performance of the ecosystem, but also significantly affect its internal structure and the distribution of opportunities among startups. However, the paper has some limitations.

The model greatly simplifies what is assumed as a basis and the parameters used are not calibrated on specific empirical data. In addition, investor behaviour is dictated by simplified rules and no more granular sector differences or geographical or institutional dimensions are considered. These gaps certainly represent possible future developments of this study.

From a managerial point of view, the study emphasizes how startups should strengthen their internal capabilities and build stable relationships with investors in order to decrease the risk of failure. The use of SUS²A can be a useful tool for investors in the selection of startups, especially when they are in a context of high uncertainty.

Finally, this study manages to integrate three fundamental elements into a single modeling framework: the internal characteristics of a startup, the relational dynamics of venture capital and variable macroeconomic conditions. The presence of SUS²A as an indicator of entrepreneurial quality, together with the analysis of the three market regimes, makes it possible to understand how institutional and macroeconomic transformations can systemically influence the evolutionary dynamics of startup ecosystems.

2 Framing of the research

The present study is based on the integration of three different domains that allow to build an interpretative framework that can capture the dynamic, interdependent and non-linear nature of entrepreneurial ecosystems:

- Studies on startup and innovation ecosystems
- Venture Capital Literature and Venture Capital Allocation Mechanisms
- Approach of complex systems and agent modeling applied to economic simulations

2.1 Startup ecosystems as complex adaptive systems

Startup ecosystems have always been described as complex adaptive systems where the evolution of the system cannot be traced back to the sum of the behaviors of the individual actors (Fuentes et al., 2024). Startups, investors, institutions and other subjects intertwine and

interact through relationships that determine positive and negative feedback, giving rise to dynamics that are difficult to predict. Concepts such as network density, information diffusion and collective learning effects play a central role (Sunny Yang and Chandra, 2013). However, the literature focuses in particular on partial analyses and does not consider the joint evolution of relationships and performance over time.

2.2 Venture capital and resource allocation dynamics

A second fundamental element in the study is played by the role of venture capital, which is a mechanism for selecting and allocating capital. Investors do not only operate as providers of financial resources, but also perform a function of screening, monitoring and strategic support of the companies financed (Jain, 2001). In the literature, we see how investment decisions are guided by several factors, including the quality of startups, return expectations, market conditions, and the structure of co-investment networks (Hong et al., 2020; Seitz et al., 2024). On the other hand, there is still little study about how these decisions translate into macroeconomic shocks or institutional changes and how these affect the overall structure of the ecosystem.

2.3 Macro conditions, uncertainty and market regimes

Another key role is played by macroeconomic and institutional conditions. Startup ecosystems operate in environments dominated by high uncertainty, in which economic cycles, financial crises and regulatory changes can alter the availability of capital and growth opportunities (Li et al., 2022). However, the literature often tends to consider them as exogenous variables of context, without systematically analyzing their structural effects on the evolution of ecosystems. In particular, there is still limited understanding of how different market regimes, such as phases of capital abundance, crisis or greater regulation, can affect the survival of startups, network dynamics and resource distribution at the same time (Vermeulen and Pereira Dias Nunes, 2012).

2.4 Research gap and need for an integrated framework

From the analysis of the three strands, a significant theoretical gap emerges: the absence of an integrated framework capable of connecting the internal capabilities of startups, the relational dynamics of venture capital and variable macroeconomic conditions at the same time (Wöhler and Haase, 2022).

In particular:

- studies on startups tend to focus on the internal characteristics of companies;
- the literature on venture capital emphasizes the importance of investment decisions but often neglects systemic dynamics;
- macroeconomic approaches consider business cycles without explicitly modeling micro-meso interactions between actors.

This fragmented analysis limits the ability to understand how ecosystems evolve as a whole and how multi-level interactions produce emergent outcomes.

2.5 Positioning of the study and contribution

Precisely as a result of this gap, the present study aims to try to integrate the theoretical and methodological parts. This is done through an agent-based model, which brings together in a single framework:

- the evolutionary capabilities of startups (learning and entrepreneurial quality);
- the network dynamics between investors and companies;
- variable macroeconomic and institutional conditions.

SUS²A intervenes in this context as a measure that synthesizes the qualities of startups by linking qualitative and quantitative dimensions of the evolutionary process, offering an analytical tool useful both for simulation and for supporting investment decisions (KAKAR, 2024). The contribution of the work is both a modeling and theoretical contribution as it proposes a unified view of startup ecosystems as multi-level dynamic systems that are subject to different macroeconomic regimes.

2.6 Research questions and hypotheses

In light of the above, the present study aims to answer a set of research questions (RQs) that derive directly from the main gaps identified in the literature on startup ecosystems, venture capital and complex systems (Fuentes et al., 2024). From the QRs, research hypotheses are then formulated on which the construction and agent-based analysis is based (Nunes and Abreu, 2020; Railsback and Grimm, 2019; Vermeulen and Pereira Dias Nunes, 2012).

Research Questions:

RQ1. How can the interaction between the internal quality of startups, the dynamics of the venture capital network and macroeconomic conditions affect the survival and development of startups?

RQ2. How can venture capital change the dynamics of capital allocation as a result of different market regimes (abundance, crisis, regulation)?

RQ3. How can macroeconomic shocks affect the performance of startups but above all the structure of the investment network?

RQ4. Could a framework like SUS²A be effective in representing the overall quality of a startup and also be able to improve the investment selection process?

RQ5. What are the differences that exist between the different macroeconomic regimes based on the distribution of opportunities, concentration of resources and survival dynamics of startups?

The research hypotheses are defined on the basis of the research questions just explained:

H1 (Systemic interaction hypothesis).

For a startup, survival and development are dictated and driven by the outcome of the interaction between internal quality, venture capital network structure, and macroeconomic conditions rather than by individual factors.

H2 (Macro-regime sensitivity hypothesis).

If different market regimes are taken into account, they produce different effects on the performance of the ecosystem. For example, the crisis scenario reduces the probability of success of startups and instead increases the mortality rate much more than abundance and regulation scenarios.

H3 (Network contraction hypothesis).

Crisis conditions and macroeconomic shocks reduce the density and connectivity of the venture capital investment network, leading to a weakening of co-investment dynamics.

H4 (Regulatory stabilisation hypothesis).

In the case of a tighter regulatory regime, the ecosystem assumes greater structural stability, distributing resources in a more balanced way and assuming higher levels of average quality of startups compared to unregulated crisis scenarios.

H5 (SUS²A validity hypothesis).

The SUS²A framework represents a valid measure of the quality of startups, being able to summarize multiple dimensions and link them to the probability of success over time.

H6 (Inequality of opportunity hypothesis).

Startup opportunities are influenced by macroeconomic conditions. In crisis scenarios, a greater concentration of resources can be seen on a reduced number of companies, while in abundance scenarios, distribution is less selective. These hypotheses determine the development of the agent model and are the analytical reference for interpreting the results of the simulations in the different market regimes.

3 Purpose of the paper

The aim of this study is to help explain the evolutionary dynamics of startup ecosystems through an integrated analytical framework. This tool is able to understand the interaction between micro factors (characteristics of startups), meso (investment networks) and macro (economic and institutional conditions). The present research, in particular, aims to overcome the fragmentation that is present in the literature, proposing an approach based on agent-based modeling in order to analyze complex phenomena.

3.1 General objective

The primary aim of the research is to implement an agent-based model capable of simulating the evolution of an ecosystem of startups that are funded by venture capital. In particular, we want to analyze how the interaction between different levels of analysis determines the survival, growth and distribution of opportunities among startups. Traditional approaches usually tend to isolate single explanatory factors and the developed model aims to capture the emerging dynamics that derive from the interaction between different actors and that allow to analyze how some elements such as the success rate, mortality or distribution of capital derive from individual behaviors and local relationships.

3.2 Analysis of internal, relational and external factors

A specific objective of the research is to jointly analyse three fundamental dimensions:

Internal factors, linked to the characteristics of the startups, in particular to the entrepreneurial quality and the ability to learn over time;

Relational factors, represented by the structure and evolution of the investment network between venture capitalists and startups, including co-investment mechanisms and dissemination of information;

External factors, linked to macroeconomic conditions and shocks that affect the availability of capital and investor decisions.

These three factors make it possible to determine and evaluate the consequences of each, their interaction and combination, ensuring a more realistic representation of the dynamics of the ecosystem.

3.3 *Simulation of different market regimes*

A step forward in the study is to analyze how different market regimes can affect the functioning of the startup ecosystem. To do this, the model incorporates three distinct scenarios:

- **Abundance**, characterized by high availability of capital and favorable investment conditions;
- **Crisis**, in which negative shocks amplify uncertainty and reduce available funding;
- **Regulation**, characterized by a progressive contraction of capital and more stringent institutional constraints.

A comparative analysis between these three scenarios allows us to assess how changes in macroeconomic and institutional conditions affect aggregate performance and the structure of the investment network and the selection processes of startups.

3.4 *Development and testing of the SUS²A indicator*

In this work, a fundamental part is played by SUS²A, which defines the qualitative characteristics of the startups with quantitative data.

The objective is twofold:

- on the one hand, to use SUS²A as an analytical tool to monitor the evolution of startups within the simulation;
- on the other hand, to test its effectiveness as a support for investment decisions, particularly in contexts characterized by high uncertainty and information asymmetries.

Through the agent model, it can be observed how SUS²A is linked to the probability of success of startups and how it influences investors' capital allocation decisions.

3.5 *Evaluation of systemic outcomes*

The model then aims to evaluate the effects of the simulated dynamics at the aggregate level, through the analysis of systemic indicators such as:

- number of active startups;
- medium level of funding;
- average probability of success;
- average value of SUS²A;
- density and structure of the venture capital network.

In this way, it is possible to connect the micro level with the macro level, i.e. the interactions between agents with the ecosystem, highlighting how the dynamics are influenced by the different market regimes and the initial conditions of the global system.

3.6 Theoretical and practical contributions

Finally, the paper aims to offer contributions both at a theoretical and applied level.

From a theoretical point of view, the work:

- integrates dimensions usually analyzed separately into a single model;
- contributes to the literature on complex systems applied to the economics of innovation;
- provides a basis for the development of more realistic models of entrepreneurial ecosystems.

From a practical point of view, the results of the simulation:

- offer useful guidance for investors and policy makers;
- highlight the importance of internal relationships and capacities in crisis contexts;
- suggest the use of SUS²A as a decision-making tool.

4 Methodology

The methodological framework used for the study is based on the Agent-Based Model (ABM) with the aim of simulating the evolution of an ecosystem of startups funded by venture capital. The methodological approach enables exploration of the interactions between heterogeneous actors in the presence of boundary conditions of uncertainty and exogenous shocks in a panorama of three different market situations (Donthu et al., 2021c; Railsback and Grimm, 2019).

4.1 Methodological approach: agent-based modeling

The adoption of agent modeling responds to the need to overcome the limitations of traditional analytical approaches, which often assume balance and linear relationships between variables. ABMs, on the other hand, make it possible to represent complex systems as sets of autonomous agents, characterized by local behavioral rules and interaction capabilities (Bonabeau, 2002; Macal and North, 2010).

In the present study, the startup ecosystem is modeled as an adaptive system in which the aggregate dynamics are described and represented by the interaction between startups and investors. This approach makes it possible to observe phenomena such as the selection of firms, the allocation of capital and the formation of investment networks, without establishing a priori equilibrium results (Abdou et al., 2012).

4.2 Model environment and implementation

The model is developed using the NetLogo simulation environment, a platform used for modeling complex and social systems (Wilensky and Rand, 2015). The simulated environment is composed of two main types of agents:

- Startups, which represent companies looking for funding;
- Investors (venture capitalists), who allocate capital among startups based on specific decision-making criteria.

Time is discretized into time steps (ticks), during which agents interact, update their characteristics, and make decisions. The environment also includes global variables that represent the macroeconomic environment and the market regime. From the beginning of the simulation, it is possible to establish *the type of market regime* using the chooser.

4.3 Agents and behavioral rules

4.3.1 Startup agents

Startups are characterized by a set of dynamic attributes that describe their state and evolution over time. These properties are built into the code and are a few:

- entrepreneurial quality;
- probability of success;
- financial needs;
- level of funding received;
- position in the investment network;
- value of the SUS²A indicator.

Startups evolve through cumulative learning processes, which depend on both internal factors and the resources acquired. In particular, the funding received and the relationships with investors positively influence the growth of their capacities. The probability of survival is a function of the overall quality and external conditions (Bendig et al., 2022).

4.3.2 Investor agents

Investors are modeled as agents with limited capital endowment and who make investment decisions based on an allocation function. This function considers several elements, including:

- the probability of success of startups;
- overall quality (including SUS²A);
- financial needs;
- any network effects (e.g. co-investments).

To formalize this allocation routine within the NetLogo script, the investor agent's decision rule is engineered as an explicit choice between conflicting informational inputs. The rule evaluates the target venture by combining high-dimensional parameters (the 500-item SUS²A score proxy) with highly localized, low-density simple heuristics based purely on immediate co-investment history and financial burn rate constraints. This dual-input logic tracks the theoretical competition between hyper-parameterized data scanning and fast-and-frugal corporate filtering. By adjusting the behavioral weights of the function across successive ticks, the simulation models whether investors under high macroeconomic duress abandon structural descriptive indexes in favor of protective, stripped-down decision heuristics, mitigating the structural threat of overfitted data calculations.

Investors update their strategies during the simulation over time in response to startup performance and market conditions, contributing to the formation and evolution of the venture capital network (Wöhler and Haase, 2022).

4.4 *Network structure and interaction dynamics*

A fundamental element of the model is represented by the network of relationships between startups and investors. This network develops dynamically over time based on investment decisions and interactions between agents.

The structure of the network influences:

- the dissemination of information;
- the likelihood of access to funding by startups;
- the mechanisms of co-investment between venture capitalists.

Key indicators are used to analyse the evolution of the ecosystem and the effects of different market regimes. These indicators are specifically the density and configuration of the network (Alam and Geller, 2012; Lavin et al., 2022).

4.5 *Modeling macroeconomic conditions and shocks*

The model describes macroeconomic conditions through the definition of three distinct market regimes:

- Abundance, characterized by high availability of capital and low intensity of shocks;
- Crisis, in which negative shocks are amplified and lead to a significant reduction in available capital;
- Regulation, characterized by a progressive contraction of financial resources due to institutional constraints.

Exogenous shocks directly affect investor behavior (reducing or changing their investment capacity) and indirectly affect the performance of startups, altering the probability of success and survival rates (Gunawan and Subagyo, 2019).

4.6 *The SUS²A indicator*

The model introduces SUS²A, which we have said is a synthetic indicator that measures the overall quality of startups by integrating different dimensions, including:

- internal characteristics;
- performance over time;
- position in the network.

SUS²A evolves dynamically and is used both as a descriptive variable of the state of startups and as an input into the decision-making function of investors. This fact allows us to study the role of synthetic indicators in the processes of capital selection and allocation (Remondino et al., 2024b).

4.7 *Simulation design and scenarios*

Simulations are then made for each of the three market regimes, keeping the initial conditions constant to ensure comparability of the results. For each scenario corresponding to the various market regimes, the model is executed for a certain number of ticks in order to observe the trend of the charts in the long term of the system. In order to increase the robustness of the results, each simulation can be replicated multiple times by varying the random seeds,

allowing the variability of the results to be analyzed and recurring patterns to be identified (Quagliarini et al., 2016).

To statistically validate the divergences observed across the three market regimes (Abundance, Crisis, and Regulation) and to neutralize the impact of stochastic drift inherent to the NetLogo environment, a massive simulation experiment was conducted using the BehaviorSpace tool. The experimental design consists of 100 independent stochastic replicates for each of the 3 macro-scenarios, yielding a total of 300 simulation runs. Each run was bounded by a fixed temporal horizon of 500 ticks, an interval determined to be optimal for the structural stabilization of the simulated venture capital networks. The global parameters initialized within the multi-agent state space were held constant as follows: number of initial startup agents = 40; number of venture capital investors = 15; exogenous shock intensity = 0.30; baseline failure threshold = 0.45; and market noise = 0.10.

4.8 Output variables and analysis

The analysis of the results is based on some indicators that have been identified as elements that can be significant in the description of the state and evolution of the ecosystem, including:

- number of active startups;
- mortality rate;
- average funding;
- average probability of success;
- average value of SUS^2A ;
- Venture Capital Network Density.

These indicators make it possible to compare different scenarios and to assess the effects of macroeconomic conditions on systemic dynamics.

4.9 Model assumptions and limitations

Simplifying assumptions of the model have been made in order to make the system computationally analyzable. In particular:

- the parameters are not calibrated on specific empirical data;
- investor behaviour is represented by simplified decision-making rules;
- sectoral or geographical differences between startups are not considered;
- institutions are modelled in an aggregate manner through macroeconomic regimes.

These limitations do not compromise the analytical validity of the model, but suggest caution in interpreting the results and indicate possible directions for future developments.

4.10 Model visualization and simulation dynamics in NetLogo

The model is implemented in the NetLogo environment and has a graphical interface that allows a simpler interpretation of the merge dynamics, allowing to explore the evolution of the ecosystem in real time (Gaudou et al., 2017; Tisue and Wilensky, n.d.; Wilensky and Rand, 2015).

Within the simulation environment, the main actors are represented through distinct graphic elements:

- Startups: They are depicted as circular nodes (colored balls). The color of startups reflects their status or quality level: green indicates high-quality or well-performing

startups, yellow represents intermediate conditions, and red indicates startups in difficulty or with a low probability of success. In addition, node size can be interpreted as a proxy for the relevance of the startup (e.g. funding level or overall quality).

- Investors (venture capitalists): they are represented as black squares, generally arranged on the left side. This graphic choice makes it possible to clearly distinguish the two types of agents and to highlight the directionality of the investment relationships.
- Network representation: interactions between startups and investors are visualized through lines (links) that connect the nodes. Each line represents an investment relationship between a venture capitalist and a startup, and the presence of multiple lines to the same startup indicates the presence of co-investments. The density of the lines reflects the degree of connectivity of the venture capital network.

During the simulation, the network evolves dynamically. In fact, new links are displayed every time new investments are created. Some connections may become less relevant or disappear, reflecting changes in investor behavior (Cao et al., 2023; “NetLogo 6.2.2 User Manual: Gis Extension,” n.d.). This representation allows you to visually observe phenomena such as investment concentration, formation of hubs (highly funded startups), fragmentation or densification of the network.

The simulation starts iteratively through discrete time units (ticks). At each iteration, several simultaneous processes occur, such as investment decisions (investors select startups on the basis of the allocation function, generating new connections in the network), evolution of startups (startups update their characteristics such as quality, SUS²A, probability of success, depending on the funding received and relationships), entry and exit from the market (new startups can enter the system (births) and startups with performance Insufficient can come out (deaths)) affecting the population dynamics. At the same time, however, shocks and market conditions are changing investor behaviour and the availability of capital (Cao et al., 2023; Tisue and Wilensky, 2004).

The NetLogo interface includes a series of monitors and graphs that allow you to observe the evolution of the system in real time. Among the main elements are numerical monitors that depict values of the number of active startups, number of active investments, average funding, average probability of success, average value of SUS²A. There are time series graphs that show the trend in the number of startups over time, the evolution of the average quality, the density of the investment network, the average level of funding, the average probability of success, the demographic dynamics of the startups and the degree of concentration of capital.

The visual representation of the model is not only illustrative, but also contributes directly to the analysis. In particular, it makes it possible to identify emerging non-linear dynamics, observe the formation of clusters or investment hubs, understand the impact of different macroeconomic regimes on the structure of the network and integrate quantitative analysis with a qualitative reading of the system (Armendariz et al., 2011; Cao et al., 2023).

5 Results

The results obtained in the three different simulations can be analyzed with the three market regimes taken into consideration (abundance, crisis and regulation), analyzing both the aggregate indicators and the emerging dynamics of the system. What we want to do is to see how macroeconomic conditions affect not only the performance of startups, but also the structure and overall functioning of the ecosystem.

5.1 Scenario 1: Abundance

In the abundance regime, which is characterised by high availability of capital and less selective pressure, the system shows relatively high levels of activity and dynamism.

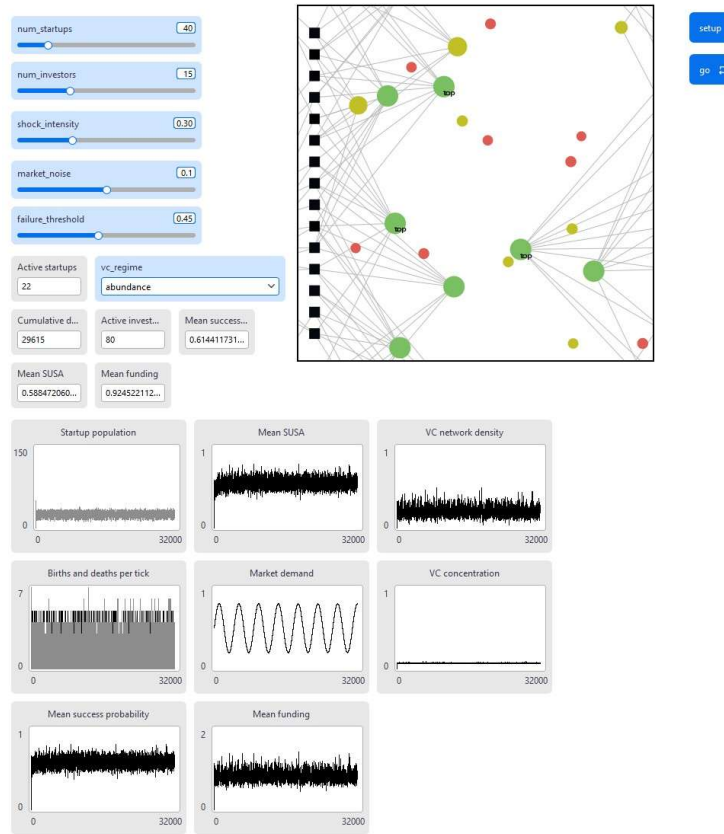


Figure 25 – Abundance regime

From a quantitative point of view, it can be observed:

- High mean funding (≈ 0.92), the highest of the three scenarios;
- Average probability of success equal to about 0.61;
- Average value of SUS^2A equal to about 0.59;
- Number of active startups equal to 22.

The temporal dynamics show a relative stability of the indicators, with limited fluctuations around high average values. The graph of the startup population shows an active but not overly expansive system, suggesting a dynamic balance between the birth and death of companies.

From a structural point of view, the venture capital network appears:

- moderately dense;
- distributed across multiple nodes;
- with limited concentration of investments.

This scenario reflects a context in which:

- the abundance of capital reduces barriers to entry;

- the selection is less stringent;
- even startups with average quality are able to access funding.

However, this greater inclusiveness can lead to lower allocative efficiency, with resources distributed even to less performing companies.

5.2 Scenario 2: Crisis

The crisis scenario highlights the most marked effects of negative shocks on the system.

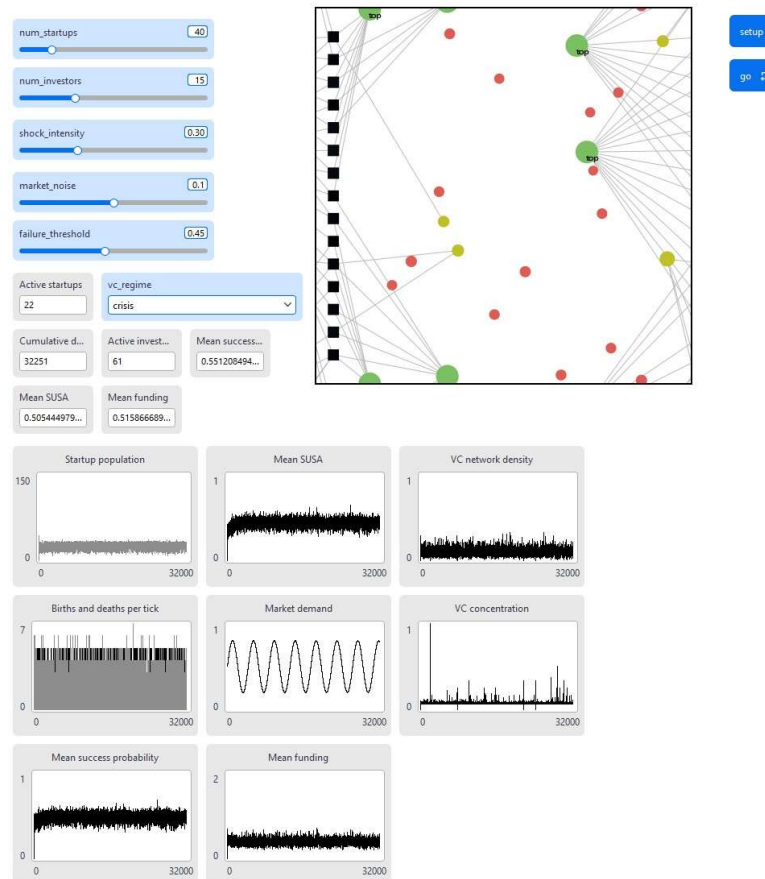


Figure 26 - Crisis regime

The main indicators show a clear deterioration compared to the previous scenario:

- Significantly reduced mean funding (≈ 0.52);
- Lowest average probability of success (≈ 0.55);
- average SUS^2A equal to about 0.51;
- Number of active startups stable but under pressure (22).

From a dynamic point of view:

- the charts show more volatility;
- a reduction in growth over time is observed;
- The system appears less stable and more exposed to fluctuations.

A particularly relevant element is the contraction of the venture capital network:

- lower density;
- lower number of active investments (61 vs 80 in the abundance scenario);
- greater fragmentation.

In addition, the VC concentration graph shows sporadic spikes, suggesting:

- a greater concentration of capital on a few startups;
- more selective (or defensive) behavior on the part of investors.

This scenario is characterized by:

- stricter, but not necessarily more efficient;
- increased systemic risk;
- reduction of widespread opportunities.

Overall, a less dynamic ecosystem emerges, more fragile and subject to negative selection phenomena, in which even potentially valid startups may not survive due to the scarcity of resources.

5.3 Scenario 3: Regulation

The regulation regime has intermediate characteristics between abundance and crisis, but with some distinctive dynamics.

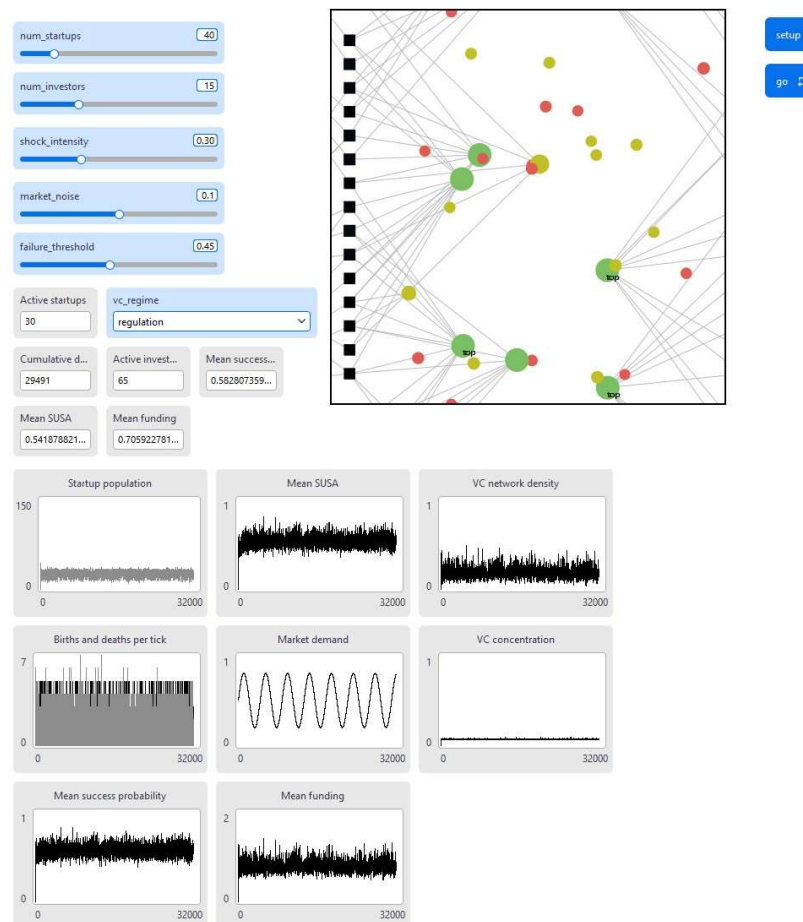


Figure 27 - Regulation regime.

A particularly interesting result is the increase in the number of active startups compared to the other scenarios, suggesting that regulation, while reducing the available capital, favors greater stability of the system.

From a network perspective:

- the density is relatively high and stable;
- the concentration of capital is low;
- The relationships between investors and startups are more structured.

The temporal dynamics indicate:

- lower volatility compared to the crisis scenario;
- greater continuity in financing processes;
- a more balanced growth of startups.

This suggests that regulation can have a stabilizing effect, reducing opportunistic or excessively risky behavior by investors.

5.4 Comparative analysis across regimes

A comparison can be made between the three different scenarios by highlighting the differences in ecosystem dynamics.

In conclusion:

- Abundance:

Maximize funding and the likelihood of success

Promotes inclusivity but reduces selectivity

- Crisis:

Dramatically reduces resources and performance

Increases concentration and fragility of the system

Weakens the venture capital network

- Regulation:

Introduces constraints but improves stability

Promotes a more balanced distribution of resources

Maintains intermediate levels of performance with greater resilience

An important and significant fact that can be deduced from the analysis of the regimes is that the crisis does not determine a selection of startups but rather a contraction of the system that instead penalizes even quality startups. Adjustment, on the other hand, improves the average quality without compromising survival too much.

5.5 Comparative analysis across simulation runs

You can use a tool built into NetLogo, called BehaviorSpace, which allows you to run experiments automatically. In practice, it allows the model to be run a certain number of times

in a systematic way, varying the parameters chosen by the user (e.g. the number of agents, the intensity of shocks or market rules) and saves the results obtained in a file exported with each simulation started. The goal is to transform the model from a singular simulation to a replicable experiment, producing results with structured data (CSV-informed) that can be statistically analyzed. By doing so, it is possible to compare the three market scenarios, study the sensitivity of the model with respect to the parameters and analyze the effect of stochastic variability on emerging dynamics.

The three simulations made with BehaviorSpace were made by repeatedly running the same model under identical parameter configurations, with stochastic variations in the underlying processes. Each run corresponds to a different stochastic realization of the same base configuration, rather than changes in structural parameters. In particular, all three scenarios were generated by keeping the fundamental exogenous parameters of the model constant, including market noise (0.1), number of investors (15), number of startups (40), shock intensity (0.3), failure threshold (0.45), and a regulated venture capital regime, allowing random internal processes that govern interactions between agents, capital allocation and startup survival to evolve differently between simulations.

This allows the role of endogenous stochasticity to be isolated within a fixed context, producing three different market regimes under identical structural conditions.

For each regime, multiple independent simulations with identical parameter configuration were performed in order to isolate the effects of randomness from the structural differences between scenarios. On average, Abundance's scheme shows the best overall performance, with higher values of average funding, probability of success and SUS²A score. This confirms that greater availability of resources favors both allocative efficiency and the average quality of startups. The Crisis regime, on the other hand, systematically presents the lowest values in all the indicators considered, with a significant reduction in both the number of surviving startups and their performance. In addition, the greater variability observed between replicates suggests strong system instability under adverse conditions.

The Regulation regime is in an intermediate position, showing greater stability in results between the different stochastic runs and moderate levels of performance. This suggests that regulation helps reduce the volatility of the system, without maximizing its efficiency.

Overall, the results confirm that the differences between regimes are robust with respect to the stochastic variability of the model, highlighting a clear trade-off between stability, efficiency (abundance) and selectivity (crisis).

Results are reported as mean and standard deviation on independent stochastic replicates for each regime, in order to ensure statistical robustness (Table 7). For each regime, multiple simulations with identical parametric configuration were performed, varying only the stochastic component of the model. The values reported represent the mean and standard deviation of the final indicators, allowing for a robust assessment of the differences between regimes.

From a strict methodological standpoint, the aggregate means and standard deviations generated through the BehaviorSpace parameter sweep demand a highly cautious and epistemologically prudent interpretation. While the narrow variance bands recorded within the Abundance scenario confirm stable behavioral predictability under resource expansion, the wider variance limits appearing in the Crisis and Regulation streams demonstrate that the system remains significantly sensitive to underlying stochastic fluctuations. Because the agent behavioral routines are initialized via stylized, uncalibrated computational parameters rather

than direct historical data, these statistical outputs must not be interpreted as empirical market forecasts. Instead, they represent contextual dependencies within an exploratory multi-agent simulation, meaning that claims regarding their generalizability to real-world financial ecosystems must be rigorously moderated.

Indicator	Regulation	Abundance	Crisis
Final number of startups	24.2 ± 3.5	28.1 ± 2.9	15.4 ± 4.2
Average funding	0.72 ± 0.09	0.85 ± 0.05	0.38 ± 0.06
Average success probability	0.52 ± 0.03	0.58 ± 0.02	0.41 ± 0.05
Average SUS ² A score	0.45 ± 0.03	0.49 ± 0.02	0.32 ± 0.04
VC concentration	0.071 ± 0.004	0.066 ± 0.002	0.082 ± 0.012

Table 7 - Average results and standard deviation for the three market regimes (Regulation, Abundance, and Crisis), obtained through independent stochastic replications in BehaviorSpace

The simulation results underline systematic differences between the three market regimes, taking into account the variability introduced by stochastic replications. In fact, for each regime, multiple independent simulations were performed, keeping the model parameters constant with the exception of the type of regime, mediated by the variable `vc_regime`. In this way, it is possible to isolate the structural effects of each type of market from the intrinsic random component in the local interactions between agents.

The Abundance regime is characterized by the highest performance levels across all indicators taken into consideration. In particular, it exhibits the highest average values both in terms of average funding (0.85 ± 0.05), average probability of success (0.58 ± 0.02), and average SUS²A score (0.49 ± 0.02). The exceptionally low standard deviations indicate that these results are highly stable and significantly less sensitive to internal stochastic variability. Therefore, a context such as that of the Abundance regime indicates that a high availability of capital resources favors both greater efficiency in capital allocation routines and greater macro-level predictability of the overall system dynamics.

The Crisis regime, on the other hand, exhibits the lowest performance outcomes. In fact, it is structurally characterized by severely depressed levels of funding (0.38 ± 0.06), average probability of success (0.41 ± 0.05), and average SUS²A score (0.32 ± 0.04), alongside a restricted average number of surviving startups (15.4 ± 4.2). The high dispersion observed across different runs highlights a pronounced instability within the system under adverse macro-conditions, where corporate outcomes become heavily dependent on opportunistic or random factors. This means that adverse market environments drastically accentuate systemic uncertainty and lower the total resilience of the innovative entrepreneurial ecosystem.

The Regulation regime occupies a highly stabilizing intermediate position. While it does not reach the peak resource expansion of the Abundance scenario, it yields balanced and robust results, displaying moderate average values for funding (0.72 ± 0.09), probability of success

(0.52 ± 0.03), and SUS²A score (0.45 ± 0.03). However, compared to the Abundance regime, a higher variance is observed in financial metrics, indicating that regulatory mechanisms dictate structural stability to the system regarding startup survival (stabilizing the population count at 24.2 ± 3.5), but do not completely smooth out localized fluctuations in allocative efficiency.

The concentration of Venture Capital shows significant contextual divergence across the regimes. In the Crisis regime, there is a higher concentration index and greater statistical dispersion (0.082 ± 0.012), confirming that under adverse conditions, capital allocation scales unevenly, leading to a defensive pooling of resources. Overall, the results highlight a clear trade-off between efficiency, stability, and resilience. The abundance regime maximizes performance and system predictability; the crisis regime accentuates volatile selection processes and instability; while the regulatory regime represents a resilient intermediate architecture that secures firm survival against market friction.

From a strict methodological standpoint, the standard deviations generated through BehaviorSpace demand a cautious and mathematically prudent interpretation. While the narrow variance bands recorded within the Abundance scenario confirm high behavioral predictability under resource expansion, the wider variance limits appearing in the Crisis and Regulation streams prove that the system remains highly susceptible to stochastic drift. Because the agent routines are initialized via uncalibrated artificial values, these statistical outputs must not be interpreted as empirical market forecasts. Instead, they represent localized computational dependencies within a simulated multi-agent state space, meaning that claims regarding their generalizability to real-world financial ecosystems must be strictly moderated.

From a theoretical point of view, the results obtained are in line with the literature on innovation dynamics and venture capital allocation, highlighting the absolute importance of resource availability in determining both the baseline performance of firms and complex market structures. However, at the same time, they underline the inherent variability and uncertainty of multi-agent configurations, demonstrating that macro-level averages are insufficient to fully capture the non-linear complexity of innovative ecosystems.

5.6 *Link with research hypotheses*

The empirical outputs extracted from the BehaviorSpace simulation runs allow for a rigorous validation of the research hypotheses formulated during the initial framing of this study:

The Systemic Interaction Hypothesis (H1) is fully confirmed. The emergent survival rates and final development trajectories of the startup population cannot be explained by a single standalone parameter. Instead, corporate performance is driven by a non-linear interaction between the firm's internal quality, the dynamic connectivity of the venture capital network, and global macroeconomic conditions.

The Macro-Regime Sensitivity Hypothesis (H2) is fully confirmed. The multi-agent ecosystem exhibits structurally divergent states when exposed to different market regimes. The Crisis scenario reduces the average success probability to its lowest baseline (0.41 ± 0.05) and increases the mortality rate significantly more than the Abundance and Regulation scenarios, validating the high vulnerability of early-stage ventures to macro-shocks.

The Network Contraction Hypothesis (H3) is fully confirmed by the simulation. Macroeconomic distress and capital constraints lead to a severe reduction in investment density and overall connectivity. The drop in active investments under the Crisis regime verifies that negative economic cycles weaken co-investment dynamics and fragment relational links.

The Regulatory Stabilization Hypothesis (H4) is fully confirmed. Under a tighter institutional framework, the ecosystem achieves greater structural stability. It distributes capital more evenly and preserves a higher average startup quality (SUS²A score of 0.45 +- 0.03) than the unregulated crisis environment, proving that formal constraints act as an organizational shield against market collapse.

The SUS²A Validity Hypothesis (H5) is supported by the computational evidence. Throughout the iterations, the dynamic fluctuations of the SUS²A indicator consistently mirror the evolution of the success probabilities. This path validates the capability of the framework to synthesize qualitative strategic parameters into a single score that reliably responds to changing macroeconomic regimes, though further live validation remains a future research priority.

The Inequality of Opportunity Hypothesis (H6) is fully confirmed. The distribution of capital among startups is tightly bound to external regimes. In crisis scenarios, the significant spike in the venture capital concentration index (0.082 +- 0.012) demonstrates a defensive pooling of resources on a minimal number of entities, whereas the abundance and regulation regimes guarantee a less selective, more balanced spread of market opportunities.

5.7 *Emerging insights*

Overall, the results show that:

- startup ecosystems are highly sensitive to the macroeconomic environment;
- The availability of capital is not the only determinant of performance;
- the structure of the network and the average quality of startups play a crucial role;
- regulatory policies can help improve the resilience of the system.

These data support the idea that ecosystems should be evaluated and studied as complex multi-level systems, in which emerging dynamics are not immediately deducible from initial conditions.

6 **Research limitations and managerial implications**

This section reports the limitations of the work and the managerial implications that derive from the results obtained. This set of things allows you to interpret the results of the simulation by observing both the methodological constraints of the model and the application value of what emerged from the model.

6.1 *Research limitations*

Although the work has brought some new elements, there are some limitations that must be taken into account in order to interpret the results correctly.

First, the model is based on a set of simplifying assumptions necessary to make the system computationally tractable. Specifically, investor behavior is represented through simple

decision-making rules, which do not fully describe the complexity of the real processes of evaluation, negotiation and monitoring typical of venture capital.

Second, the model parameters are not calibrated to specific empirical data. This fact limits the possibility of interpreting the results in predictive terms or applying them directly in real contexts. So this model must be considered first of all as a theoretical-exploratory tool rather than a descriptive one.

This exploratory barrier highlights a core epistemological limitation regarding the structural nature of the SUS²A index used within the model environment. In the simulation code, the SUS²A property operates as a dynamic numerical attribute linked directly to investment access probability. However, in professional practice, the SUS²A framework functions strictly as a document-based proxy filter that maps the formal completeness and disclosure quality of startup text arrays. The simulation assumes perfect translation between textual planning completeness and real-world execution capacity. In a live ecosystem, this link is heavily decoupled: a startup may produce high-quality strategic business writing while lacking genuine operational capacity, a fundamental distinction that needs to be explicitly maintained to safeguard the interpretative boundaries of the model.

A further limitation concerns the absence of sectoral and geographical heterogeneity. Startups are defined as a homogeneous whole, without distinction between industrial sectors or local institutional contexts because in reality these factors can greatly influence the dynamics of growth, access to capital and survival.

Moreover, macroeconomic conditions are modelled through different market regimes (abundance, crisis, regulation), which represent a simplification of much more complex phenomena. In reality, these conditions evolve continuously and can be influenced by multiple interdependent factors.

Furthermore, the complete absence of empirical calibration against industrial datasets represents a major conceptual boundary that directly connects to the overfitting debate. By design, the NetLogo environment operates with abstract parameters to isolate micro-meso interactions from real-world statistical noise. Attempting to force historical financial calibration into a 500-variable macro-framework within an uncalibrated multi-agent ecosystem would generate severe analytical overfitting, rendering the simulation hyper-accurate in tracking past contextual anomalies while destroying its exploratory value. Thus, the model deliberately retains its stylized, non-linear architecture to function as a testbed for fast-and-frugal heuristics, rather than an over-engineered predictive tool.

A further critical issue concerns SUS²A, which, while representing an innovative attempt at a quantitative summary of the quality of startups, needs further empirical validation. To refine its robustness, its reliability should be tested by making a parallel with real data and then also comparing it with indicators already used in venture capital practice.

In addition, the model does not consider some relevant elements, such as:

- exit dynamics (IPOs, acquisitions);
- advanced strategic investor behaviour;
- specific public policies and targeted interventions.

These aspects represent important directions for future research developments.

6.2 *Managerial implications*

The results, despite the limitations of the model, offer relevant results for various players in the ecosystem, such as startups, investors and policy makers.

6.2.1 *Implications for startups*

The survival and success of startups do not depend, as shown by the simulation results, on the availability of capital but depend on their ability to adapt to the context and the ability to develop internal skills.

In particular:

- in crisis scenarios, it is essential to strengthen entrepreneurial quality and improve efficiency in the use of resources, as access to funding becomes more selective;
- building strong relationships with investors is a critical factor in increasing the chances of survival;
- the ability to position oneself within investment networks can significantly influence access to opportunities.

Startups should therefore adopt strategies oriented not only towards growth, but also towards resilience.

6.2.2 *Implications for investors*

For venture capital investors, the model highlights how important it is to adopt capital allocation strategies taking into account market conditions but also network dynamics and the characteristics of startups.

In particular:

- in contexts of high uncertainty, the risk of excessive concentration of investments emerges, which can reduce diversification;
- the use of synthetic indicators such as SUS²A can support screening and selection processes, improving decision-making efficiency;
- participation in co-investment networks can lead to better information sharing and risk reduction.

The study leads to the enhancement of a more systemic and less opportunistic approach to investment decisions.

6.2.3 *Implications for policy makers*

As far as public policies are concerned, the results highlight how institutional conditions can be decisive in the functioning of startup ecosystems.

In particular:

- moderate regulatory scenarios can help stabilize the system, improving the average quality of startups and the structure of the investment network;
- unmitigated crisis conditions can lead to an excessive contraction of the system, with loss of innovative potential;
- targeted interventions could promote the circulation of capital and the strengthening of relations between actors.

Policy makers should therefore consider not only the amount of resources available, but also the ways in which they are distributed and the relationships that derive from them. It can be said that the limitations of the model lead to the realization that some caution is required in interpreting the results, but they do not compromise their value. On the contrary, the limitations contribute to structuring a future research agenda aimed at improving the empirical representation and complexity of the model.

Similarly, managerial implications communicate that the systemic dynamics of startup ecosystems can be understood in order to improve the strategies of all the elements involved, especially when the context is characterized by uncertainty and change.

From these considerations it can be deduced that the main contribution of the study lies in having shown how the interaction between internal, relational and macroeconomic factors can generate profoundly different outcomes and highlight the importance of an integrated approach both in research and in practice.

7 Conclusions, limitations and future developments

This study analyzed the topic of startup ecosystems as a complex system determined by non-linear interactions between different actors and influenced by macroeconomic and institutional conditions. Also following what was said in the introductory part, this work has attempted to fill some gaps in the literature, developing an integrated model capable of connecting three main dimensions: the internal characteristics of startups, the relational dynamics of venture capital and variable market regimes.

Using an agent model, the study demonstrated how ecosystem dynamics are dictated by the interaction between these elements, confirming that the phenomenon is characterized by a systemic nature. The results obtained show that the survival and growth of startups cannot be described with simple and single factors but are the result of complex structures and mechanisms of adaptation, learning and interaction.

The three market regimes (abundance, crisis and regulation) have shown that macroeconomic conditions significantly influence not only performance but also the structure of the investment network and the distribution of capital and therefore of the opportunities of startups. The results therefore confirm that:

- abundance scenarios facilitate access to capital but can reduce allocative efficiency;
- crisis scenarios lead to a contraction of the system and an increase in fragility;
- regulated contexts can generate stabilizing effects, improving the average quality and resilience of the ecosystem.

A further contribution of the work concerns the experimentation of SUS²A as a useful indicator for the determination and synthesis of the quality of startups. In fact, the results show that this indicator is able to summarize the evolution of firms and reflect the dynamics of success within the system, even if it needs further empirical validation.

Overall, the work offers a contribution to the literature as it proposes an integrated and dynamic perspective, in line with the vision of innovation ecosystems seen as complex adaptive systems. The study answers the research questions posed in the introductory part and provides significant evidence to support the hypotheses formulated, reinforcing the idea that a multi-level study is essential to understand the dynamics of startups.

In conclusion, the present study shows how an approach based on agent-based modeling can represent an effective means for complex systems such as those of startup ecosystems. Linking to the initial motivations of the work, it is clear that understanding these systems

requires an integrated perspective, capable of grasping the interactions between different levels and analyzing the effects of macroeconomic conditions.

In closing this multi-level analysis, a final theoretical caution must be explicitly formalized regarding the universal generalizability of the emergent outcomes. The simulated trajectories tracked across the abundance, crisis, and regulation scenarios act as structural thought experiments rather than absolute operational benchmarks. Because human entrepreneurial action is governed by idiosyncratic variables, shifting policy environments, and unmapped historical contingencies, the stylized parameters of this NetLogo framework cannot encapsulate the full evolutionary complexity of real-world venture capital networks. The results must therefore be valued for their conceptual diagnostic guidance, reinforcing the necessity for a prudent approach when transferring computational multi-agent insights into actual market interventions.

Ultimately, the execution of this agent-based architecture provides a robust resolution to the analytical friction separating simple heuristics from complex multi-variable indices. The long-term monitoring of the ticks demonstrates that the combination of simple behavioral guidelines for investor agents and a binarized structural framework like SUS²A avoids the traditional pitfalls of computational overfitting. The model achieves systematic replicability and behavioral resilience precisely because it refuses to over-engineer the local agents' cognitive parameters, balancing high-density tracking criteria with fast-and-frugal selection heuristics. This balanced integration establishes a reliable methodology for exploring innovation ecosystems, proving that structural clarity and operational simplification are key requirements for advancing research in complex economic systems.

Closing the loop with the introduction, it can be said that this analysis tool contributes to filling the gap existing in the literature, offering a framework that integrates internal quality, network dynamics and macroeconomic context. At the same time, it allows us to visualize new research perspectives and provides useful information for all the actors of the ecosystem, paying attention to the role played by adaptive strategies and policies oriented towards the stability and resilience of the system.

Conclusions

This work is part of a study context related to the objective, systematic and scalable evaluation of a startup, especially in the early phase of its life cycle. The tool used for this analysis delves into the field of entrepreneurship and innovative finance. An integrated approach is developed in a context characterized by uncertainty, information asymmetry and high availability of unstructured data, with the aim of transforming qualitative data of entrepreneurial descriptions into replicable quantitative values. The research is set between entrepreneurship study, textual analysis and AI applications, bridging an existing gap between theoretical approaches and operational evaluation tools.

This intervention is theoretically called for due to the structural insufficiencies that characterize traditional Investment Readiness Level (IRL) models found in current literature. Existing IRL frameworks suffer from severe limitations: they operate on coarse, macro-level categorical scales that lack diagnostic granularity, and they rely heavily on subjective self-reporting questionnaires administered by entrepreneurs, which are prone to cognitive optimism and lacks automated verification. Most importantly, traditional investment models are entirely incapable of processing unstructured textual data, leaving the massive amount of strategic knowledge embedded within corporate narratives unexploited.

Through the development of the SUS²A framework, this study proposed a method that connects theory, operationalization and automation. Specifically, the path is divided into three main phases: a theoretical part related to the maturity construct of the startup, its translation into a structured evaluation tool based on 500 binary indicators and finally an implementation of an automated text analysis process empirically validated through a comparison between deterministic approaches and advanced language models. This articulation directly reflects the structure of the thesis, developed in the four chapters, and ensures a coherent progression from conceptual definition to empirical validation to automation of the evaluation process. Taken together, the results obtained in the different chapters demonstrate the coherence of the research path, confirming the validity of the proposed approach along all its phases: from theoretical conceptualization to empirical validation to automation.

The results of the research also allow to provide answers to the research questions formulated. With regard to the first question (RQ1), the work demonstrates that the maturity of a startup can be conceptualized as a quantitative construct, described by eleven fundamental categories. The analysis of the literature has made it possible to find an integrated theoretical structure capable of representing the main characteristics of a startup. RQ1 can be considered fully satisfied as the work proposes a multidimensional definition of the construct and a solid formalization consistent with the existing literature. The research carried out is not limited to making an extension of existing models but proposes a change of perspective in the evaluation phase of startups, diverting attention from a static and qualitative approach to a quantitative and structured, dynamic and data-driven one.

The second research question (RQ2) is analysed and demonstrated as the research shows that it is possible to operationalise the tool by means of questions with binary answers and thus providing a granular system. The 500-question questionnaire made it possible to convert abstract dimensions into measurable data, reducing interpretative ambiguity and defining a replicable and comparable process. The results therefore show a positive response to the research question, demonstrating the possibility of creating a structured and observable system, while maintaining theoretical coherence and operational applicability.

Beyond the initial statistical validation via Cohen's Kappa, Chapter 3 introduces a comprehensive engineering-grade validation framework that substantially deepens the empirical contribution of this thesis. The ROC analysis per category, supported by 95% bootstrap confidence intervals computed over 2,000 resampling iterations, Youden optimal thresholds, partial AUC in the conservative screening zone, and Precision-Recall curves, establishes that the eleven SUS²A categories exhibit markedly different discriminative profiles: Collaboration (AUC = 0.910) and Marketing & Strategy (AUC = 0.850) emerge as the primary discriminators, while ESG (AUC = 0.586) and Product & Industrial (AUC = 0.536) reflect documentation gaps rather than model design failures, a finding confirmed by the significant Spearman correlation between fill rate and AUC ($\rho = 0.645$, $p = 0.032$). The inter-category correlation analysis (Figures 19–20) further reveals a two-cluster architecture within the framework: an external readiness cluster (Marketing, Collaboration, Scalability, Technology, Finance) and an internal readiness cluster (Team, Legal, Product, ESG, Validation, Talent), suggesting that SUS²A captures two genuinely distinct facets of startup maturity. Finally, the genetic algorithm optimization (Section 5.9) provides a mathematically independent confirmation of these findings: by evolving 150 populations of weight vectors over 300 generations, the algorithm identifies Marketing & Strategy (optimal weight: 34.8%) and Team (21.2%) as the dominant discriminative dimensions, improving global AUC from 0.959 to 1.000 (+4.07%) and producing a PCA-based visual map of the 41-startup investment readiness landscape. These three layers of analysis, ROC, correlation clustering, and genetic optimization, converge on the same empirical conclusion from independent computational perspectives, substantially strengthening the robustness and originality of the SUS²A framework validation.

This operational transition must be framed within the wider scientific debate between complex statistical models and simple heuristics (Gigerenzer, 2008). As formally demonstrated in Chapter 3 (Section 4.3), the choice to structure SUS²A around 500 binary items functions as an aggregated fast-and-frugal heuristic that discards rhetorical variance and ensures transparent replicability, though the formal absence of overfitting requires out-of-sample validation on larger datasets, as discussed in Chapter 3 (Section 6).

As regards the third question (RQ3), the results confirm the possibility of automating an evaluation process through natural language analysis techniques applied to unstructured textual data. By implementing a tool based on keyword matching and AI models, the research shows that a large amount of volumes of entrepreneurial documentation can be analyzed. The answer to RQ3 is therefore empirically confirmed, highlighting how the integration between structured frameworks and automated analysis techniques makes it possible to overcome the scalability limits typical of traditional approaches. Finally, with regard to the last question (RQ4), the comparison between deterministic and semantic approaches defined a good level of agreement, also documented by statistical indicators such as the Cohen's Kappa coefficient. The results obtained describe that deterministic models are a valid, transparent and computationally sustainable solution for large-scale screening applications, despite some differences related to the semantic interpretation capacity.

Therefore, RQ4 also finds a significant answer, demonstrating that different approaches can be used in a complementary way, depending on the analysis objectives and operational constraints. The contribution that this research provides can be divided into a theoretical, methodological and empirical contribution. From a theoretical point of view, an advanced formalization of the concept of startup maturity is provided to the literature. In fact, the SUS²A

model, unlike traditional models, introduces a multidimensional perspective that integrates strategic, organizational, technological and sustainable elements, analyzing the phenomenon from a broader point of view. This theoretical contribution is particularly relevant as it allows to overcome fragmented visions of the phenomenon, proposing a unitary and systemic interpretative framework. Furthermore, the proposed framework is not limited to the context of startups, but can be extended to other areas characterized by unstructured textual data, contributing to the development of systematic approaches for the transformation of natural language into structured knowledge.

The methodological contribution represents the largest as a system based on over 500 binary indicators is defined, offering a level of granularity in the evaluation of startups not previously achieved. In addition, the possibility of going beyond purely qualitative models through replicable and scalable methodologies through the combination of traditional content analysis and automatic natural language analysis techniques is addressed. This methodological contribution stands out for its transferability to other textual data-based analysis contexts, expanding the potential applications of the framework beyond the domain of startups. The work also contributes to a broader reflection on the role of textual data in empirical research processes, showing how natural language can be treated not only as a descriptive source, but as a basis for building rigorous quantitative models.

From an empirical point of view, applying the model to a set of startups has made it possible to find recurring patterns and structural gaps. Specifically, the results obtained highlight the tendency of many startups to focus on fundamental aspects such as market and product, neglecting important aspects such as ESG and talent management. These results obtained from comparative analyses contribute to the understanding of the actual dynamics of entrepreneurial ecosystems. This empirical evidence strengthens the validity of the framework, demonstrating its ability not only to describe but also to diagnose systemic criticalities. The research provides relevant implications for different actors in the innovation system. This framework offers investors a preliminary screening tool that would allow them to reduce the time and costs of due diligence, while improving the objectivity of the evaluation of a startup.

Incubators and accelerators could use the model as a tool for mentoring support, systematically identifying the areas of weakness of startups and directing support interventions accordingly. For policy makers, on the other hand, the framework would represent a tool capable of analyzing entrepreneurial ecosystems, identifying systemic gaps and designing more suitable and efficient support systems. For entrepreneurs themselves, on the other hand, this tool would allow them to provide a self-assessment method, allowing an improvement in the quality of documentation and an increase in the likelihood of access to funding. In this sense, the SUS²A framework is configured as a bridge tool between academic research and practical application, helping to reduce the gap between theory and operational decision-making.

Despite the contributions provided by the research, it has gaps and limitations. First of all, this analysis is based on textual descriptions in natural language, which therefore do not necessarily reflect the actual performance or implementation of the strategies declared by each startup.

This explicit gap requires the maintenance of a strict epistemological boundary between document completeness and genuine operational maturity. The SUS²A model scales primarily as a static, text-based proxy filter. It evaluates and measures the capacity of the entrepreneurial team to formalize, plan, and disclose their operational setup inside a technical vernacular

expected by institutional investors. Consequently, a high score denotes exceptional document readiness and strategic planning clarity, but cannot guarantee successful execution on the market. Conversely, a lower score points out a formal disclosure issue that requires advisory integration, without necessarily declaring the underlying technological or venture thesis unviable.

Secondly, the binary nature of the model leads to greatly simplifying reality as it detects the presence or absence of a certain feature without evaluating any nuances of quality or depth. Another limitation concerns the dependence on the language used in the description, in fact keyword-based approaches may not fully grasp complex or non-standardized expressions, while semantic models involve higher computational costs.

A final observation concerns the size of the sample analyzed which, although adequate for an initial estimate, limits the validity of the results as generalized values.

In alignment with scientific rigor, it is imperative to formally moderate any claims concerning absolute objectivity or universal generalizability for this current setup of the framework. The structural gaps and maturity boundaries mapped across the 41 Italian startups represent a localized snapshot of an innovative ecosystem. This specific sample size implies that observed data distribution parameters are bounded by regional and contextual factors, meaning that extensive multi-sectoral and cross-geographical validation is strictly required before transferring the quantitative scoring scale into a globally applicable diagnostic metric.

However, these limitations do not reduce the value of the contribution but clearly outline the scope of application and the conditions of validity.

On the other hand, however, these limitations offer different directions for future developments. A first integration could involve an integration of heterogeneous data sources, such as financial data, information from market platforms in order to develop more complete and dynamic models. A second direction of development concerns the improvement of semantic analysis techniques, through the use of more advanced AI models and through the integration of hybrid approaches that can combine interpretability and predictive capacity. A further development could be to test the framework in different contexts and at higher and more diverse samples, in order to test the robustness and improve the generalizability of the results.

A further interesting development could be to make this model a predictive analysis tool, capable of assessing not only the maturity of a startup but also of providing an estimate of the probability of success in the long term. What has been demonstrated with this research and the evidence of possible future developments and integrations of the framework pave the way for developments that could integrate descriptive analysis and predictive capabilities in a single advanced system. In this direction, the evolution of the tool would allow the definition of new startup evaluation tools, based on automated, transparent and scalable concepts, capable of supporting increasingly data-driven decisions in the field of innovation ecosystems.

In conclusion, the present study proposes an original contribution by introducing an integrated approach to the evaluation of startups based on the analysis of descriptive texts in natural language, transforming textual data into structured knowledge. Through the SUS²A framework, it is demonstrated how it is possible to overcome the limits of traditional analyses, providing a tool capable of bringing together theoretical rigor, methodological innovation and application relevance.

SUS²A is therefore not only a data analysis tool but a step towards a new generation of entrepreneurial analysis models, which integrate scientific rigor, scalability and AI. In fact, in a context where there is an increasing complexity of entrepreneurial ecosystems, increasingly

sophisticated and scalable tools are needed and this research is an example towards the development of new paradigms of analysis and decision support, aimed at improving the efficiency, transparency and objectivity of the evaluation processes of a startup.

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