



The image shows a smartphone screen with the ChatGPT interface. At the top, the time is 7:23 and the browser address bar shows 'chat.openai.com'. Below the address bar is a hamburger menu icon. The main heading is 'ChatGPT' in large white letters. Underneath is a sun icon followed by the word 'Examples'. There are three example prompts in white text on dark blue rounded rectangles: 'Explain quantum computing in simple terms' with a right arrow, 'Got any creative ideas for a 10 year old's birthday?' with a right arrow, and 'How do I make an HTTP request in Javascript?' with a right arrow. At the bottom, there is a lightning bolt icon followed by the word 'Capabilities'. Below that, the text 'Remembers what user said earlier' is partially visible. In the bottom right corner, there is a circular gold seal of the University of Lund, featuring a lion holding a sword and a book, with the Latin text 'SIGILLUM CAROLINAE AD VTI RVMQVE' and '1622'.

How Venture Capital Could Use Large Language Models to Screen Sustainability Impact Startups

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LTH, Lund University

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MADE IN SWEDEN 

Preface

This master's thesis has been authored by Karl-Gustav Elf and Måns Tivenius, students in Industrial Engineering and Management, for the Division of Environmental and Energy Systems Studies at Lund University of Technology (LTH).

The authors would like to pay tribute to the interview candidates which added on to the relevancy of the thesis with knowledge from the venture capital industry. Thank you Gustav von Sydow, Anna Skarborg and Alexander Paterson Pochet! Furthermore, the authors are thankful for the important brainstorming session conducted with Kye Andersson. The session sparked ideas, leading to the development of the final method used and the discussion about future use cases.

Finally, it is with great gratitude that the authors of this thesis would like to thank our supervisors Lars J Nilsson and Joachim Peter Tilsted at LTH. Your support and constant feedback has been extremely valuable and we are happy that you have allowed us to explore different paths, letting the scope of the thesis grow from venture capital and impact investing to eventually also incorporate artificial intelligence and large language models.

Abstract

This study investigates the potential of large language models (LLMs), such as ChatGPT, to aid venture capitalists in the screening of startups that maximize sustainability impact. To determine the scope that maximizes impact for venture capitalists' and to identify effective screening criteria, the study utilized theoretical research and interviews. The thesis suggests that the ideal investment space is investments into high-risk, software-centric companies contributing to a sustainable system change that maximizes outcome impact instead of optimizing for environmental, social and governance metrics. This investment space along with other defined critical success factors were then deployed in an effort to test LLMs' efficacy in targeting companies maximizing impact. Two prompting techniques were trialed, one question-based prompt where questions on critical startup success factors were asked, and another using a comparative method where the characteristics of screened startups were matched with investor profile preferences. In both versions of the model, the provision of context proved indispensable to analyze relevant startups, given GPT-4's knowledge cut-off in 2021. Without context, the LLM often could not provide an answer or provided an imaginary one, especially for younger startups. The question-based prompting could accurately address some specific questions, while the investor profile prompt showed the most promising results by being able to efficiently summarize and present relevant output text on the given areas of interest. It was also found that the quality of the data input in the model directly affects its efficacy and it is therefore necessary to pick data carefully to avoid biases and greenwashing. This was especially true for question-based prompting, since the investor profile prompt was better at conducting an overall assessment of the companies with scarce information, but did still struggle to produce insightful ratings. In terms of the specific screening for impact startups, the model shows potential for targeting the ideal investment scope suggested by the thesis. The paper concludes by suggesting an immediate use case for the investor profile prompting technique in ChatGPT, supplemented by future use cases for automated systems to conduct outbound and inbound screening at scale.

Keywords: Large Language Models, Venture Capital, Impact Investing, Prompt Engineering, GPT-4, ChatGPT, Impact, Sustainability, Artificial Intelligence, Startup success, Impact startup, Impact measurement, Screening, AI for good

Abbreviations

- **AI** - Artificial Intelligence
- **CSF** - Critical Success Factor
- **ESG** - Environment, Social and Governance
- **EU** - European Union
- **II** - Impact Investing
- **IRR** - Internal Rate of Return
- **LLM** - Large Language Model
- **SDG** - Sustainable Development Goal
- **SFDR** - Sustainable Finance Disclosure Regulation
- **UN** - United Nations
- **VC** - Venture Capital

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1. Introduction

1.1 Background

The effects of climate change and global warming have been more present than ever the last couple of years, with melting polar ice and an increased number of climate disasters. To halt the damage, financing climate action and green projects is recognized as an important factor for change (Masson-Delmotte et al., 2018). Until recently, capital for companies tackling social or environmental issues came largely from governments and foundations (Clarkin & Cangioni, 2016). Since then consciousness about these issues also spread among private investors. As such the field of Impact Investing (II) emerged, in which investors are now actively screening for sustainable companies. II now spans all asset classes from public stocks, green bonds to private equity (Croce et al., 2021). Most of the II however, is done by large companies because of the availability and transparency of sustainability data in these enterprises. For venture capital (VC) firms that mainly invest in early-stage startups, the process of incorporating sustainability is more challenging. Because of the difficult nature of II in the VC space, there exists an acceptance of the neglect of sustainability in place of other aspects. However, according to Anna Skarborg, Head of Sustainability at Northzone, many VC firms and investors are now changing their view and realizing the potential of making sustainability a priority early on in the company life-cycle (Skarborg, 2022). Given VC's capacity to disrupt the economy and society as a whole, this shift in industry perspective holds significant weight (Dunbar & Leitner, 2022). Voices inside the academia have since earlier also recognized the potential of VC in the sustainable transition. Research so far has mainly been directed towards empirical findings in green VC and the role of VC in the sustainable transition. Yet, left to explore is how VCs can identify and invest in the companies with the greatest potential for impact (Dhayal et al., 2023). At the same time, great progress has been made with large language models (LLMs), a promising and emerging field within natural language processing. LLMs show surprising potential in generating text and reading comprehension, tasks previously needing human attention (Devlin et al., 2019). The model's applicability is therefore being tested in a wide range of disciplines, from finance to climate issues (BlackRock, 2023; Vaghefi et al., 2023; Yang et al., 2020). Although artificial intelligence (AI) has been applied in investing decisions for a long time, current models suffer from poor explainability which has inhibited their adoption in the industry (Cao et al., 2022). The inner workings of an LLM also suffer from the same transparency problem, but is, nevertheless, able to provide motivations and justifications for specific outputs and thus has the potential to improve explainability. This thesis seeks to contribute both to interdisciplinary research in the field of LLM and fill gaps in research regarding impact investing in VC. This is explored by understanding how LLMs can be used to effectively screen and identify the impact investments with the highest potential in contributing to social, environmental and economical sustainability.

1.2 Purpose

This thesis will investigate how LLMs can be used to screen startups that maximize sustainable impact. By understanding the role of VC in the sustainable transition and the

patterns that define successful sustainable ventures, an optimal investment scope is determined. This then serves as input into a LLM to be used to screen high impact investments for VCs. The following research question will be answered:

- How could large language models maximize venture capital's sustainability impact by enabling a more sophisticated screening process that identifies high-potential startups?

1.3 Delimitations and Scope

The scope of this thesis will touch upon the screening process of impact investments. More specifically, the main focus will be on outbound screening, when VCs actively seek out investment objects. Inbound screening, when startups looking for funding contact VCs, is also an important way to generate investment opportunities. Therefore, a short discussion about how LLMs could be applied in inbound screening will be included. The sustainability aspect is of relevance in all parts of the VC deal process, not only the screening. Further research should therefore be made to determine whether LLMs could aid in scaling, developing and selling impact startups.

1.4 Structure of Thesis

Chapter 1- Introduction: From a short background section, the purpose, scope and limitations are specified.

Chapter 2 - Theory: In the following section, the academic research that lays the foundation of the thesis is presented. The research is used both to define what is investable for VCs in the sustainable transition and Critical Success Factors (CSFs) for identifying successful impact ventures. This is followed by an overview of AI, its usage in VC and a presentation of LLMs and GPT-4.

Chapter 3 - Method: In this section the method used in the thesis is outlined. Focus is on synthesizing critical success factors into prompts and optimizing them to be used as input into the LLM model.

Chapter 4 - Results and Analysis: The fourth chapter presents the final output, an evaluation of the model and analysis of the results.

Chapter 5 - Discussion: The fifth chapter includes a summary of the learnings from the model. Conclusions from the analysis are used to suggest future use cases and discuss LLMs' ability to contribute to the maximization of impact for VCs.

Chapter 6 - Conclusion: The final chapter provides an answer to the research question given the findings of the thesis.

2. Theory

2.1 Sustainability

To gain insight into the integration of sustainability into VC practices, it is essential to define the concept. This however, proves difficult since the meaning of the term sustainability has evolved a lot throughout the years and continues to do so (Bjørn & Røpke, 2018). The United Nations (UN) Brundtland Commission described sustainability as “meeting the needs of the present without compromising the ability of future generations to meet their own needs” (Secretary-General & Development, 1987). With this definition sustainable development was brought high up on the agendas of decision makers, and created a broad consensus around its importance. Three distinct interpretations emerged from the definition, *Weak sustainability*, *Strong sustainability* and *Very strong sustainability*. Advocates for the *Weak sustainability* interpretation, argue that as long as natural resources are being used to create human welfare, they can be exploited. *Very strong sustainability* instead takes a restrictive stance in relation to the Brundtland Commission, claiming that no finite resource can ever be extracted in a world of sustainable development. The *Strong sustainability* interpretation is a middle ground of the two, recognizing the need for exploitation of natural resources for creating human welfare up to a certain limit (Bjørn & Røpke, 2018). The exploitation threshold is defined by two rules:

- Output rule: Waste outputs are within the limit of the natural absorptive capacities of the environment.
- Inputs rule: (a) For renewable inputs, harvest rates should not exceed regeneration rates. (b) For nonrenewable inputs the rate of depletion should be equal to the rate at which renewable substitutes can be developed. (Daly, 1995).

With the other definitions of sustainability being claimed as either too loose or too restrictive, strong sustainability became the more accepted stance of the Brundtland report. Subsequent evolution of the term set out to further concretize the limits defined in strong sustainability in different areas such as ozone emission or fresh water use. The concept of planetary boundaries thus emerged, a safe operating threshold of exploitation of the planet’s resources for human welfare (Bjørn & Røpke, 2018).

With the intention of putting a limiting boundary for global emissions, the Paris Agreement, an international treaty, was reached by top leaders at the UN Climate Change Conference in 2015. It represents a legally binding commitment made by 193 countries and under the agreement, parties have pledged to reduce greenhouse gas emissions to limit global warming to a maximum increase of two degrees Celsius, but preferably, 1.5 degrees. To achieve the goals of the Paris Agreement, a global state of carbon neutrality, net-zero emissions, needs to be reached by 2050 (Falkner, 2016). The treaty has a top-down structure, setting broad targets for countries and institutions which trickle down to smaller objectives for individual companies. To help with this the Science Based Targets initiative was created. The initiative aims to show, guide and help set goals for companies to reach net zero emissions by setting goals that are aligned with the 1.5 degrees goal. The year 2021, over 1000 organizations and leading companies were part of the initiative (Giesekam et al., 2021).

The same year as the Paris Agreement was established the UN also established the agenda for sustainable development 2030 and the sustainable development goals (SDGs) framework. These goals were a sequel to the millennium development goals, which were a set of eight goals related to social issues to be resolved. The new agenda incorporated 17 goals to achieve by 2030, an expanded list incorporating not only social issues but also economical and

environmental issues. This reflected how the definition of sustainability had evolved into three main pillars, social, economical and environmental issues (Mio et al., 2020). Although the agenda puts the ultimate responsibility on countries, the private sector's role in achieving the agenda and pursuing the goals is unquestionable. Overall the reaction from industry of the SDGs framework has been positive although critics raised issues of not providing enough incentives for companies to follow it (Mio et al., 2020).

The introduction and acceptance of these overarching political actions was a big success for the European Union (EU), an organization that has long prioritized sustainability. Thus came bigger incentives for the union to reduce emissions and improve sustainability, leading to the introduction of the green deal initiative, a goal of becoming the first net-zero continent. The initiative covers a wide range of areas, and it has since then developed specific frameworks for finance and investing (Siddi, 2020). The EU Taxonomy is an example of this, a classification system for sustainable activities performed in the EU. Based on the EU's energy and climate targets for 2030, the framework helps investors differentiate sustainable investments from those that are not, leading to greater financing for sustainable initiatives. The Taxonomy Regulation, published by the EU in 2020, establishes six environmental objectives (Establishment of a Framework to Facilitate Sustainable Investment, and Amending Regulation, Regulation 852/2020):

1. Climate change mitigation
2. Climate change adaptation
3. The sustainable use and protection of water and marine sources
4. The transition to a circular economy
5. Pollution prevention and control
6. The protection and restoration of biodiversity and ecosystems

An economic activity is considered sustainable, and hence investable for a sustainable investor, if it positively contributes to one of the six objectives without significantly harming any of the others (Establishment of a Framework to Facilitate Sustainable Investment, and Amending Regulation, Regulation 852/2020).

The Sustainable Finance Disclosure Regulation (SFDR) is another new regulation from the European Union related to finance. The purpose of SFDR is promoting greater financing to sustainability efforts by requiring funds to disclose more information on sustainability risks and negative impact. All funds in the EU are now classified into three categories depending on which approach they have to sustainability. *Article 9 funds*, also called dark green funds, are funds that aim to contribute to a more sustainable society. *Article 8 funds* are described as light green, making investments that promote some environmental or social factors. Finally, *article 6 funds* have no consideration for sustainability risks. By disclosing more information about sustainability efforts in combination with the categorisation system, investors are encouraged to make more sustainably conscious decisions. (Sustainability-related Disclosures in the Financial Services Sector, Regulation 2088/2019).

2.2 Venture Capital

VC firms can in short be described as fund managers raising capital from large institutional investors, often pension funds, and allocating it in high-growth ventures to accelerate their growth trajectory (Cornelius & Persson, 2006). The types of companies that VCs invest in are often referred to as startups, a concept that is subject to multiple definitions and understandings.. In this thesis Paul Graham's definition is used: a company designed to grow

fast, and prioritizing growth over profits in the forthcoming future (Graham, 2012). Depending on the timing of the investment, VCs provide funding at various stages of a startup's development. This thesis will specifically concentrate on seed funding, Series A, and Series B stages. Seed stage capital is provided at an early stage to companies which typically have an established business plan and a functioning prototype of their product. These investments are normally between five hundred thousand and two million euros. For Series A investments, the company should demonstrate increased traction and seek to raise around three to eight million euros. Series B is given to revenue generating companies wanting to scale their business and the size of the investment is approximately around ten to twenty five million euros (Ohr, 2023). VC firms provide companies with capital but also other supportive capabilities. In comparison to banks, private equity or other external providers of capital, VCs can be considered to take larger risks considering their early entry in unlisted, potential high-growth companies along with their short investment horizon (Cornelius & Persson, 2006). Therefore, typically only a small percentage of portfolio companies will generate significant returns. In fact, it is common for as much as 80 percent of investments to result in complete failure or insufficient return. To make up for the losses in the portfolio, VCs set out to find a few high-potential companies that can generate returns of five to ten times the invested amount (Ramsinghani, 2021).

The funds that VCs manage are evaluated based on mainly a few financial key metrics, although the most prevalent one is internal rate of return (IRR). The IRR makes a good measurement of the given investment since it takes both the generated cash flows, initial investment and time period into account, meaning it captures both the value of returns but also the speed of getting to those returns (Ramsinghani, 2021). VC funds invest in high-risk projects, and therefore pursue projects with high IRR, often close to 30 percent. Because of the high IRR, the time-value of money is of large importance in the VC business, putting pressure on the VC firms to reach high returns as soon as possible (Ramsinghani, 2021; Titan, 2022).

There are several reasons why a startup or smaller business would be interested in partnering with a VC firm. The most obvious answer is the access to capital provided by the VC firm, making it possible for the venture to expand and grow faster. In a German study it was shown that VC-backed firms, in terms of number of employees, grow 170 percentage points faster than ventures without external capital. At the same time, companies who received other external capital instead achieved a 50 percentage points higher growth rate than firms without any backing (Engel, 2002). Evidenced by the study, the financing alone is not the only aspect that VC can support with, other aspects have also been proven to play an important role. The ownership and capital brought in by the VC firm allow the owners to share some of the risk of the venture. Furthermore, VCs help support the venture on strategy formulation and introducing the team to valuable contacts within their network (Amit et al., 1990). Being backed by a VC also brings credibility to the company, making it easier to partner up with customers and suppliers as well as attracting new employees (Davila et al., 2003).

2.2.1 The Screening Process and Biases

VCs use several different sourcing channels to find potential investments in the screening stage. The three main channels are; referrals, outbound and inbound screening with the majority of deals coming from referrals of different types. A study made on 885 VCs at 681 firms shows that 58 percent come from referrals of which 30 percent are from professional networks, 20 percent from other investors and 8 percent from existing portfolio companies. Furthermore, around 30 percent of the deals are generated by outbound screening, the

company actively seeking out targets, and 10 percent from inbound screening, founders actively seeking funding by contacting the VC. Consequently, it is important for the VCs to engage in an active deal generation through building out the network of the VC firm or developing the outbound sourcing process (Gompers et al., 2020).

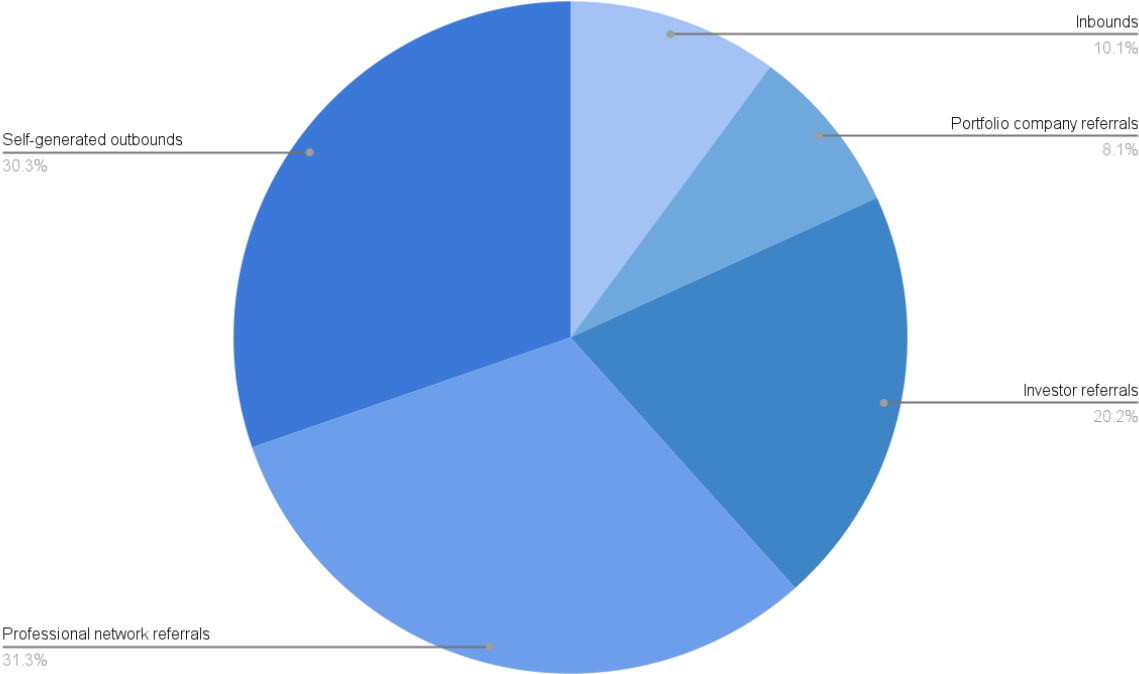


Figure 1: Share of screening methods used by VCs (Gompers et al., 2020).

The number of investment opportunities screened by a VC firm per year varies, but Ramsinghani (2021) estimates that top-tier VCs can screen around two thousand to ten thousand companies. The rule of thumb is that for every two hundred companies, twelve are subject to due diligence and four result in actual investments. Considering the large volume of screened companies, many VCs apply a data-driven approach to the proactive part of their sourcing process. Some firms, like the VC SignalFire have taken it one step further by prioritizing data-driven decision-making throughout the whole investment process. SignalFire’s founder Chris Farmer has a strong belief that the future of VCs will be determined by data, going so far to call it the new oil in the landscape of VC, implying that the data itself is not especially valuable but the ability to gather and use it properly is vital (Ramsinghani, 2021).

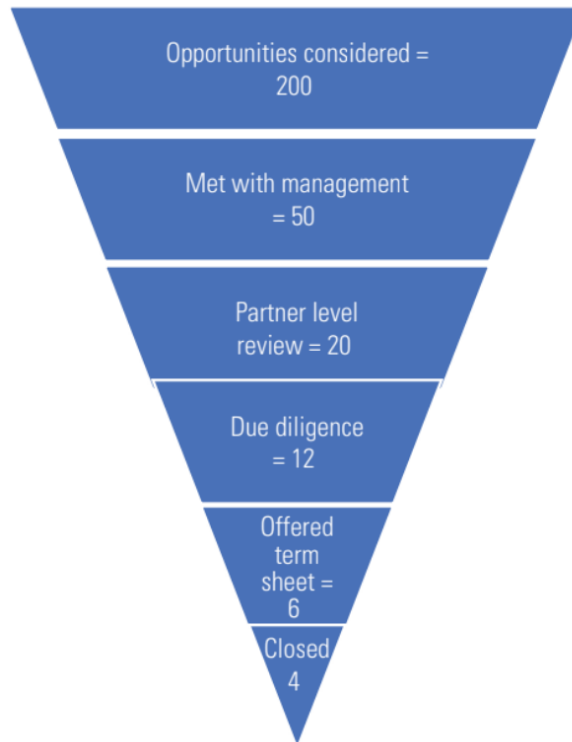


Figure 2: The deal source funnel in VC investing ((Ramsinghani, 2021).

The main reason for using digital tools is to find the investments in an early enough state for the growth potential to be attractive and the company to be valued at a reasonable level. The tools can help filter and evaluate companies based on soft values like information about the founders or similar. Typically however, the screening tools are focused on quantitative data and more specifically financial metrics. One of the most popular tools is Crunchbase, a software with a large database of companies where teams and individuals can find new potential deals through automated prospecting, filtered search criterias and access to company data. Among the information that can be found and filtered through the software, previous funding rounds tend to be of highest importance for investors (Crunchbase, 2022; Paterson Pochet, 2023). Previous funding rounds play a crucial role since backing from a highly reputed investor typically is a great indicator of startup success. It is therefore important to keep track of early funding rounds to make sure no opportunities where other skilled investors have invested are missed. Screening is however very stage dependent and investors looking at investments in earlier stages can naturally not rely on the track record of previous funding rounds, since the companies could be seeking their first or among their first funding. In those cases, it becomes increasingly important to understand soft values of the companies, such as the attributes of the founding team and the market. This part of the screening process is more qualitative and often involves meeting founders and quickly trying to understand the potential of their startup. According to von Sydow, these meetings are quite repetitive; he estimates that around 30 percent of meetings could be avoided by simply getting answers to a couple of critical questions regarding risks and the possibility of reducing those risks through the capital provided from the VC firm. However, since these questions are industry and case specific, they cannot simply be replaced by a static questionnaire (von Sydow, 2023).

The screening process of the VC, just as with any investment situation, is exposed to a set of biases which affect the judgment of investors (Franke et al., 2006; Monika & Sharma, 2015).

These biases hinder the investor from making an objective analysis of a company which leads to worse investment performance. One such bias is the availability bias, which states that people tend to judge frequency of events on information that comes readily to mind. Because recent investments are easier to recall, screeners tend to be heavily influenced by the characteristics of those deals (Zacharakis & Meyer, 2000). People also have a tendency to be better at remembering successes rather than failures, which is why investors tend to repeat the same mistakes (Zacharakis & Shepherd, 2001). For example when a new venture has the same market characteristics as a recent successful investment, they automatically assume that it is a great investment and might overlook other relevant information or red flags (Zacharakis & Meyer, 2000). This seems to be aligned with what Gustav von Sydow, Entrepreneur in Residence at EQT Venture, has seen out in the industry. According to him, a screener's most recent successful investment will heavily impact which factors their next investment will be based on (von Sydow, 2023).

A study from Zacharakis & Shepherd (2001) showed that the overconfidence bias, the tendency to overestimate the likely occurrence of a set of events, is present in the decision process of VCs. In an experiment VC participants were given a set of information about companies and then asked to predict either success or not followed by a number from 1-7, based on how confident they were in the prediction. The results show that 49 of the 51 VC participants showed overconfidence in their perception of the startup's success compared to the actual information given. The results show that overconfidence was also shown to strongly be correlated with worse investor performance. When there was high availability of information it seemed to increase confidence of investors, since they felt like their decision was well informed. However, information is only useful if there is capacity to analyze it. Investors believed that they were considering more parameters than they actually were and had the capacity for. Depending on the structure of the information presented to the investor, the effect of this bias seems to decrease. When presented with information that is structured in a familiar way, investors are better at processing and interpreting the data and hence accuracy of investments are increased. Although overconfidence might not directly lead to an incorrect decision, the bias is likely to make it harder to learn and improve the decision process. Overconfident VCs are likely to not fully consider all relevant information and neglect the search for additional context (Zacharakis & Shepherd, 2001).

Franke et al. (2006) also showed a similarity bias, the tendency to perceive people that are similar to oneself more positively in VC investing. Looking at 26 VC firms, the results indicate that VC investors look positively towards founders with a similar background as themselves. If the investor had experience from startups or larger companies, founders who have gone the same path were preferred. Also, investors with an engineering and managerial background were much more likely to choose a founding team where both backgrounds were represented. It was however not shown by Franke et al. (2006) that age, experience in a leading team or level of academic achievement affected the decision.

2.3 Impact Investing

In the world of investing, the term II generally refers to investments that contribute to positive environmental or social impact. Investment objects vary from organizations solving specific issues like providing anti-malaria beds in Africa to companies with the general goal of improving the social or environmental situation (Clarkin & Cangioni, 2016). II spans all financial asset classes, from bonds, public offerings, private equity and VC. Whether or not a financial return is to be expected from an impact investment is contested. Therefore Brest & Born (2013) instead chose to categorize II into concessionary investments, those that sacrifice

some of the expected financial return and non-concessionary, those that expect a market-rate return of the investment.

By far the biggest contribution of capital to II comes from green bonds and large-cap companies such as pension funds (Randjelovic et al., 2003; Brest & Born, 2013). Their strategy mainly consists of trying to find profitable companies that are actively trying to reduce their footprint in their operations, although the main purpose of the business does not necessarily need to be linked to a sustainability purpose. In general, companies are considered good from a sustainability point of view if they perform better in social or environmental aspects compared to their competitors. However, many investors argue that companies within industries who significantly harm any of the objectives in the EU Taxonomy, could never be considered sustainable with their current offering, no matter how superior they are to their competitors. Examples of these industries are the tobacco or oil and gas industries (Randjelovic et al., 2003; Ekman et al., 2022).

In the case of the VC firm, II is often done through the creation of a dedicated green fund as part of their offering. Green funds only invest and support companies that they consider contributes to positive social or environmental effects (Crifo & Forget, 2013). Since II can be considered to have a higher purpose than just financial returns, the VC sometimes opt for a less strict IRR (Barber et al., 2021). Often green funds are created because of investor pressure and engagement. Following the implementation of SFDR, large pension funds have undertaken steps to align themselves with the SFDR regulations. One notable example is the Swedish public pension fund AP7, which has obtained the classification of an article 8 fund (Pensionsmyndigheten, n.d.). This classification signifies that AP7 has allocated all of its capital to investments that adhere to article 8, thereby reinforcing the establishment of a dedicated green fund structure for VCs looking to attract investments from environmentally conscious institutional investors. The creation of a green fund could also be a tool for the VC firm to manage risk and diversify their portfolio (Crifo & Forget, 2013). There are VC firms that exclusively operate green funds, these firms are sometimes referred to as social impact venture capitalists (SIVCs; Croce et al., 2021).

Cohen (2021) categorizes investments in sustainability as two-folded, working with outcome impact or environmental, social or governance (ESG) principles. ESG is looking at the internal processes of a company and making sure that it complies and improves according to preset principles. Impact, or outcome impact, instead refers to the positive social or environmental improvement that is a direct result from the company's business. The outcome impact is the positive difference between the scenarios where the company does and does not exist (Paper et al., n.d.).

2.3.1 Environmental, Social and Governance Principles in Venture Capital Investing

ESG frameworks are widely used in VC investing. In a report based on two pan-European surveys, the largest surveys conducted on the VC market as of 2020, the European Investment Fund found that around 70 percent of all VC firms apply some kind of ESG consideration to their investment (Botsari & Lang, 2020). ESG refers to a set of often divergent approaches to evaluate the internal processes of a company using non-financial data to evaluate its environmental, social and governance performance. It is most commonly applied in the screening process, filtering away the companies that pose an ESG risk based on chosen criteria (Botsari & Lang, 2020). When a company has been acquired by a VC, the VC can through its votes influence the processes and management of a portfolio company and as such

also the ESG performance. This can be powerful as they can early on in the company's life-cycle assist in avoiding to scale environmental or social problems and costs (Randjelovic et al., 2003).

There are, however, problems with applying an ESG approach in VC investments. The survey performed by the European Investment Fund indicates that the key barriers for a proper implementation of an ESG metric is that VCs usually have limited expertise in the area and that early-stage companies lack proper quality data for the analysis (Botsari & Lang, 2020). Also the method of ESG itself has received quite a lot of criticism recently. Introduced as a way of easily comparing and bringing II out from a niche practice to a far broader audience, the metrics are often too materiality-driven and by definition does not account for the positive or negative externalities that come out of the company's business. For example, using the ESG score of one prominent provider on 143 companies together with deforestation risk score put some companies with the highest deforestation risk at the top of the ESG chart (Crona et al., 2021).

Furthermore, there is a lack of standards of ESG criteria across industries and how the companies apply them varies a lot (Crona et al., 2021). Some VCs choose to double down on a single factor which then guides their decision. With the lack of a standard, potentially any company could comply with at least one ESG criteria in one specific framework (Goraya & Usman, 2011). A standardized system for measuring companies' ESG performance is widely desired. However, according to Crona et al. (2021), the challenge of standardizing ESG lies in balancing accuracy and precision. Accuracy involves ensuring that companies are working on the right issues, while precision involves ensuring that companies strive for the same ESG goals (see Figure 3). While creating a standardized ESG framework is proposed as the solution to improving ESG, it may actually worsen the problem. It is impossible to capture all aspects of social and environmental issues sufficiently in a single ESG framework. Thus, a standardized system could result in a bias towards certain ESG issues, neglecting others. For instance, prioritizing climate over biodiversity. This would enhance the precision of ESG work, as companies strive for the same goals, but it would reduce accuracy, as companies miss important issues and challenges (see B to A in Figure 3).

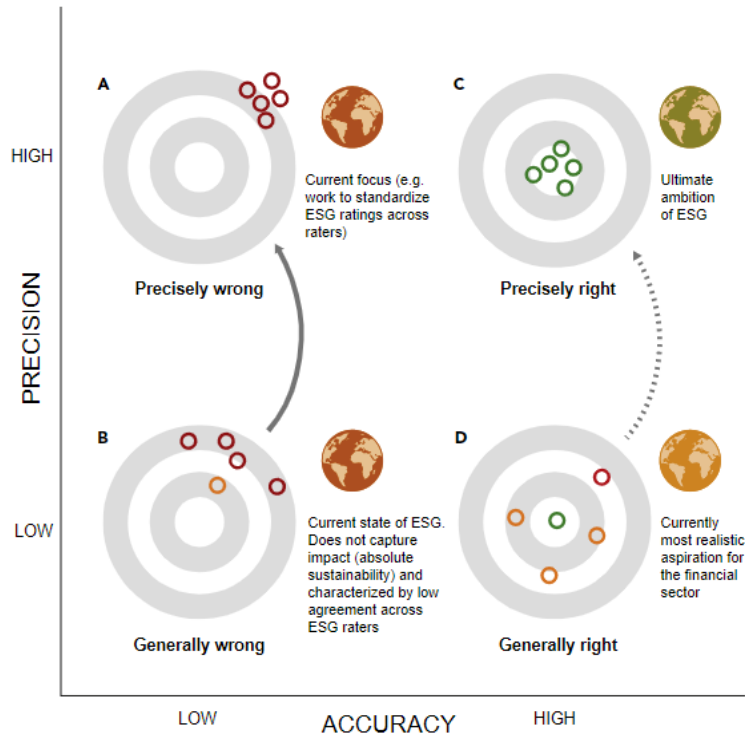


Figure 3: Accuracy and precision of current sustainable finance approaches (notably ESG) in relation to declared sustainability ambitions (Crona et al., 2021).

2.3.2 Impact in Venture Capital Investing

The other way of incorporating sustainability in VC is investing in outcome impact through impact startups. Instead of focusing on the internal processes of the company, the actual business model and outcome is evaluated in terms of environmental and social good (Paper et al., n.d.). Impact startups are those ventures that from the start have the vision of creating a positive impact on society or the environment. They typically address a pressing problem and if they succeed with scaling their solution, it will result in a sustainability net benefit (Horne & Fichter, 2022). To test if a company is to be considered an impact startup, VCs can for example evaluate their alignment with one of the SDGs (Paterson Pochet, 2023).

One of the difficulties of incorporating outcome impact in the VC portfolio has been that traditional impact ventures typically revolve around some kind of physical product. This implies a longer development cycle to reach market-breakthrough and explosive growth than service-oriented products. While VC generalists focus on fast-growing industries such as IT and communication, most green capital is put towards solar, wind and industrial process technologies. Many green ventures are therefore refused capital because the type of technology innovation does not impose a breakthrough fast enough to reach the IRR goals of the traditional VC firm (Randjelovic et al., 2003). Some investors, though, do see investing in outcome impact as fulfilling a higher purpose and thus accept a lower IRR. It was shown in a recent study that on average a typical investor is willing to accept a 2.5-3.7 lower IRR if investments were made in sustainability efforts (Barber et al., 2021). Managing a green fund, with a premium financed by investors, could then allow for VCs to finance green projects that traditionally would not be financed. The problem with not tying the investment to a high enough financial goal however, is that it will create a portfolio characterized by low risk, low return and in turn low impact projects (Brest & Born, 2013).

Brest & Born (2013) argues that if the same strict requirements for financial return are put on impact ventures most of the portfolio will surely fail, but the projects that succeed will achieve such high returns and impact that it compensates for the failures. A philosophy that is in line with a traditional VC portfolio strategy. This is now what is starting to happen within VC investing, where several impact startups have experienced high growth and hence high returns for investors while creating a sustainability net benefit. An indication of this is the accelerating growth in the amount of impact unicorns, impact startups valued above one billion dollars. As of 2022 over 200 companies created on the basis of any of the UN SDGs are now valued above one billion dollars (see Figure 4) (*Unicorns | Impact Tech, n.d.*).

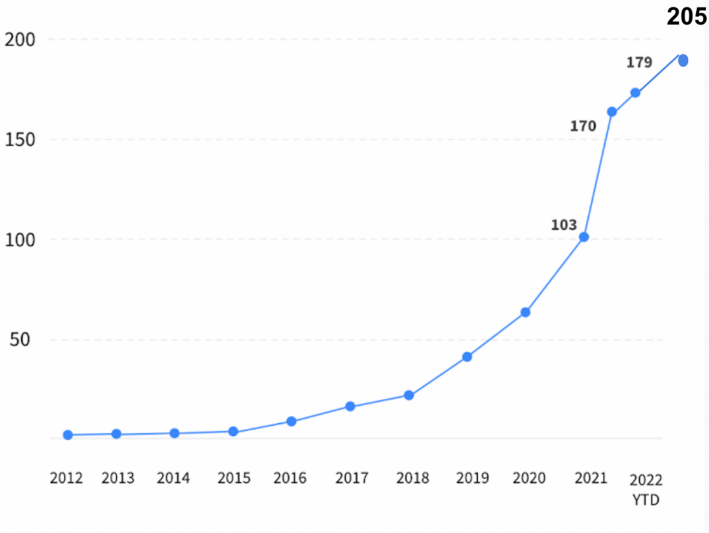


Figure 4: The number of impact unicorns in the world 2012-2022 (*Unicorns | Impact Tech, n.d.*).

2.3.3 The Optimal Investment Scope for Venture Capital in Impact Investing

Given the different approaches in incorporating sustainability ESG and impact, the question still remains: What should be the role of VC firms in II and how can they achieve the biggest impact? Schot (2022) advocates that not all green innovations are equal and that some types of efforts have a clear advantage in impact over others. Schot categorizes transformations in magnitudes of impact in three groups from lowest to highest: optimization, partial redesign or system change (see Figure 5). In the case of ESG, it could be seen as a form of optimization, while impact outcome investing could, depending on the investment, target any of the three. Efficiency improvements in companies and projects do often only lead to a marginal positive impact in the short-term but in doing so also preserves the underlying unsustainable dominant system in the long term. Therefore investments into efficiency investments are not enough to facilitate a system change but rather might delay sustainable breakthroughs. In the context of ESG this could be to make processes in the oil and gas industry less pollutive, making combustion engines relevant for longer. Electrification would be an example of partial redesign, this directly removes the in-use emissions by removing the combustion engine, but unsustainable processes still remain in production. Lastly, system change comes from innovation that completely redesigns the system and in the transport sector, it is likely to come from new ownership models, self-driving or digital solutions to reduce the need for transportation. Contributing to partial system redesign or system change does not necessarily only mean to work directly on the main drivers of a transformation such as solar cells for the

renewable energy transition. Products that simplify, make the transformation cheaper or more convenient also contribute to partial or complete system change (Schot, 2022).

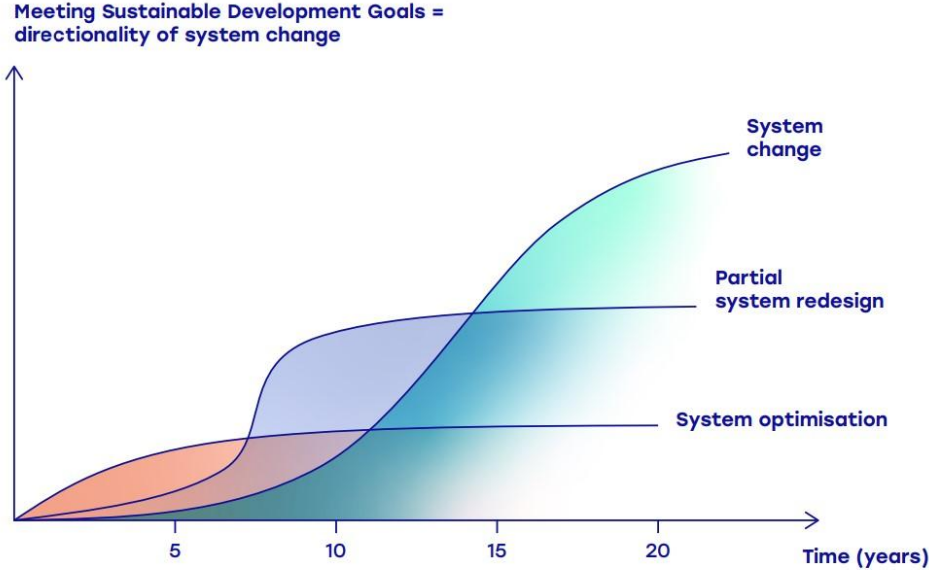


Figure 5: Magnitudes of sustainability transformations (Schot, 2022).

VCs have a chance to use their existing strategy when entering II if they avoid capital intensive projects that heavily rely on the construction of a physical product, and instead steer their investments into technology that facilitate system change. Ghosh and Nanda (2010) describes this positioning of VC capital as a focus on investments with high technology risk, but low capital intensity (see Figure 6). This is a space considered too risky for both debt investors and large corporations that instead tend to focus on projects with a low technology risk. The consequence of this is that capital intensive projects with low technological risk, such as wind farms, still receive funding although VCs do not provide it for them. Incremental innovations positioned in the lower left box, e.g. wind components of proven technologies, do not either face any challenges to receive debt capital or capital from existing firms since they rely on a proven concept. The space of high-risk, low capital intensity hence seems to be an area for startups to exploit and VCs to act as the capital provider, enabling the innovation growth so that these innovations can reach their full potential (Ghosh & Nanda, 2010).

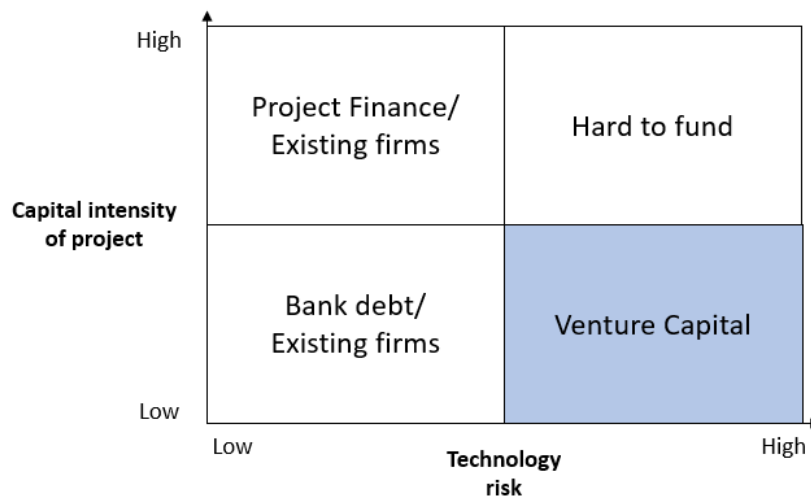


Figure 6: Ghosh and Nanda's Focus of VC Investments Matrix, where the axis of Technology risk could also be described as the more general term of business risk or innovation risk (Ghosh & Nanda, 2010).

The findings propose that the role of the VC firm should be to focus on investing in startups that lead directly or indirectly to a partial or complete system change with a focus on companies that involve a high risk but low intensity of capital. This space within II is an area that, from a pure impact point of view, helps promising sustainable businesses receive funding when debt investors and large corporations consider the investments too riskful. Although it does not solve the funding issues for high-risk projects with high-capital intensive projects, the backed enterprises could still act as enablers for these capital intensive projects. An example of this would be that VCs invest in energy efficiency softwares that could act as the enabler for a more capital intensive project such as commercial plants for green steel, taking away some of the risk for the more capital intensive projects. The importance of enablers in contributing to system change allows for more digital firms to be incorporated in II, which is more in line with many VCs current investment capabilities. This allows VCs to reach the fast breakthroughs and the high IRR they demand, while still contributing to system change and eventually impact at magnitude. In line with VCs' strategy of high risk, high reward, investing in transitions imply a lot of uncertainty but could potentially totally disrupt the current system. To find potential areas to invest in this space VCs could, from a visualized preferred system change, say for example self-driving cars, understand the different problems needed to be solved and from this figure out which companies to invest in. Examples of investments could be companies providing marketplaces for electric batteries, technology that enables automation or anything else that catalyzes the desired sustainable shift.

2.4 The Success of an Impact Investment

In order to effectively identify successful impact startups, it is necessary to provide a clear definition of success in the context of this thesis. Anna Skarborg (2023), Head of Sustainability at Northzone, argues that while a large increase in valuation is often used as a signal of success for regular startups, it does not have the same relevance for impact startups. This is due to the fact that a high market capitalization does not necessarily align with creating impact, since it is when the service or product is sold that the impact is realized. For example, companies aiming to produce green steel have recently received high valuations due to their potential positive impact, but the actual impact will not be achieved unless they are

able to substitute non-green steel at large volumes. A more accurate measure of impact success would therefore be to examine top-line growth, since for a true impact company, every dollar generated creates another unit of impact. Therefore, successful impact startups both have to demonstrate factors for general startup success, to be able to generate high revenues, and factors specifically linked to sustainability to ensure that revenue is strongly tied to impact. Subsequently the objective in the thesis is to identify impact startups with potential to generate large revenues, as it encapsulates the notion of success in the impact space more accurately.

2.4.1 Factors for Startup Success

To find startups that have the potential to become successful investments for a VC, patterns of success are identified and from this a set of critical success factors is determined. The findings are based on a McKinsey study that identifies five Ts for startup success: Teams, Total addressable market, Timing, Technology and Traction (Berger-de León et al., 2022). Academic resources are used to back up and complement these findings.

A majority of successful teams consists of at least two or more people where the founders' abilities compliment each other, preferably a mix of natural sciences, technology and business. Level of education is also important, more than 95 percent of successful founders had completed a higher academic degree. Going to university not only gives you valuable knowledge, it also exposes you to a big network to leverage (Berger-de León et al., 2022). However, simply education is not enough, most successful startups also had experience either from industry or previous entrepreneurial endeavors before founding their current startup. This is especially of importance early on in the life of a startup, where the team's joint knowledge of the external environment plays an important role in driving the company's growth (Hashai & Zahra, 2021).

Another important factor for startup success is access to investment. Startups that manage to receive funding and external capital can more easily transform ideas into actual business functions, market and develop the product or service, employ talented people and access other resources (Rodrigues et al., 2022). The number of funding rounds and amount of capital raised is thus an important aspect to look for and evaluate when predicting startup success (Cao et al., 2022).

Addressable market is often regarded as one of the most important success factors for a startup. If the market is small, it significantly limits the potential of the company which makes it an important metric for investors when estimating the opportunity of obtaining a successful return (Bouhayya, 2022). Although there are unicorns in smaller markets, most of them usually develop in bigger markets and therefore participating in those industries results in the most successful results. Following big business trends, sustainability for example, often leads to big new markets and gives the potential launch of hundreds of new unicorns. With 11 different investment areas of sustainability, it is expected to foster a large number of new impact startups (see Figure 7) (Berger-de León et al., 2022).

Addressable market size in 2030, selected categories, \$ billion

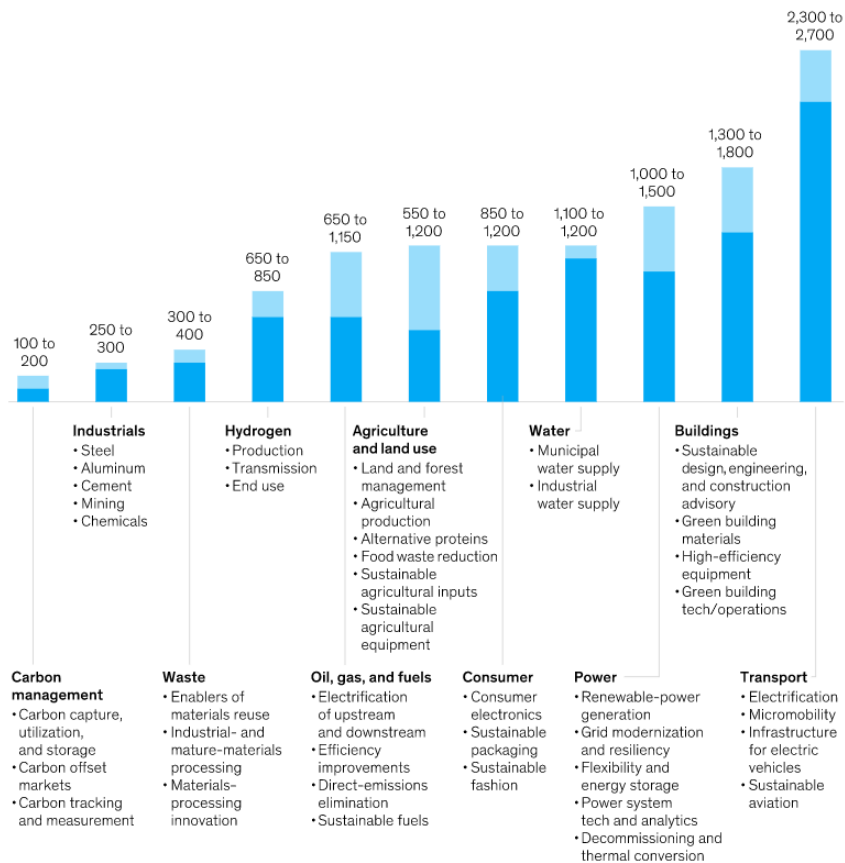


Figure 7: Eleven high-potential value pools in the climate economy (Berger-de León et al., 2022).

Having the right timing is also an important aspect for startup success. Being a first-mover in a market allows the company to establish a strong position in the market, enjoy higher margins and faster growth (Berger-de León et al., 2022). While being far ahead of competitors is usually a positive, being too far ahead of the market can be undesirable. Moving before the market is detrimental as the company runs out of funding before revenues start to flow in. Furthermore, the first-mover also risks having high R&D costs with long payback time, lack of supporting technologies, standards and distribution channels. Hence, the timing of the product is crucial to harvest the advantages of being a first-mover, while not experiencing too many of the downsides (Schilling, 2008:88-91). To make sure that the timing for the product is right, it is vital to keep close contact with customers and learn about their needs and requirements. Even though the startup is delivering a product or service that is ahead of the mainstream market's needs, there is typically a more niched customer cluster that can be targeted and used to receive customer feedback (Lizarelli et al., 2021).

Between 2010 and 2020, the majority of venture capital was used to fund technology startups and in the first quarter of 2021, the share of venture capital invested in technology was as high as 70 percent (Schallehn & Johnson, 2021). Technology is often what makes businesses able to scale up and realize extreme growth. Therefore, VCs generally find bigger success in software solutions as they do not require the complex logistics and maintenance that hardware does. Many firms are either born digital or pivot more towards software solutions as they grow (Berger-de León et al., 2022).

A successful startup is expected to show a clear path to profitability. This is often done through looking at customer acquisition cost and customer life-time value. As the company matures, the ratio should shift towards having a much larger customer life-time value than customer acquisition cost indicating that the solution is sustainable in the long-term (Berger-de León et al., 2022). Another way to identify that a company is on their way to profitability is that there is a plan towards profit maximization. This has been established to be a key aspect in investment decisions and hence heavily affect startups opportunities to survive, attract capital and succeed (Tanrısever et al., 2012).

The success factors documented in business literature can be complemented by additional factors identified through attempts to predict startup success using AI models. These models usually employ a deep learning neural network that has been trained on a variety of data points related to team, industry and founding which are said to be predictive of a successful startup. Deep learning is a subset of machine learning, which in turn is a subset of AI and can most easily be described as an artificial neural network using hidden layers of neurons to process data in a human-like way. Cao et al (2022) carried out a literature review on the usage of deep learning models to predict startups success and synthesized popular startup success criteria. Below the most frequent criterias found in the literature review are highlighted, defined as having been found three or more times in literature. Although these are the most prevalent factors and thus could give a general understanding of what factors to consider, it is important to note that no positive or negative correlation was stated for specific variables in the studies that have been made. In other words it is unknown whether or not several years since the founding of the company results in lower or higher chance for success compared to a younger company and neither if it is uncorrelated.

Table 1: Criteria for predicting startup success in deep learning (Cao et al., 2022)

Funding	<ul style="list-style-type: none"> ● Total number of funding rounds ● Total amount raised ● Funding types ● Elapsed time since latest funding ● Size of last funding ● Type of seed funding ● Average size per round ● Time between consecutive rounds ● Raw-time series of rounds
Product/Serviceing	<ul style="list-style-type: none"> ● Industry ● Sector ● Sub-sector ● Textual description of offering ● Project specification on crowdfunding platforms ● Learning from product videos and images
Meta information	<ul style="list-style-type: none"> ● Time since founded ● Textual description of company ● Geographical description ● If the company has social media account

	<ul style="list-style-type: none"> ● Domain name
Founder/owner traits	<ul style="list-style-type: none"> ● Founding team size ● Founding team experience in industry or other startups ● Founder ID ● Gender/Ethnicity ● Founder social media account info ● Founder functional skill
Team	<ul style="list-style-type: none"> ● Team size
Investors	<ul style="list-style-type: none"> ● Number of Investors ● Investor performance or ranking
Web	<ul style="list-style-type: none"> ● Rank of website ● Visitors ● Duration of visit ● Bounce rate ● News count ● Topics of news/article ● Twitter statistics of company ● Count of websites that mentioned the company

2.4.2 Factors for Impact Startup Success

The attributes and success factors of an impact startup are typically aligned with the attributes for a regular startup, considering the fact that both types depend on achieving growth and a scalable business. In an article made by Rodrigues et al (2022) a review of current literature has been made to see where critical success factors for circular economy initiatives are overlapping with CSFs for startups. More specifically the study is made on startups in industry 4.0, which means technology startups contributing to areas such as big data analytics, internet of things, cybersecurity, etc. The results show that the most common CSFs are access to investment, management commitment, organizational culture, organizational strategies and public policies. These are all important aspects for any startup, but differ in the way that principles and concepts of sustainability are clearly stated in the management commitment, organizational culture and strategy. Furthermore, public policies are considered extra important for sustainable businesses since most of them probably already comply with the new regulations whereas their competitors do not. Therefore, public policies, regulatory frameworks, and legislative measures play a crucial role as facilitators for impact-driven startups, providing them with a distinct advantage in their pursuit of market dominance over competitors who may face challenges in complying with these regulatory requirements (Cantú et al., 2021).

Rodrigues et al., (2022) emphasize the importance of management commitment in impact startups and that founders are genuinely driven by a purpose or passion that goes beyond creating profits (FasterCapital, 2023). This commitment has been seen to play a crucial role in the continuous growth when for example funding is tight or the technology of the company is still not fully developed (Bowcott et al., 2022). An important CSF for impact startups is the

ability to establish partnerships and meaningful collaborations. Impact-focused startups should share knowledge and information along the entire value chain, thereby optimizing production and ensuring sustainability across all stages of the product life cycle (Rodrigues et al., 2022).

Another CSF for impact startups is the formulation of the business model. If a business case is not properly built around the impact case, the business will not be scalable and consequently not able to make a true, full-scale impact (FasterCapital, 2023). Furthermore, building in circularity and sustainability into the business model will help startups increase their differentiation to industry competitors, while being able to reduce sustainability related risks (Khan et al., 2020).

Working with sustainability can usually mean a value-add to the product or service that a company is offering. Negative ecological challenges provide opportunities for entrepreneurs to create new companies. Performing above the benchmark on these issues however, often implies higher costs for the company. Because of this it is crucial to capitalize on sustainability efforts. In order to do so it is important that the company takes time to describe, analyze and communicate the value proposition to its customers. This work should be strategic, establishing a clear sustainable message to effectively target sustainability conscious customers. Failing to do so could result in clients not recognizing the company's sustainability work and thus an unwillingness to pay a premium (Kuckertz et al., 2019).

It is also important that companies address the right sustainability topics for their specific industry. The concept of materiality is often used in financial reporting, but it could also be used when referring to sustainability by pinpointing the most crucial sustainability areas. The identification of the most relevant sustainability topics could be done by placing the detected issues in an industry-specific map, ranking them according to impact potential and business relevance (see Figure 8, where an example of Klarna's materiality map is shown). Companies that want to manage their sustainability work effectively must thus choose to address the right sustainable issues to not only have a big enough sustainable impact, but to make it relevant for the kind of business they operate (NYU Stern - Center for Sustainable Business, 2019).

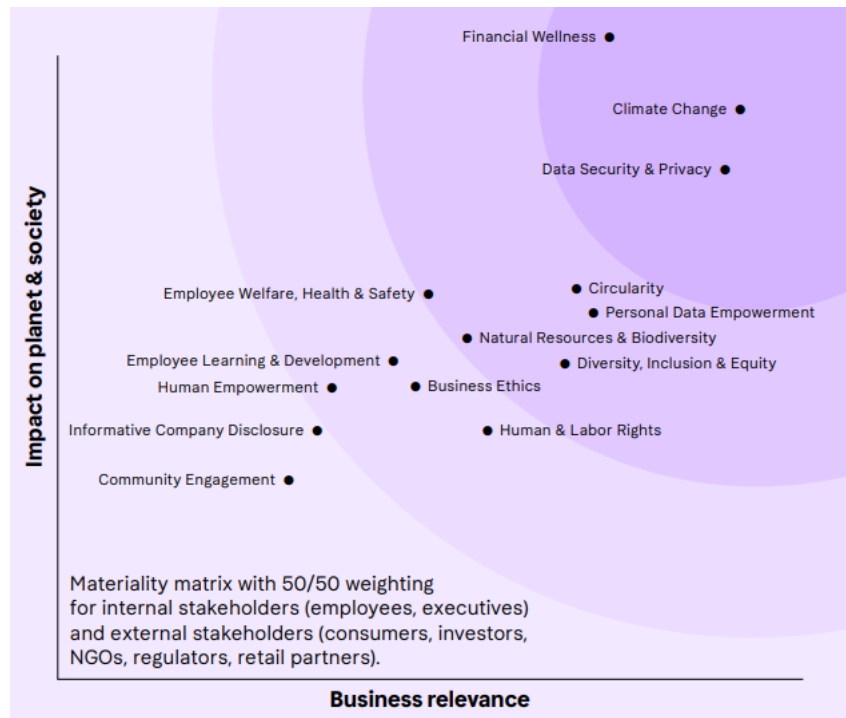


Figure 8: A materiality map for Klarna 2021 (Klarna Holding AB, 2021).

2.5 Artificial Intelligence and Its Usage in Private Equity and Venture Capital Investment Decisions

Although overall adoption still remains low, the last decade saw the number of private equity and VC firms using AI in their investment process increase rapidly. The models used vary from helping only part of the process to full scale end-to-end decision making tools (Åstebro, 2021). The investment process for a VC firm can be divided into four different stages (Stahl, 2021):

- *Deal Sourcing*: Finding relevant companies with high potential
- *Deal selection*: Choosing which companies to invest in
- *Contract negotiation*: Determining valuation and price
- *Value Creation*: Managing and growing the companies

AI tools are mainly applied in the deal making, the two first steps of the process, either screening companies or trying to predict success of a particular startup. By automating this process, firms can significantly increase their capacity to evaluate potential investment opportunities, and also to be more objective, decoupling the process from human biases (Åstebro, 2021; Cao et al., 2022; Stahl, 2021). VC investments typically are made relatively infrequently, which leads to a low learning rate and thus concentrating experience among the senior partners who often have very limited time. Research has demonstrated however, that prediction models consistently beat the performance of a VC partner to find successful companies. This might be a consequence of it being particularly hard for humans to make decisions when information is scarce, like in the VC space. Thus leveraging AI support in the investment process, VC firms can take less biased decisions, increase operational efficiency and potentially free time for partners of the firm (Åstebro, 2021).

2.5.1 Large Language Models and GPT-4

In March 2023, OpenAI released GPT-4, their latest large language model. While less capable than humans in some day-to-day scenarios, GPT-4 exhibits performance on par with humans in many professional and academic benchmarks. GPT-4 significantly outperforms its predecessor, GPT-3.5 which was released a year earlier, in many tasks (OpenAI, 2023). Openai's ChatGPT chatbot interface powered by GPT-3.5 and GPT-4, propelled the potential of LLMs into the mainstream. Within a mere two months of its release, ChatGPT attracted an astounding user base of 100 million individuals. ChatGPT is today the most famous and widely used AI chatbot on the market, although other companies such as Google now have developed competing software (Wilson, 2023).

To be able to get the most accurate answers from the GPT-4 model it is important to know what it can and cannot do. The AI which is used in the model is more specifically a large language model that generates a response by constantly predicting the next token (part of a word) in a sentence. By providing the model with text input, a prompt, the model generates a response (OpenAI, 2023). For example by providing the LLM with ingredients of a fridge, it can use its knowledge of the training data where these ingredients have been paraphrased and based on this context give suggestions on meals to cook. Not only will it give suggestions of the meals, it will provide a step-by-step cooking guide (Wilson, 2023):

- *Prompt: I have mushrooms, fresh pasta, cream and onion in my fridge. Give me an example of a dish I can cook.*
- *GPT-4: Start by boiling your fresh pasta as per the instructions on the package. While your pasta is cooking, dice your onion and sauté it in a pan until it's soft. Next, add your sliced mushrooms to the pan and cook them until they're browned. Pour in the cream and let it simmer until it thickens. Once your pasta is cooked, drain it and toss it into the pan with your creamy mushroom and onion mixture. Season it all with salt and pepper to your taste. Enjoy your creamy mushroom pasta!*

Being trained on a large set of data it has learned to interpret human speech and generate plausible answers given the context. OpenAI does not state what specific datasets the model is based on but reveals that both internet data and data that has been licensed by third-party providers have been used. Although the main language it has been trained in is English, the model also understands and shows strong generative capabilities in many other languages (OpenAI, 2023). GPT-4's memory is cut off from September 2021 meaning that it has no notion or information of what happened after then. This is because the data that the model has been trained on is dated before September 2021 and that the model cannot learn from experience (OpenAI, 2023).

It is important to understand that the LLMs are not all-knowing models or calculators, but rather predictors of words or language. This is something to keep in mind when trying to understand why a certain answer was generated or why illogical reasoning is presented (Wilson, 2023). It usually does a good job of formulating its output, but sometimes GPT models write well-articulated answers that are incorrect or nonsensical, something known as hallucination. This results comes from a bias in the training towards giving an output instead of refusing to answer. When instructed to be more cautious, GPT tends to decline both questions that it can and cannot answer. Ideally, the models would ask follow-up questions when there is ambiguity in the prompts for example with contested definition of words, but instead the model tends to just predict what it thinks the user wants (Openai, 2022). This behavior has been significantly improved in the GPT-4 version, but some hallucination and

reasoning errors remain. The model also still has a tendency to miss out on details and focus on common sayings. For example:

- *Prompt: Son of an actor, this American guitarist and rock singer released many songs and albums and toured with his band. His name is "Elvis" what?*
- *GPT-4: Presley*

In this case it chooses “Presley”, despite him not being the son of an actor and the correct answer being “Perkins” (OpenAI, 2023).

As mentioned in section 2.5, AI is already being used when making investment decisions. A majority of these models utilize both hard quantitative data such as team size and total funding, but also qualitative data of more soft aspects. Gathering qualitative data is, however, tedious having to either be surveyed from a group of humans or approximated (Cao et al., 2022). LLMs could be a tool to facilitate and improve decisions in the private equity and VC industry. The natural language processing of the model makes it suitable to make company analysis, summarizing news and in general facilitate and shorten the search for information when analyzing and searching for company data. It can also be used to analyze financial data and thus work as an important tool for investors (BlackRock, 2023). There is however, a big disadvantage of using an already trained large language model as opposed to a deep learning model. As with conventional statistical work, using GPT-4 to evaluate different companies needs to start with a hypothesis statement of factors to look for in a great company which could be a difficult task. When training a deep learning model there is no hypothesis of what parameters are most important for a good startup, and the model will automatically find which inputs most correlate with success (Cao et al., 2022).

A big criticism of deep learning startup success prediction models is that they are black boxes, meaning that it is difficult to explain why a certain decision was made. Explainability is crucial for investment professionals. Although there are methods for analyzing the decision-making process of a deep learning model it is not at the same level of transparency as a regression model for example (Cao et al., 2022). Deep learning models are especially bad at instance-level explainability, giving the reasoning behind a certain prediction, which is arguably the most important for investors to understand (Ross et al., 2021). Language models such as GPT-4 are also built upon deep learning models making the inner works of the model a black-box (Binder et al., 2022). What a user can do however, with a model like GPT-4 is ask for justification and motivations for the answers given. Providing the investor with more context to an investment decision than simply a yes or no, the investor could have more confidence in interpreting the AI. As discussed earlier however, since it is a LLM, it is not using logical reasoning to justify answers but rather trying to predict words from the given context. Nonetheless, since a reasoning is presented, there is a possibility of fact-checking the model and underpinning a certain output. The effectiveness of self-explanations given by LLM is subject for future research. If proven reliable, it could be a way of increasing explainability, most probably making AI tools more widely adopted in VC investment.

2.5.2 Prompt Engineering and Fine-Tuning

Prompts in the context of Large Language Models are a set of instructions given to a LLM to ensure a desired output from the model, a sort of textual programming. A prompt can be kept in the model’s memory and thus affect the following outputs. This can be used to set the context of the interaction with the model and thus highlight what is important and what is not. The process of optimizing the prompts to get a certain format on the output from the model is

called Prompt engineering. Prompt engineering is a vital step when using LLMs since the quality of the output is directly linked to the input (White et al., 2023). Because GPT-4 was just recently released, not much research has been done on the model, therefore prompt engineering insights will be drawn on findings on its predecessor, GPT-3.5.

Prompt patterns are templates that are powerful reusable tools for solving certain types of problems. White et al. (2023) gives a wide set of examples of prompt patterns of which two of them will be applied in this thesis. Firstly we will utilize the *Persona Pattern*, which makes the GPT model take on a certain point of view and perspective. An example of a *Persona Pattern* prompt would be:

- *Prompt: Answer the following questions as a sustainability analyst would.*

In the thesis this technique will be used to make the GPT model provide output more relevant to what we are trying to evaluate, sustainability in a corporate context.

The second prompt pattern we will use is the *Question Refinement Pattern*. This pattern helps figure out what types of questions to ask the GPT model to get a more relevant and specific answer. An example of a *Question Refinement Pattern* is:

- *Prompt: From now on, whenever I ask a question, suggest a better version of the question to use that incorporates information specific to impact startup investment and ask me if I would like to use your question instead.*

In the thesis this technique will be used iteratively to perfect the prompts to get the desired output from the GPT model.

A VC investor is only able to analyze a small fraction of startups in the relevant investment scope and an even smaller portion can be further considered for funding. Moreover, it makes sense to only present the companies that have the greatest potential to investors. Cao et al. (2022) therefore suggest that deep learning models to be used in VC-screening should aim for high precision, meaning that the model classifies very few false positives. This correlates with a high recall, the model being restrictive in giving a positive classification, resulting in a lot of false negatives. Because of the vast number of prospects, a sufficient number of successful companies can be generated making the trade-off worth it in the context of VC investing (Cao et al., 2022). To implement this idea in the context of GPT-4 and prompt engineering, prompts will be stated as such so that the model will not give a positive answer unless it is confident. An example of this could be to add the confidence word “significantly” so that the model acts more restrictive. For example using:

- *Prompt: Will Einride significantly help to reduce emissions?*

Instead of:

- *Prompt: Will Einride help to reduce emissions?*

In the documentation of the ChatGPT model, the developers state the different use cases of the model. The ones that are interesting in the context of company analysis are *Factual Response* and *Classification* use cases. The model can give factual responses based on the data it has been trained on, for example providing info about a company's sustainability

efforts. Classification is describing a rule and letting the model classify statements according to it (*OpenAI API*, n.d.). In this thesis we will use these use cases together to first generate information about the companies and then classify whether or not they fit into a predefined criteria. To optimize the model to perform these use cases, the documentation recommends that certain settings and prompt snippets are used. As discussed earlier the model has a bias towards giving an answer, being made up or not, instead of not giving a response to a prompt. There are two ways of limiting the likelihood of the model making up an answer and in turn giving a better factual response. Firstly, the temperature parameter can be set to zero, which then removes the aspect of randomness in the answer. This makes the model deterministic and always chooses the answer with the highest probability, in other words limiting the “creativity” of answers. Secondly, if it is stated in the initial prompt that the model is allowed to respond that it does not know an answer, the model can be refrained from guessing (*OpenAI API*, n.d.). An example is provided below.

- *Prompt: If you are unsure of an answer please answer with “Unsure”.*

To make it a better classifier, documentation says not to provide too much context to the model. This tends to make the model drift and forget the task at hand (*OpenAI API*, n.d.).

The *OpenAI API* (n.d.) offers the service of fine-tuning the GPT model which could improve its performance. The OpenAI models have been trained on a vast amount of data on the internet, but when given a prompt it can often narrow down its scope and intuit what task the user is trying to perform. Fine-tuning the model improves this ability which should make it achieve better results when performing certain tasks. The process of fine-tuning requires the user to provide examples of prompts followed by the ideal responses to it. For example:

- ***User-generated prompt:*** *Describe venture capital in 50 words!*
- ***User-generated ideal answer:*** *Venture capital is financing provided to startups in exchange for equity. Investors support promising ventures, offering capital, expertise, and connections. They aim for high returns upon successful exits like acquisitions or IPOs, fostering innovation and growth.*

After fine-tuning the model it requires less context in the prompts given to respond with a relevant answer. OpenAI brings up some examples on fine-tuning. One of them is as a customer chatbot, where training the model on product specific issues can help guide customers step-by-step to solve the issue. Another use case is writing engaging advertisements based on wikipedia articles. In this case it would learn what data is important and mimic the writing style of the input. Openai states that 500 samples is a good starting size for the dataset to train the model (*OpenAI API*, n.d.). In the context of VC investment analysis, fine-tuning a model would mean giving a prompt on a set of investment criteria and company data. Through human analysis an ideal investment analysis would have to be generated for each sample company. The model would expectedly learn and improve its ability to extract important information from the input prompt, refining its ability to perform future investment analysis.

3. Method

The thesis uses theoretical research from academic articles together with interviews to formulate a number of CSFs. These CSFs are then formulated as questions and used as input in an LLM or AI model that evaluates the impact potential of a set of companies. First, the prompt is tested without any additional information and thereafter, it is provided with relevant texts and articles about the screened firms. A second prompt will also be tested in which the CSFs are summarized into what the thesis will refer to as an *investor profile*. Given the investor profile, the model is asked to try to identify the sought-after characteristics described in the profile, in the investment prospects. The output from the two prompts is then used to understand the potential usage of an LLM model to identify successful impact startups and hence answer the research question of how LLMs could be used to maximize sustainability impact and in what way such a model could contribute to a more sophisticated screening process. As mentioned in section 2.5.2, fine-tuning the model could potentially improve the performance, in this thesis however, this opportunity will not be explored. OpenAI recommends at least 500 high quality samples for the fine-tuning of the model. Considering the need for access to a sample of high quality financial analysis, that type of project would probably have to be done by a VC firm.

3.1 Knowledge Gathering

In this thesis academic and business literature serve as the foundation of knowledge on the topics of sustainability, impact investing, venture capital, startup success and are used to identify an optimal investment scope for VCs within impact investing. From these insights, academically aligned CSFs are formulated which together with prompt engineering research are used to understand how the CSFs can be turned into input in an LLM to get the desired result. The literature research is complemented by interviews with people working in VC to further ensure a comprehensive understanding of the industry, the problems experienced in the screening process and making CSFs sure are anchored in the business milieu (see Appendix A for an overview of the held interviews). An important brainstorm session was also conducted with Kye Andersson, strategist for major Impact Initiatives at AI Sweden, to discuss potential enhancements for the model and lay the groundwork for future use cases.

3.2 Definition of Critical Success Factors

Based on the theoretical research conducted in sections, 2.1 Sustainability, 2.3 Impact Investing and 2.4 The Success of an Impact Investment, the CSFs for general startups as well as those for impact startups in particular has been synthesized into two tables.

Table 2: Critical success factors for general startup success

Category of critical success factor	Critical success factor
Founding team	<ul style="list-style-type: none"> • The founding team has a diverse set of skills, preferably a mix of a technology and business background • Founders have completed an academic degree • Founders have work experience from the industry • Founders have experience of previously founding a company
Access to capital	<ul style="list-style-type: none"> • The startup has received previous funding rounds
Addressable market	<ul style="list-style-type: none"> • The addressable market is big • The startup's solution is following a business trend
Timing	<ul style="list-style-type: none"> • The company has first-mover advantage in their market • The company is moving and growing together with its market • The company keeps a close relationship with customers
Technology	<ul style="list-style-type: none"> • The offering involves a software solution
Financials	<ul style="list-style-type: none"> • The company has a clear path to profitability
Web	<ul style="list-style-type: none"> • The company's website has increased traction

Table 3: Critical success factors for impact startup success

Category of CSF	CSF
Impact startup qualifier	<ul style="list-style-type: none"> • The company is founded with the purpose of creating a positive impact on society or the environment • The company is complying with the EU Taxonomy • The company is complying with the Paris Agreement • The company is contributing to one or several of the United Nations Sustainable Development Goals

Management and organization	<ul style="list-style-type: none"> ● Management and the organization as a whole has a commitment to sustainability and it is included in the strategy of the company ● The founders and management act in a purpose and passion-driven way to pursue an impact goal and not only high profits
Public policies	<ul style="list-style-type: none"> ● Public policies are in place, or will soon be introduced, that support the business and the sustainability efforts that the company is contributing to
Supply chain commitment	<ul style="list-style-type: none"> ● The company enforces sustainability along its supply chain
Business model	<ul style="list-style-type: none"> ● Sustainability is embedded as a key part of the business model ● The business model is scalable ● The business model is for-profit
Communication	<ul style="list-style-type: none"> ● The company is strategic in how it communicates its impact efforts
Sustainability focus	<ul style="list-style-type: none"> ● The company is addressing a relevant sustainability issue for its industry ● The company's solution contributes to a transformative sustainable change

3.3 Candidate Selection

What data is important to effectively screen startup companies varies a lot depending on the growth stage the company is in. The earlier the stage, the more soft aspects about team, technology and potential market are weighed in. In late-stage companies, analysis of the company's financial statement plays a far bigger role in the investment decision (von Sydow, 2023). As previously discussed LLM's strength lies in evaluating soft aspects but is not as efficient in analyzing numerical data. With this in mind it would be of a higher value to investors if this method is used early on in the startup stage. However, LLMs uses data that has been published on the internet, therefore the smaller the company, the less probable that there is information available and that the model knows about the company. Based on these opposing forces the thesis will investigate the model's effectiveness at multiple stages, from companies that have received seed to series B funding. The selected companies in this thesis successfully secured funding in each growth phase from VC firms Northzone and Norrskan in their latest funding rounds. Northzone is a generalist VC firm and one of the leading early-stage investors in Europe and has been active in the industry since 1996. Northzone primarily invests in technology startups with a focus on consumer internet, enterprise software, and deep technology among other sectors (Northzone, n.d.). Norrskan VC is a

Swedish venture capital firm that focuses on early-stage investments in startups and is what can be defined as an impact VC. Norrsken VC primarily invests in companies that have the potential to make a positive impact on society and address global challenges, such as sustainability, education, healthcare, and poverty (Norrsken, n.d.). Choosing to analyze companies that are already part of Northzone and Norrsken’s portfolio allows for the model to be tested on both conventional and impact startups that is by definition part of the investment scope of VCs.

Table 4: Companies evaluated

Candidates	Funding Round	VC investor	Last funding	Founded
Troop	Seed	Northzone	2022	2021
Hidden Door	Seed	Northzone	2022	2020
Goals	Series A	Northzone	2023	2021
Yonder	Series A	Northzone	2023	2020
Infogrid	Series B	Northzone	2023	2018
Katana	Series B	Northzone	2022	2017
Lun	Seed	Norrsken VC	2023	2021
Grünfin	Seed	Norrsken VC	2023	2020
Liefergrün	Series A	Norrsken VC	2022	2020
Elypta	Series A	Norrsken VC	2022	2017
Einride	Series B	Norrsken VC	2021	2016
Northvolt	Series B	Norrsken VC	2020	2016

3.4 Using Question-Based Prompts to Evaluate Startups

From each CSF in table 2 and 3, a question is formulated so that GPT-4 can give an answer whether it believes the startup fulfills it (see Appendix B.1). As discussed in 2.5.2 Prompt Engineering, the *Question Refinement Pattern* is then applied to acquire precise questions and the *Persona Pattern* is applied to give further contextualization to the model. To improve the model’s performance at *Classifying* and *Factual Response* use cases, the model is given the choice to answer “Unsure” and the temperature setting is set to zero. Lastly, by adding strengthening words such as “significantly” the model is encouraged to be more restrictive, with the intention to produce less false positives. By optimizing the selected prompts, a final list of prompts was compiled and presented to the model in a list together with the following initial prompt:

- Prompt: “In the following conversation I want you to act as a sustainability analyst and provide me with yes or no answers followed by short motivations on my questions. Always begin each answer with a yes or no. If the answer is anything other than a strict yes or a strict no, please start the sentence with “unsure”. “

Table 5: The optimized general question-based prompts

CSF	Prompt
The funding team has a diverse set of skills, preferably a mix of a technology and business background	Does XXX's founding team have a background in both business and technology?
Founder have completed an academic degree	Have the founders of XXX completed an academic degree?
Founders have work experience out in industry	Do the founders of XXX have relevant previous work experience from the industry they are acting in?
Founders have experience of previously founding a company	Have the founders of XXX any previous experience of entrepreneurship and founding companies?
The startup has received previous funding rounds	Has XXX received a funding round?
The addressable market is big	Does the main offering of XXX address a big market?
The startup's solution is following a business trend	Does the main product of XXX follow a business trend? An example of a business trend is digitalization
The company has first-mover advantage in their market	Does XXX have a first-mover advantage in the market they address?
The company keeps a close relationship with customers	Does XXX keep a close relationship with their customers?
The offering involves a software solution	Does XXX's main offering revolve around a software solution?
The company has a clear path to profitability	Does XXX have a clear path towards profitability?
The company's website has increased traction	Has XXX's website had increased traction?

Table 6: The optimized sustainability question-based prompts

Impact CSF	Prompt
The company is founded with the purpose of creating a positive impact on society or the environment	Was XXX founded with the purpose of creating a positive impact on society or the environment?
The company is complying with the EU	Does XXX comply with the EU taxonomy?

Taxonomy	
The company is complying with the Paris Agreement	Can XXX's main product help the world comply with the Paris Agreement?
The company is contributing to one or several of the United Nations Sustainable Development Goals	Was XXX founded with the purpose of contributing to one or several of the United Nations Sustainable Development Goals?
Management and the organization as a whole has a commitment to sustainability and it is included in the strategy of the company	Is XXX committed to sustainability and has it included in their strategy?
The founders and management act in a purpose and passion-driven way to pursue an impact goal and not only high profits	Do the founders of XXX strive in a passion-driven way to pursue an impact goal and not only financial goals?
Public policies are in place, or will soon be introduced, that support the business and the sustainability efforts that the company is contributing to	Are there public policies in place, or that soon will be introduced that support XXX and the sustainability efforts that the company is contributing to?
The company enforces sustainability along its supply chain	Does XXX enforce sustainability along its supply chain, not only through a code of conduct but by actively engaging with suppliers?
Sustainability is embedded as a key part of the business model	Is sustainability embedded as a key part of XXX's business model, where an increased sustainable impact by the company also can be considered good for business?
The business model is scalable	Is XXX's business model scalable?
The business model is for-profit	Is XXX's business model for-profit?
The company is strategic in how it communicates its impact efforts	Is XXX strategic in how it communicates its impact efforts?
The company is addressing a relevant sustainability issue for its industry	Is XXX addressing a relevant sustainability issue for its industry?
The company's solution contributes to a transformative sustainable change	Does XXX's solution contribute to a transformative sustainable change? An example of transformative sustainable change is electrification and automation of cars, while vehicles who introduce engines who pollute less are only contributing to a sustainable optimizing

After analyzing the selected companies based on the formulated CSFs, the model is thereafter given further context to more accurately answer the question. This is done by adding the sentence:

- *Base your answers on your current knowledge along with the following information:*

[Information on XXX]

This is something that in industry could be done at scale by building a script scraping the internet for the sought-after information. For all companies to be evaluated, the model is in the prompt provided with information from the company homepage along with recent articles on the internet up to 6000 tokens. Providing the model with additional information gives it more context, which could translate into greater performance.

3.5 Using an Investor Profile Prompt to Find Fit between Startup and Investor

The second prompt tested instead focuses on identifying sought-after characteristics and giving a ranking of how similar the investor profile is to the assessed startups. The profile consists of four areas; Investor strategy, Founding team, Sustainability and Market. Each area describes what the investor values in each segment. The investor strategy area is created based on given information on the chosen example of a generalist VC firm, Northzone, while the other areas are summarized characteristics based on the most important CSFs connected to each area (see Appendix B.2 for Northzone investor profile). To then instruct the model to perform the analysis the following prompts are presented:

- *Prompt 1: Hi, I would like you to act as an analyst at VC firm X. In order for you to know how to think, I will give you an investment profile of VC firm X along with information on what you should look for in the areas of Founding team, Sustainability and Market.*

Investor profile of VC firm X is given below.

[Investor profile]

- *Prompt 2: Based on the different investment profiles and information about Startup Y, please let me know how good of a fit Startup Y is with the profile of VC firm X and the preferences described for Founding Team, Sustainability and Market. Always start with the rating, for example “5/10” and then follow that by a justification of the given rating. The format should hence look like below, four paragraphs where x is replaced with the rating you would like to give to the fit with preferences, and then a motivation following each ranking:*

Investor Strategy: x/10

Write a motivation here. Please address as many of the similarities or differences as possible.

Founding Team: x/10

Write a motivation here. Please address as many of the similarities or differences as possible.

Sustainability x/10

Write a motivation here. Please address as many of the similarities or differences as possible.

Market: x/10

Write motivation here. Please address as many of the similarities or differences as possible.

Information about Startup Y is given below.

[Data gathered on Startup Y]

Just as with the question-based prompt, after testing the prompt once for each company, it is run a second time while given company specific information, company homepage and relevant articles. The last sentence of the prompt “*Information about Startup Y is given below.*”, is hence only given in the second contextualized version of the prompting, while the first prompt only uses the model’s pre-trained knowledge.

4. Results and Analysis

4.1 Question-Based Prompting without Context

The results from the question-based CSF prompting without context are synthesized into two graphs. The first graph highlights the results for each individual company and the second graph shows the distribution of answers for each question. To access the full results, see the Excel in Appendix C.

Number of CSFs fulfilled - without context

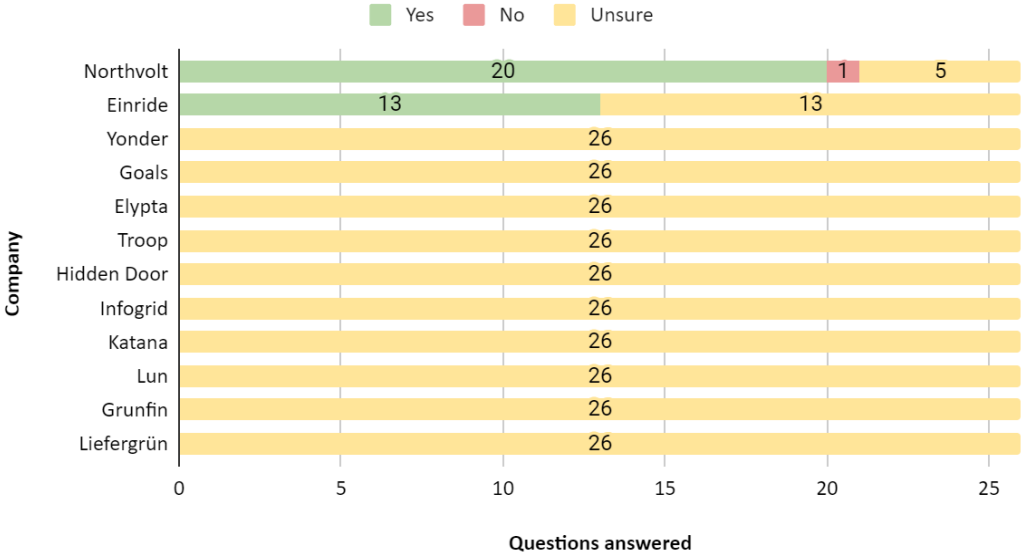


Figure 9: Number of CSFs fulfilled for each company - without context.

Share of answers for each question - CSF without context

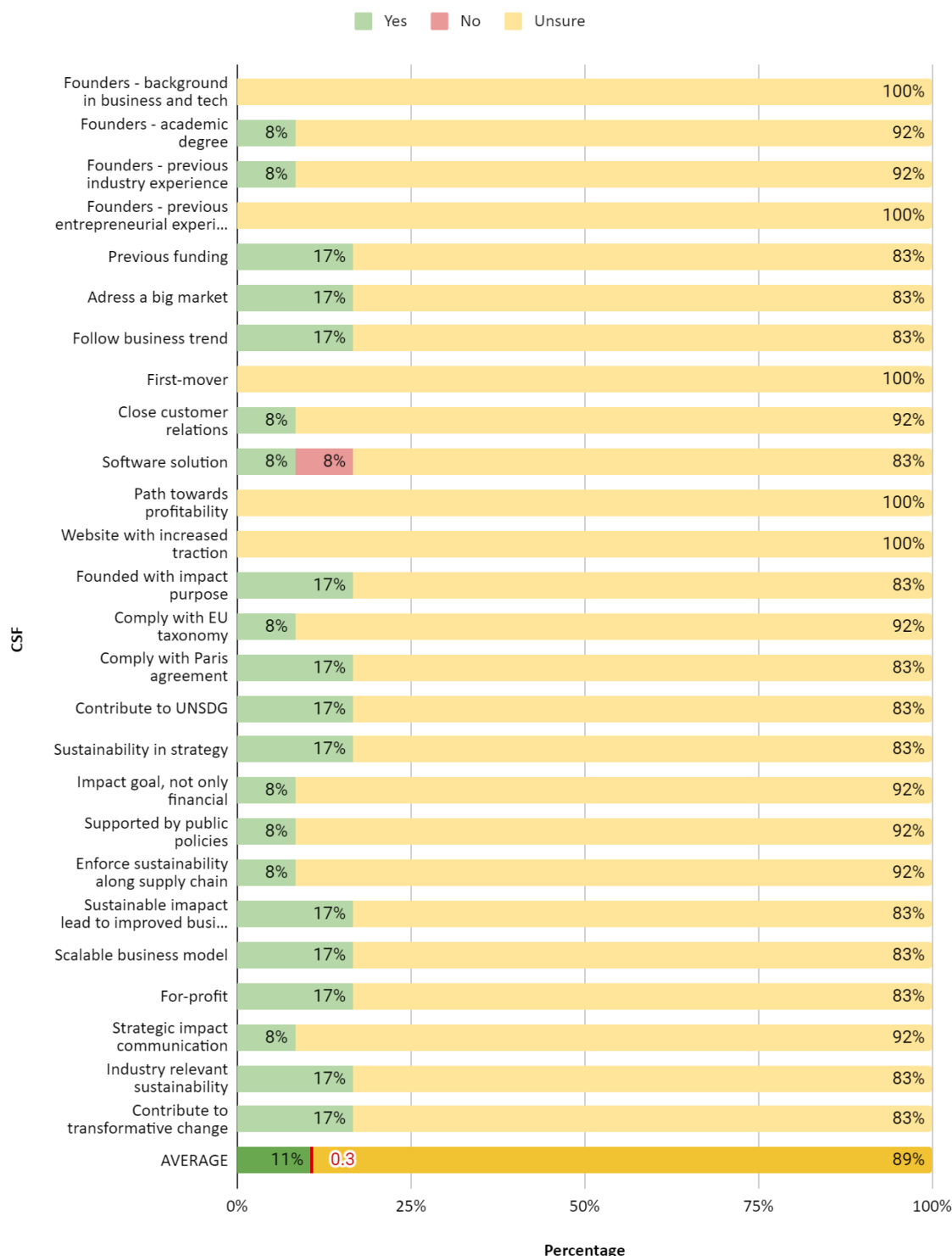


Figure 10: Distribution of “Yes”, “No” and “Unsure” for each question - without context.

The model struggled to evaluate critical success factors when no extra context about the company was provided (see Figure 9). Out of the 12 companies analyzed, 10 received exclusively “Unsure” answers on all 26 questions. Einride and Northvolt however, stood out

with Einride receiving 13 “Yes” answers and Northvolt 20 “Yes” and 1 “No” answers. Overall only 11 percent of prompts resulted in a definite answer (see Figure 10). The model explains that the majority of “Unsure” answers is due to a lack of information.

- Prompt: Do the founders of Lun have a background in both business and technology?
- GPT-4: Unsure, as I do not have information about Lun's founding team background.

Most non-unsure answers generated by the model had answers and following reasonings that were logical and plausible. For example:

- Prompt: Does the main offering of Einride address a big market?
- GPT-4: Yes, Einride's main offering, autonomous electric transport solutions, addresses a big market as the transportation industry is vast and in need of sustainable alternatives.

The reason for the poor performance of the model is most likely just as the model explains, a consequence of there not being enough information. If there is little data about a company publicly available, the information does not end up in the training dataset of the GPT-4 model and as such the model has little or no knowledge of the company. This is not surprising given that most of the companies analyzed had been founded in 2021, the knowledge cut-off date of the GPT-4 model, or just before. The same reason would explain why the model was able to answer questions regarding Northvolt and Einride, since they are the oldest companies who also have received a lot of traction and media attention. It is clear that GPT-4’s knowledge cut-off date creates problems for this type of analysis and that additional information on the companies is needed.

4.2 Question-Based Prompting with Context

As with the previous section, the results from the question-based CSF prompting with context are synthesized into two graphs highlighting the results for each individual company and distribution of answers for each question. To access the full results, see the Excel in Appendix C.

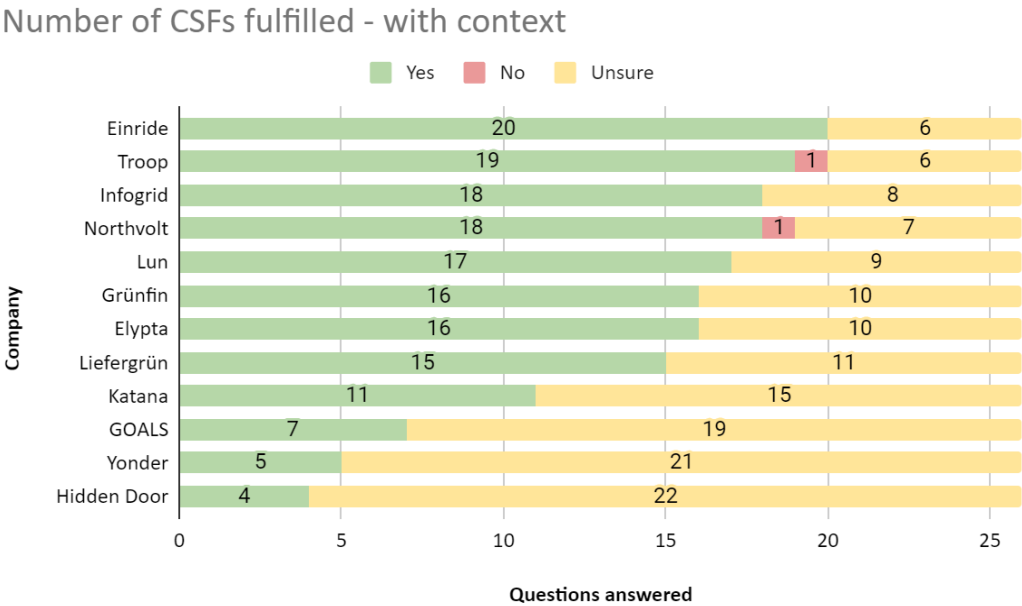


Figure 11: Number of CSFs fulfilled for each company - with context.

Share of answers - CSF with context

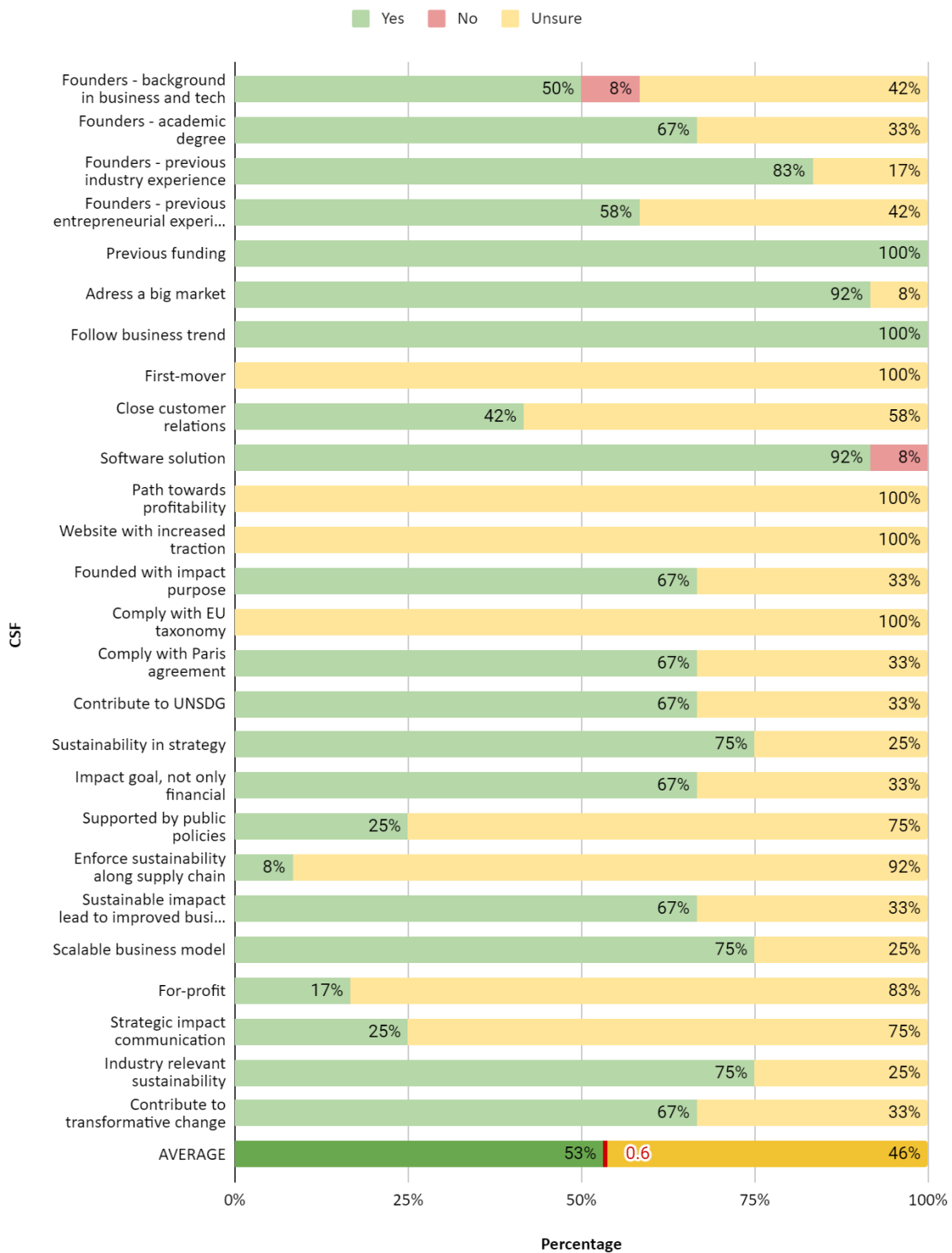


Figure 12: Distribution of “Yes”, “No” and “Unsure” for each question - with context.

Providing context and more information to the model significantly improved the model’s ability to generate an answer (see Figure 11). With context 53 percent of prompts received a

“Yes” answer, although the share of “Unsure” answers was still high, at 46 percent (see Figure 12). The share of “No” was low, representing only 0.6 percent of answers. This could be simply because the startups chosen, portfolio companies of two prominent VC firms, naturally comply with many of the CSFs shown by successful companies. Another hypothesis is that the model is biased towards giving an “Unsure” answer instead of a “No” answer when there is no explicit information about a subject. For example, if there is no concrete evidence that the company was founded with the purpose of creating a positive impact, it is most likely because it was not. In this case the model tends to answer “Unsure” even though a “No” answer would probably be more appropriate. Few companies like to talk about how they fail to fulfill certain positive criteria. This could explain why the model seems to produce a lot of “Unsure” answers regarding the sustainability related questions. The model seems to perform the best on questions regarding market size, business trends, funding and if it is a hardware or software solution. One hypothesis for why this is occurring is that these areas are more often mentioned in articles and on company websites, making them more likely to end up in the input data. Therefore it is reasonable to believe that general performance of the model would be improved if the input data is chosen in a more thoughtful way. One way of doing this would be to more intelligently choose keywords such as “sustainability” and “market” when looking for relevant information.

When looking at specific answers it is clear that the model refrains from giving an answer when it does not have access to the specific information that is requested in the input data. Instead of using knowledge from the data acquired through pre-training the model, it exclusively relies on the provided information and context even despite being told explicitly not to do so:

Without context:

- *Prompt: Is Einride's business model for-profit?*
- *GPT-4: Yes, Einride's business model is for-profit, as they aim to generate revenue through their sustainable transportation solutions.*

With context:

- *Prompt: Is Einride's business model for-profit?*
- *GPT-4: Unsure, there is not enough information provided to determine if Einride's business model is for-profit.*

Yet, when the model requests an answer where the corresponding data actually can be found in the given data, the model shows its strength in processing texts and provides short, well-put answers.

- *Prompt: Was the startup Elypta founded with the purpose of contributing to one or several of the United Nations Sustainable Development Goals?*
- *GPT-4: Yes, Elypta was founded with the purpose of contributing to the United Nations Sustainable Development Goals, specifically Goal 3: Good Health and Well-being.*

At times however, the model suffers from drawing illogical conclusions and hallucinating.

- *Prompt: Can the Elypta's main product help the world comply with the Paris Agreement?*
- *GPT-4: Yes, Elypta's main product can help the world comply with the Paris Agreement by contributing to the prevention of cancer mortality through early detection, which can lead to better health outcomes and reduced healthcare costs.*

The model claims that Elypta's main product, a cancer detection software, helps the world comply with the Paris Agreement. This is obviously illogical as the Paris agreement treaty is about reducing greenhouse gasses emitted globally. Examples like this are not uncommon in the answers generated. A hypothesis for why this occurs could be that the Paris Agreement is often mentioned in conjunction with sustainability, which in turn is mentioned with cancer prevention and health care. Consequently, the model may mistakenly draw the conclusion that a company's general sustainability initiatives automatically imply compliance with the Paris Agreement.

It is clear that providing the model with context and additional information significantly improves the performance of the model. With additional information, the answers are based on up-to-date news and information and not restricted to only the data before the model's cut-off date, September 2021. Since startups are often newly started companies that quickly gain traction, this makes contextualizing the model a must. The problem with hallucinations still persists although with less frequency. This problem could potentially be partially solved by improving the question prompts to be more specific and explaining terminology such as the Paris Agreement further. When given the right input the model shows great potential, extracting relevant information from the unstructured data and providing logical and plausible answers. To improve the model further, more relevant data should be used as input. More specifically, it is of high value to find objective sources connected to the sustainability performance of the screened companies since this information tended to be less frequently appearing in the current dataset.

4.3 Investor Profile Prompt without Context

The Investor profile generated a motivation and a rating on the fit between the described investor profile and the segments of Investor Strategy, Founding Team, Sustainability and Market. In the below diagram, the ratings for each company by segment are outlined. In the version of the model where no context was given, the model was not able to generate any answers for Hidden Door. To access the full results, see the Excel in Appendix C.

Overall score - Investor profile without context

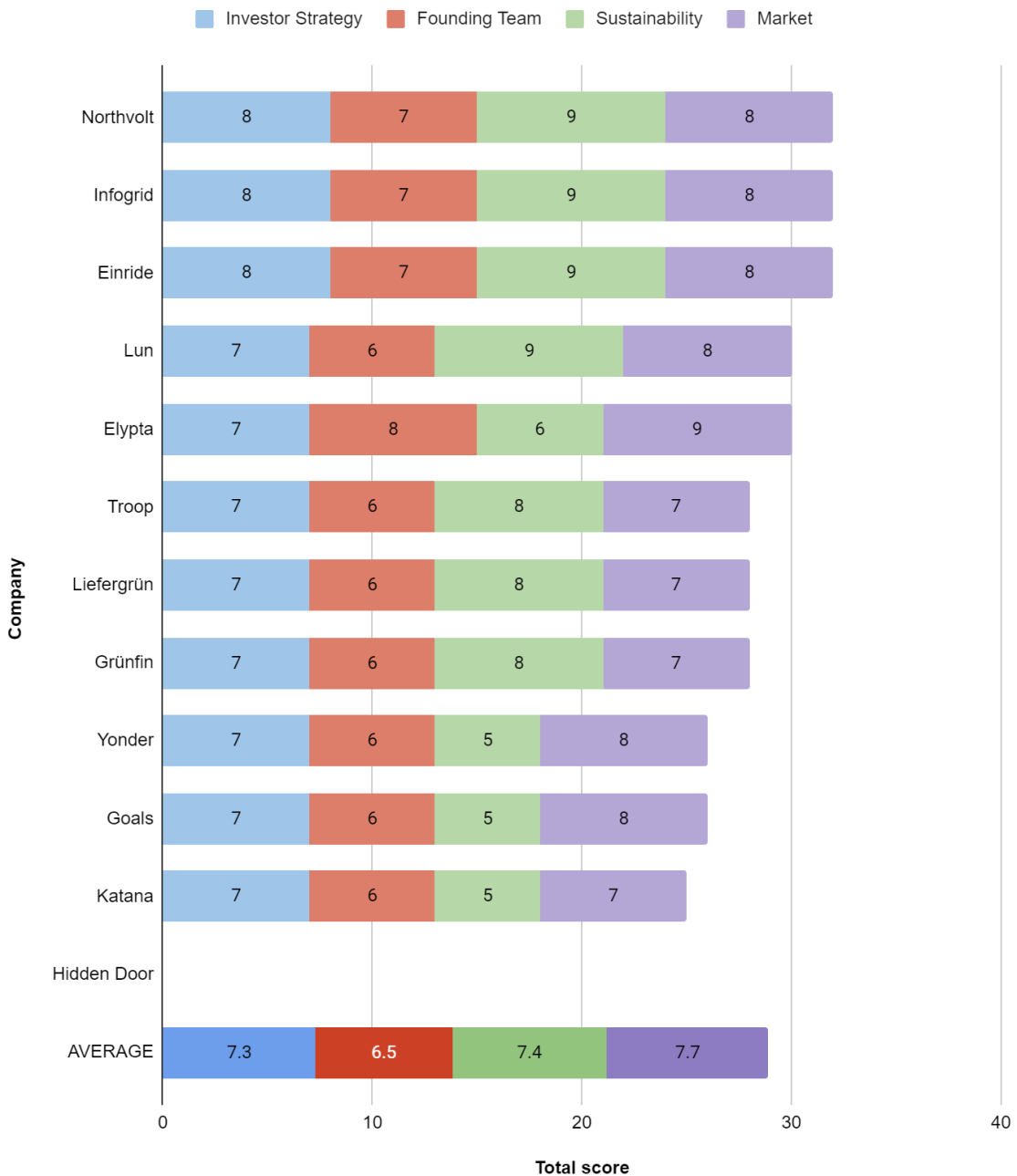


Figure 13: Overall score for investment profile prompt - without context.

According to the model, the companies performed the worst in the funding team category, with an average score of 6.5 out of 10 and received the highest average score in the market category with 7.7 out of 10 (see Figure 13). Using the Investor profile prompt generates an output that is structured, information dense and that is easy to interpret. For example:

- *Investor Strategy: 8/10*
- *Einride, a Swedish startup focused on developing electric and autonomous trucks, seems to be a good fit for VC firm X's investment profile. The company operates in the*

technology-driven sector of transportation and aligns with the firm's focus on sustainability. Einride is based in Europe, which matches VC firm X's preference for European and US-based companies. Although the exact stage of Einride's funding is not provided, it is likely within the Seed to Growth stages, fitting VC firm X's multi-stage investment strategy. The only potential mismatch is the specific industry focus, as transportation is not explicitly mentioned among VC firm X's preferred sectors.

- *Founding Team: 7/10*
- *Einride's founding team consists of individuals with diverse backgrounds, including business and technology expertise. The CEO, Robert Falck, has prior experience in the automotive industry and has held leadership positions at Volvo. However, it is unclear if the founding team members have completed academic degrees or have a history of founding other companies. Overall, the founding team seems to be a good fit for VC firm X's preferences, but more information on their academic and entrepreneurial backgrounds would be helpful.*

- *Sustainability: 9/10*
- *Einride's focus on developing electric and autonomous trucks demonstrates a strong commitment to sustainability and aligns with VC firm X's preference for companies that positively impact society and the environment. The company's mission to transform the transportation industry by reducing emissions and increasing efficiency is in line with the Paris Agreement and the United Nations Sustainable Development Goals. Einride's business model is scalable and for-profit, and its technology addresses a relevant sustainability issue in the transportation industry. The only aspect that is not explicitly mentioned is the company's communication of its impact efforts, but overall, Einride's sustainability focus is a strong match for VC firm X's preferences.*

- *Market: 8/10*
- *Einride's market potential is significant, as the transportation industry is a sizable market that is undergoing a shift towards electrification and automation. The company's electric and autonomous trucks address a growing demand for sustainable transportation solutions, and its technology has the potential to disrupt the industry. While Einride may not have a first-mover advantage, as other companies are also developing electric and autonomous trucks, its focus on sustainability and innovative technology positions it well in the market. The company's market alignment with current business trends and its potential for profitability make it a good fit for VC firm X's preferences.*

The model does in general produce logical reasoning around the score it has given the company. It is however hard to judge the exact accuracy of the ratings given since it tends to give the companies very similar scores, with the exception of the sustainability category. Because a motivation of the rating is made, it is much easier to fact-check and feel confident in trusting the model than for example a traditional deep learning model which is a pure black-box. Moreover, the model seems to perform much better in the case of insufficient data compared to the question-based prompt. Instead of not producing an answer, the model seems to weigh in the lack of information in the score it gives the company. This can be shown in the case of the market evaluation of Infogrid. In every question regarding the market in the question-based prompt, the model produced the following answer:

- *GPT-4: Unsure, as I do not have specific information about whether Infogrid's...*

When using the Investor profile prompt, the model is now able to provide a lot more information about the company and discuss similarities and lack of data to finally output a final rating and motivation. This might be explained by the model not being forced into a classifying answer and hence being able to reason more openly about the company and produce an overall assessment:

- *Market: 8/10*
- *The market for IoT and smart building technology is sizable and growing, with increasing demand for energy-efficient and sustainable solutions. Infogrid's product addresses this market need and has the potential to become a market leader in the IoT and smart building sector. The company's focus on software solutions and its clear path towards profitability align with VC firm X's market preferences. However, it is unclear if Infogrid has a first-mover advantage or if they maintain a close relationship with their customers. Despite these uncertainties, the overall market potential for Infogrid's solutions makes it a good fit for VC firm X's investment criteria.*

While the investment profile prompt seems to provide better motivations in most cases, it sometimes can also produce baseless speculations and useless ratings.

- *GPT-4:Founding Team: 6/10*
Without specific information about Troop's founding team, it is difficult to accurately assess the fit with VC firm X's preferences. However, assuming that the founding team has a diverse background with a balance of business and technological expertise, industry-specific experience, and prior entrepreneurial endeavors, the fit could be considered relatively good. If the founding team lacks these qualities, the fit would be less ideal.

The model gives a rating of 6/10 entirely based on assumptions, which makes it misleading. Although it is important to note that if the user reads the motivation it is obvious that the rating is purely based on assumptions and not to be trusted. Hence, it shows that just evaluating the rating could be deceiving and that it is important to also examine the underlying motivation provided by the model. The answer above is not an outlier and was encountered multiple times in the output using the investor profile prompt without additional information. This again highlights the need for providing the model with additional context to produce accurate answers when analyzing young companies.

4.4 Investor Profile Prompt with Context

In the below diagram, the ratings for each company by segment are outlined, this time when given additional information and context. To access the full results, see the Excel in Appendix C.

Overall score - Investor profile with context

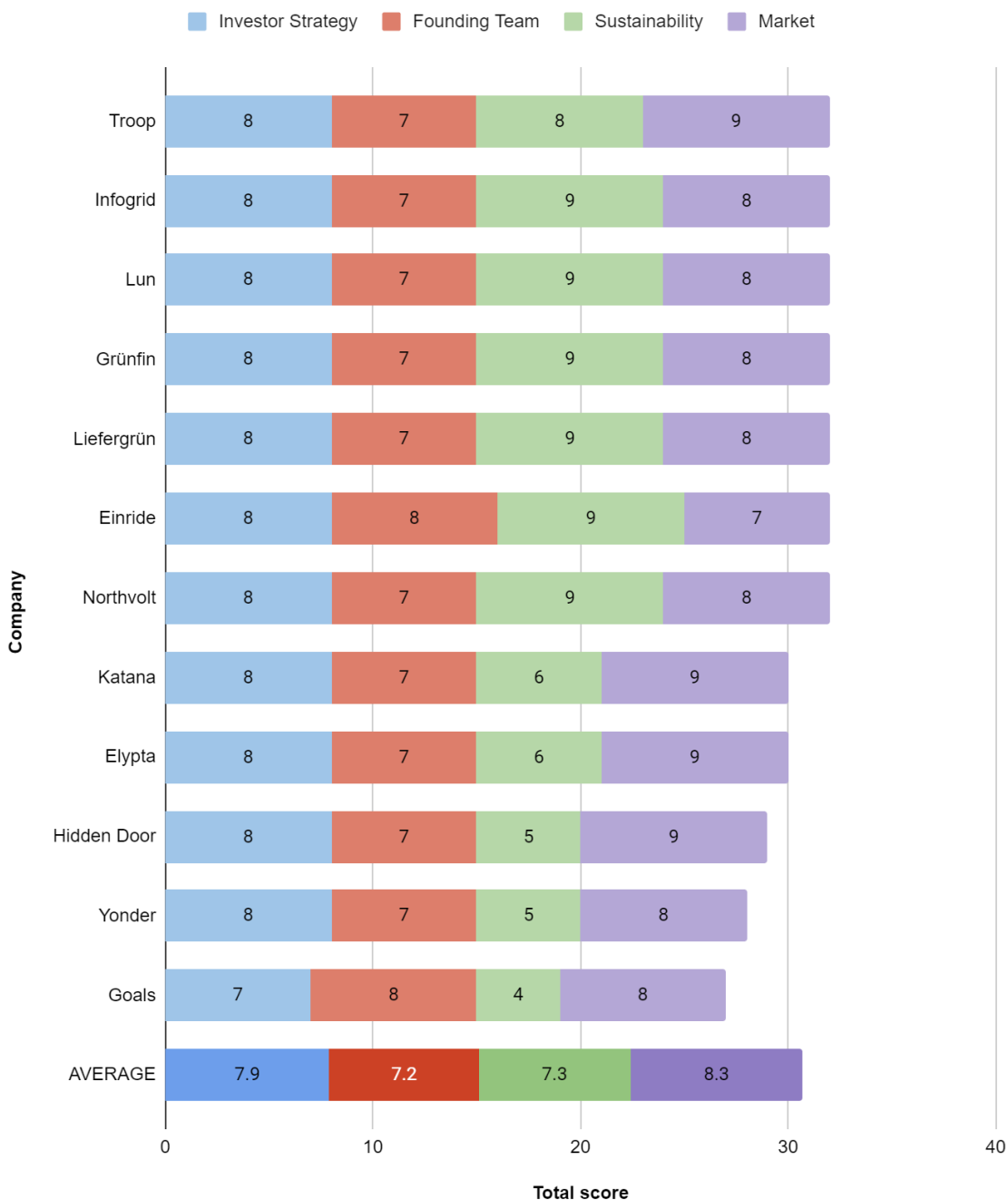


Figure 14: Overall score for investment profile prompt - with context.

As with the question-based prompt, giving the model more context solves many of the shortcomings of the prompt and improves the performance. For example, giving the model additional information completely eliminates the problem of it producing baseless speculation. Although the model does not have information on all of the aspects described in the investor profile, there is often sufficient data to at least produce a reasonable answer for each segment. Again, the lack of information is considered in the motivation and seems to lower the rating given to the company. Giving additional information increased the overall

rating of the companies but it still gives the worst average rating to the funding teams, 7.2 out of 10 and the best rating to the markets 8.3 out of 10 (see Figure 14).

Figure 14 shows that the analyzed companies perform very similarly in many of the areas, where for example five of the top seven performing companies all receive the same score in every category. Another example is the Investor Strategy area, where eleven out of twelve companies receive a 8/10 score. Consequently, the ratings seem to be generic. An explanation to this could be that these companies are all startups that have received previous funding, half of them even from the analyzed investor Northzone, and therefore demonstrate the attributes of having a good fit with regards to Investor Strategy, Founding Team and Market. Therefore, it would be wrong to expect a significant difference in their ratings. However, when looking at examples from the output data it can be seen that the rating of the investor profile prompt does not seem to be consistent with the question-based prompt nor the motivation given. In the question-based model Lun performed well on CSFs for founding, which was also reflected in the investor profile motivation but not in the rating:

Question-based prompting with context:

- *GPT-4:*
- *Yes, the startup Lun's founding team has a background in both business and technology. Martin Collignon, the CEO, has experience working in the tech industry for companies like Google and Uber, while COO Anders Valentin has a background in insurtech. Yes, the founders of the startup Lun have completed academic degrees, as they were friends from their business school days. Yes, the founders of the startup Lun have relevant previous work experience from the industry they are acting in. Martin Collignon has experience in the tech industry and climate activism, while Anders Valentin has experience in insurtech. Yes, the founders of the startup Lun have previous experience of entrepreneurship and founding companies. Anders Valentin previously co-founded Undo, the largest insurtech company in Denmark.*

Investor profile prompting with context:

- *GPT-4: Founding Team: 7/10*
- *The founding team of Lun consists of CEO Martin Collignon, who has experience working at Google and Uber and is a climate activist, and COO Anders Valentin, who has a background in insurtech and co-founded Undo, Denmark's largest insurtech company. While the founders have relevant experience in technology and entrepreneurship, their backgrounds do not perfectly align with VC firm X's preference for a balance of business and technological expertise. However, their passion for sustainability and climate action may compensate for this discrepancy.*

Lun receives a “yes” on all CSFs and the motivation from the Investor profile is also indicating that the founding team should be scored high. The rating is set to 7/10, which is on par or lower compared to all other companies. This could be compared to Yonder, who received the following question-based answers and investor profile fit:

Question-based prompting with context:

- *GPT-4: Unsure, as there is not enough information provided about Yonder's founding team's background in business and technology.*

*Unsure, as there is no mention of the founders' academic degrees.
Yes, the founders of Yonder have relevant previous work experience as they are ClearScore alumni.
Unsure, as there is no mention of the founders' previous experience in entrepreneurship or founding companies.*

Investor profile prompting with context:

- *GPT-4: Founding Team: 7/10
The founding team of Yonder seems to have a strong background in the fintech industry, with experience at ClearScore, a well-known credit scoring company. This indicates that the founders have relevant industry experience and a deep understanding of the credit market. However, there is limited information available about the founders' academic backgrounds or prior entrepreneurial endeavors, which makes it difficult to fully assess the strength of the founding team.*

The two companies receive the same rating although Lun possesses almost all of the desired characteristics, while the rating for Yonder seem to be entirely based on one past experience. Due to this, the ratings should probably rather be seen as an indicator of the company's performance than an aspect to differentiate companies on.

When it comes to sustainability, the ratings are less homogenous. A reason for this could be that some companies clearly address sustainability issues, while others do not even mention them, giving them a lower rating. The model was also able to recognize aspects of sustainability which were not explicitly stated in the prompting, such as economic inclusiveness and relate it to the business model of the company.

- *GPT-4: Sustainability: 5/10
Yonder does not appear to have a strong focus on sustainability, as its primary offering is a rewards-based credit card. While the company may be contributing to a more inclusive credit market by using open banking data to assess creditworthiness, there is no clear indication that Yonder is actively working towards environmental or social sustainability goals. The company's business model does not seem to be directly aligned with the EU taxonomy, the Paris Agreement, or the United Nations Sustainable Development Goals.*

The main strength of the contextualized Investor profile, as seen in the examples above, is its ability to summarize relevant information. For each analyzed company, the model was given a large amount of unstructured data consisting of a mixture of articles and the company's homepage. Despite the chaotic dataset, the model is able to accurately understand these texts and provide a summary related to the requested areas. The model hence shows promising results in providing the user with relevant, concise information although the ratings seems to not yet be trustworthy. To further perfect the model, similar to the question-based prompting with context, the selection and amount of data could be improved. It is also of great importance to be thoughtful when designing the prompt not to include biases. In the prompt used, emphasis was put on environmental sustainability, which meant that other types of sustainability were valued as less important. An example of this is Elypta that received a 6/10 sustainability rating despite being a company dedicated to preventing cancer.

- *GPT-4: Sustainability: 6/10*
- *Elypta's mission to prevent cancer mortality through early detection aligns with the goal of positively impacting society. However, the information provided does not explicitly mention compliance with EU taxonomy, contribution towards the Paris Agreement, or the United Nations Sustainable Development Goals. Additionally, there is no clear indication of how the company enforces sustainability in its supply chain or communicates its impact efforts. While Elypta's mission is commendable, it may not fully meet VC firm X's sustainability preferences.*

The investor profile prompt is especially well-performing under uncertainty because of its ability to perform an overall assessment without perfect information. This means that company could for example get a high rating on “Market” despite it not complying perfectly with the criteria. This is in general a desirable behavior since in every industry what is considered a great market differs. However, in some cases it could of course lead to problems when it for example neglects the significance of a first mover advantage in a market where it is particularly important to be first. This problem could potentially be addressed by stating the importance of each CSF in the prompt, making the model prioritize between the given information. On the other hand, it is not certain that the same CSFs have the same importance in every industry and the prompting would then need to be adapted for each industry, geography or other defining aspect. Naturally, such an adaptation would make the model less scalable and more difficult to put into an automated system. Based on this argument, it is important to understand that the model could work as an important tool for screeners but the results are not perfect, and it is rather a support in the first step of screening which then guides the screener on which companies are worth further investigation.

4.5 Comparison between Prompts and Summary of Learnings

In Table 7 the pros and cons with the different prompts are presented.

Table 7: Comparison between the different prompts

Prompt	Learnings
Question-based Prompt	<ul style="list-style-type: none"> + Helps the screener to get answer to specific critical questions - Suffers from hallucinations and can miss important details in the prompt - Biased towards giving “Unsure” answers in situations where “No” is more appropriate
- Without context	<ul style="list-style-type: none"> + Formulates plausible answers for bigger companies with a lot of traction + No need for data gathering - Is not able to produce answers for smaller companies and early stage startups
- With context	<ul style="list-style-type: none"> + Adding context significantly improves the performance of the model for early stage companies - Quality of input data is critical - Exclusively relies on prompt information and not on pre-trained knowledge - Needs a supporting system to gather relevant data

Investor Profile Prompt	<ul style="list-style-type: none"> + Produces easily interpreted, structured summaries on the companies + Is able to create an overall assessment even when information is scarce + Relatively easy to fact-check - Does not understand the relative importance of the different aspects in the investor profile - The ranking is not always trustworthy
<ul style="list-style-type: none"> - Without context 	<ul style="list-style-type: none"> + Produces better results when analyzing early stage companies than the question-based prompt + No need for data gathering - At times produces baseless analysis based on speculation when there is not enough information
<ul style="list-style-type: none"> - With context 	<ul style="list-style-type: none"> + Adding context significantly improves the performance of the model for early stage companies + Most suitable to target defined impact space of VCs - Quality of input data is critical - Needs a supporting system to gather relevant data

5. Discussion

In this chapter, LLMs effect on biases in the investment decisions are discussed and the learnings from prompt engineering are outlined. This section is then followed by a presentation of potential use cases for LLMs in the screening process and the implications they could have on VCs' potential of reaching their proposed optimal investment scope as an investor of high-risk, software-centric startups, contributing to sustainable system change.

5.1 Large Language Models' Effect on Biases in Venture Capital Investing

The results of this thesis could contribute to greater knowledge in the understanding of how biases would be affected by using LLMs in the investment process. As brought up in section 2.5, an argument for using AI in the VC investment process is to reduce biases present in the investment process. This thesis however, proposes that the use of LLMs could both reduce and increase the biases found in VC investment. Since the quality of the input data is critical, if the input into the model is biased then the output will also be biased. If articles and information that is overly positive towards a company is chosen, the model will rate that company higher. The model is therefore exposed to marketing tricks such as green washing. In addition, if the input data for the investment profile for example is built upon the experiences and investment record of the investor, a similarity bias could get encoded into the investment profile of the model. This could mean that underrepresented groups, for example female founders, get an even harder time acquiring funding. Moreover, such a bias would be present already before the investor gets to the stage of analysis, making it harder to spot and mitigate.

Another bias that could be affected by the application of LLMs in the investment process is the overconfidence bias. Overconfidence originates from investors having access to too much data while falsely believing that they are taking all of the information into account. Introducing LLMs would bring a lot more information to the investment decision, potentially overloading investors. However, since the investor profile prompt's summaries makes data more processable and understandable for investors it could avoid worsening overconfidence bias. The results indicate that the model performance is far from perfect and overconfidence in the performance of the model could also lead to a lot of problems. A reasonable perspective on the role of the model is seeing it as a complement and supportive tool instead of a sole dictator of the screening process. It is less clear how the tool would affect the availability bias. Making the process data-driven should reduce the overreliance on only recent experiences, but this bias would probably still be present in the next step, when choosing to move forward with only certain companies in the deal process.

5.2 Learnings from Prompt Engineering

From the results and initial testing some insights on the different prompt engineering techniques discussed in section 2.5.2 could be drawn in the context of investment analysis. In the initial testing it became clear that the *Question Refinement Prompt*, continually asking the model to suggest a better prompt, did not improve the output of the model. Important to note is that the Question Refinement Prompt was suggested as a technique for the GPT-3.5 model and not GPT-4. However, through experimentation with the GPT-3.5 model, it was still found to lack effectiveness in producing better prompts. The same lackluster result was found when trying to improve the precision of the model by making it more restrictive. Adding restrictive words such as "significant" seemed to have no effect on the output produced. While the argument for creating a high precision model still holds, further research is needed to explore

how to make the GPT-4 act in this way. These results led to the techniques being abandoned in the prompts which produced the final results of this thesis. A technique that was implemented in the final prompts was giving the model the option to give an “Unsure” answer. As predicted by the OpenAI’s documentation, this seemed to make guessing and hallucinations from the model less frequent. An unforeseen consequence, however, was that this made the model prefer “Unsure” answers over negative answers in many cases.

The *Persona Pattern Prompt*, telling the model to act as a sustainability analyst, improved the performance of the model. When given this prompt the model gave more relevant answers that were formulated in an appropriate manner. Moreover, the technique that produced the biggest improvement in the results was providing extra, company specific context. This is an interesting result as OpenAI in their documentation advised against providing too much context as this confuses the model. Although the phenomenon was demonstrated in some of the results where the model missed some details in the prompt, the upside providing extra context clearly outweighed the downside.

5.3 Large Language Models and Sustainability

In II, the different asset classes define and work with sustainability in distinct ways. It has not been clear what is investable for VC in the sustainability space, which has previously led to a neglect of such aspects. This thesis proposes that VCs should invest in, and promote startups that contribute directly or indirectly to system sustainable change with a focus on companies that involve a high risk but low intensity of capital, most oftenly being centered around a software. Although it is not a perfect description of the investing space, this finding might serve as a guideline of what is investable. With a defined role of what sustainability means specifically for VC, this could make it easier to communicate and actively incorporate into their strategy. LLM models and the investor profile prompt could also prove a strong tool for effectively finding opportunities in this sustainable investment space. Defining and inputting the VC definition of sustainability in question-based CSFs or an investment profile could lead to a more precise and less time consuming screening for sustainability. With the LLM being able to evaluate and find sustainability aspects of companies, this should bring the issue higher up on the screeners agenda. The screeners would now be able to actively seek for and target companies that actively address sustainability. Also with a sustainability summary always being available to the screener it is likely to be considered consciously or unconsciously more often in the investment process.

With future improvements and research into the rating capabilities of LLMs, the potential of a creation of an impact metric could also be opened up in the future. The strength of evaluation metrics like an ESG framework is that it easily allows for a comparison of a company’s sustainability performance. The problem with ESG however, is that it is not applicable to startups because of the lack of sufficient sustainability data, and furthermore it promotes optimization and not transformative change. Therefore, evaluating companies based on their outcome impact makes more sense in the VC space. There is however, no adequate quantifiable metric of measuring the outcome impact of a startup as it requires evaluation of qualitative aspects such as business model and vision of the company on a case-to-case basis. It is therefore difficult to compare the sustainability impact of companies on a large enough scale. LLMs and the investor profile or question-based prompting introduces a way for VCs to create a framework for evaluating impact on a large scale. By defining what different sustainability aspects are important, this technique could empower every VC to create their own unique impact key performance index for evaluating outcome impact. Just as with ESG frameworks it is important to keep in mind however, that this means that depending on how a

specific VC defines sustainability, potentially every startup can be considered sustainable. The opportunity to create standardized impact performance metrics applicable for all VCs is also opened by LLMs. Whether or not this is the right way forward is up for debate. Standardized metrics suffer from not covering enough aspects, leading to focus on a small amount of sustainability issues and the neglect and exploitation of others. On the other hand, the introduction of standardized ESG frameworks led to great progress in sustainability, changing ESG from a niche practice into a mainstream concept. An impact-centric metric could have a similar effect.

In such a future scenario it is important to recognize that selection of input data will likely become a delicate issue. It is clear in the study that providing the model with high quality and unbiased data is of great importance when screening for sustainability related issues. When choosing the most recent articles on the internet along with the company homepage, sustainability related information is often missing. Adding on to the importance of data input, it is crucial to be aware of the skewness of input data. If only the company homepage or the company's sustainability report are chosen as data sources the model risks basing its answer on a greenwashed version of the truth which is not put in contrast to any opposing views. The greenwash aspect is hence important to keep in mind when using LLMs and preferably a more nuanced dataset should be used. A further consequence of this is that questions that are too general or broad, such as if sustainability is embedded in the company strategy, are usually useless because either information is lacking or the information comes as a standard answer directly from the company itself. Instead, more specific, product or company related sustainability questions tend to yield more accurate results.

5.4 Use Cases for Large Language Models in Venture Capital Screening

5.4.1 Use Case for Large Language Model in Venture Capital Today

LLMs have great potential of contributing to VC screening, but acting rather as a complement to screeners and existing screening tools than a replacement. It is clear that the current model and prompts presented in this thesis does not produce good enough results for it to be implemented in an automated VC screening process. With improvements such as thoroughly choosing input data, updates to the underlying model and strategically chosen screening questions an automated system might be viable in the near future. Although a fully automated system is not viable today, the investor profile prompt shows the most promising results among the two prompting techniques, and could be used on a smaller scale by an individual screener to research a large number of companies. The suggested use case is to utilize a variation of the investor profile prompt proposed in this thesis to create executive summaries of investment prospects, market, founding team, sustainability and technology. Firstly the screener would tailor the investor profile prompt according to the VCs' and his or her preferences regarding stage of growth, type of technology, market etc. Then the screener would find relevant articles and information about the company and feed it all to the model, which makes a summary and extracts the most important information. Thus, the investor could quickly analyze different companies in screening without having to read through all of the information available about a company.

5.4.2 Future Use Cases for Large Language Models in Venture Capital

The model's ability to process large amounts of company data, indicates potential in startup analysis on a larger scale. Incorporated into a more complex software product, the model could prove a powerful future tool of a company's automated outbound screening process.

With input from Kye Andersson (2023), Strategist for Major Impact Initiatives at AI Sweden, a user flow suggestion for such a digital tool is shown in Appendix D under the assumption that the model’s ability to rate different companies will be improved in the future. The system would be used by screeners at the VC firm, who interact with a graphical interface. The user flow would be as such: The investor begins by defining what investments are interesting, a set of filter criterias for example type of industry, geographical location and size of company. With this filter, a trigger is created in tools such as Crunchbase, keeping track of which companies fit the requirements. These companies move on to an evaluation process, scraping the internet for each company for relevant data. This data together with the investment profile or CSFs specified by the screener is used as input to the GPT model which performs an investment analysis on the companies. From the investment analysis, the model puts a rating along with a motivation for the company and saves it in a database. The graphical interface interacts with the database and the screener to allow the user to easily look through a generated investment report of each company and filter according to rating. Screeners would then interact with the system and choose which companies are relevant and analyze further. Such a software solution would have the potential to perform outbound screening of both higher quality, but also quantity by automating the process and considering more parameters. From screening two hundred companies for every four deals closed, the VC deal funnel could be changed so that a much larger number of opportunities could be considered in the screening step. In Figure 15 below, twenty thousand is used as an illustrative number. By incorporating LLMs into the screening process and potentially elevating the quality of the screening phase, the assumption is that enhanced quality will extend throughout the entire process, culminating in more successful deal closures.

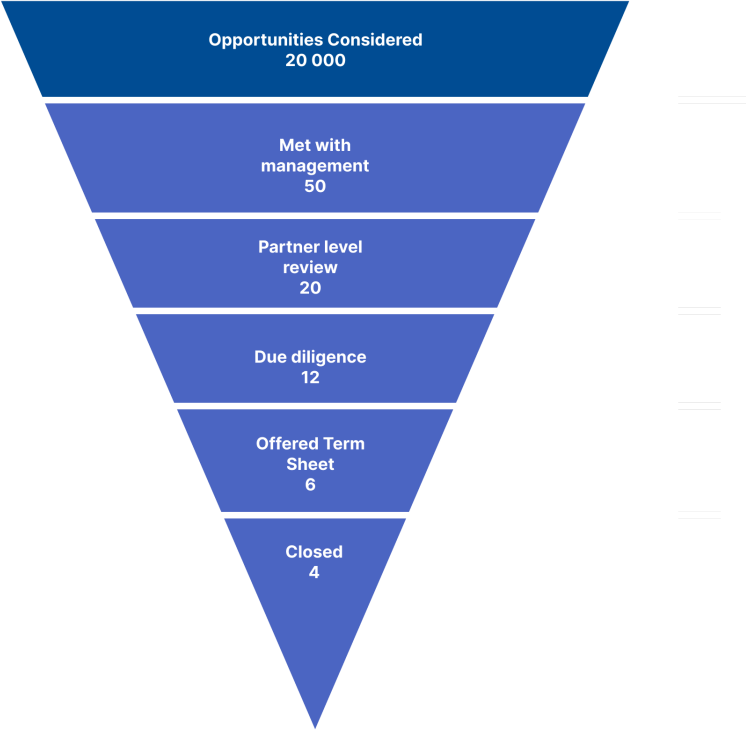


Figure 15: The effect of LLMs to a potential future VC deal funnel.

Such a system could bring a lot of value. Firstly, screening a larger set of companies would decrease the probability of missing a really good opportunity. For the same reason only the most relevant startups would be presented to the investment analyst, saving both time and money. The prompt pattern suggested in this thesis allows the screener to be highly flexible when it comes to which criteria to look for in an investment. The tool could in theory find startups that fit into specific VC preferences, personal screener preferences and preferences for a specific search. Creating profiles for the different screeners according to experience and record, the specific investment's fit for a specific analyst could be calculated. The screened startup could then be handed out to the investment analyst at the company with the most relevant background. Being able to highly target their screening scope could also prove an important piece for VCs to work towards their impact maximizing role in the sustainable transition. In other words, to actively seek high-risk, low-capital intensity startups with a direct or indirect contribution to system change.

Another potential use case discussed with Kye Andersson (2023), is leveraging the power of a LLMs in the inbound screening, when VCs are approached by founders seeking funding. A potential user flow of the software is visualized in Appendix D, again under the assumption that the rating ability will be improved in the future. Because of both the model's potential in doing investment analysis shown in this thesis and OpenAI's claim in its ability to hold a realistic conversation as a chatbot, the model might hold potential to mimic an investor interviewing founders. By gathering a dataset of the important interview questions asked during an initial meeting between investment analysts and founders, the model could be fine-tuned. In the process the model would learn how to interview founders as if it were an investment analyst. Therefore instead of just asking general questions, the model would be able to hold interviews personalized for the industry and its specific sustainability issues. For example:

- **Chatbot:** *Working in oil and gas implies a big sustainability risk, how do you intend on mitigating it?*
Founders: *Phasing out fossils and focusing and eventually transitioning to hydrogen*
Chatbot: *How would capital from Northzone help you realize phasing out fossils and lead to an increased focus on hydrogen?*
Founders: *The capital would be utilized to expand the R&D department, to decrease costs of storage and logistics of hydrogen.*
Chatbot: *Besides funding, what is the biggest barrier for decreasing costs of storage and logistics?*

This model would be put on the company website, replacing the form found on VCs' websites or email used to apply for capital funding. After the model has performed the interview the system scrapes and gathers more company data off the internet, which together with the interview data would serve as input to a GPT model. The model would then perform an investment analysis and rate the company based on previously defined CSFs or investment profile. Through a graphical interface, investment analysts could then browse companies, filter through ratings and get answers to the most critical questions. This system would reduce the many unnecessary initial investor-founders meetings brought up by von Sydow in section 2.2.1 and in turn save time. Analysts could therefore spend more time on either more relevant meetings or other activities.

5.5 Future Research

This thesis has highlighted which factors contribute to sustainability startup success as well as investigated how LLMs can be used today, but also in future use cases to screen startups in general and impact startups in particular. Both the notion of impact VC and LLMs are emerging fields, which leaves a big scope for future research. The most obvious limitation with this thesis is that the effect of fine-tuning the GPT-4 model is not explored. By training the model on a large set of investment analyzes, the performance of the model could improve. This could potentially make the ratings more accurate, by having the model train on how an investment analyst would rate each company segment. Secondly, the analysis of this thesis is based upon the authors judgment of the output's plausibility and logic. Using a labeled dataset of questions and rating of different companies, the model could be evaluated in accordance with the best practices of Machine Learning performance metrics such as accuracy.

Highlighted by von Sydow (2023), LLMs might have also had a high potential in competitive analysis in VC screening. When considering a startup it is important to understand what other startups have the same business model, to ensure that the particular startup is most likely to win the market. Therefore, would future research that explores ways to use LLMs to evaluate similarity between companies' business models contribute with useful knowledge within the area.

Finally, considering GPT-4 strengths in understanding and drawing conclusions from text-based data, a GPT model could potentially serve as a complement to traditional deep learning models for predicting startup success. The deep learning models which today struggle with text-based input, could potentially benefit from a GPT model, working as a preprocessor to convert text into numerical data for the deep learning model. This could prove powerful as it could substantially expand the amount and types of data a deep learning model could analyze. By using for example question-based prompting as described in this thesis and requesting a binary answer, GPT-4's output could directly feed into a deep learning model. Further research will tell the method's effectiveness.

6. Conclusion

Although the current performance of the model partially limits its immediate applications, future advancement into LLMs, prompt engineering and data selection could open up many opportunities for the technology in VC screening. Addressing the research question, LLMs can help increase the sustainability impact of VC firms by speeding up the process of identifying high-risk, early-stage companies that contribute to sustainable systemic change. Among the tested prompts, the investor profile prompt shows the biggest potential, with it being able to intelligently analyze and summarize company data to match it with investor preferences. With future improvements, LLMs might enable a more sophisticated screening process in which a broader range of soft aspects can be taken into account, which would benefit the VC screening process in several dimensions. Firstly, it could complement traditional quantitative tools, thereby refining early-stage investment screenings. Secondly, the tool could be used to identify startups that maximize overall outcome impact instead of optimizing for ESG criteria, which often are misaligned with the VC strategy. By integrating it with a web-scraping software for automated data collection, LLMs have the potential to significantly boost both the quality and quantity of startups assessed. Consequently, such a screening process would allow VC firms to better target startups with the highest potential for impact.

In light of these findings, it is evident that the adoption and advancement of LLMs such as GPT-4 could serve as a strategic tool for VC firms to bolster their commitment to impact investing. Their potential to intelligently analyze investment prospects and streamline the screening process points to their future usability in finding the impact winners of tomorrow.

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Appendix A Interviews

Andersson, Kye - Strategist for Major Impact Initiatives at AI Sweden

- Interview 19/4-2022

Paterson Pochet, Alexander - CFO and Head of Sustainability at J12 Ventures

- Interview 4/4-2022

Skarborg, Anna - Head of Sustainability at Northzone

- Interview 27/9-2022
- Interview 23/5-2023

von Sydow, Gustav - Entrepreneur in Residence at EQT Ventures

- Interview 30/3-2023

Appendix B Prompts

B.1 Non-optimized CSFs

Table 8: Non-optimized general CSF-prompts

CSF	Prompt
A team with a diverse set of skills, a mix of a technology and business background	Does XXX's founding team have a background in both business and technology?
Founder have completed an academic degree	Have the founders of XXX completed an academic degree?
Founders have work experience out in industry	Do the founders of XXX have work experience previous to founding the company?
Founders have experience of previously founding a company	Do the founders of XXX have experience of previous founding of companies?
The startup has received previous funding rounds	Has XXX received a funding round?
The addressable market is big	Does the main offering of XXX address a big market?
The startup's solution is following some sort of trend.	Does the main offering of XXX follow a business trend?
The company has first-mover advantage in their market	Does XXX have a first-mover advantage in the market they address?

The company keeps a close relationship with customers	Does XXX keep a close relationship with their customers?
The offering involves a software solution	Does XXX's main offering revolve around a software solution?
The company has a clear path to profitability	Does XXX have a clear path towards profitability?
The company's website has increased traction	Has XXX's website had increased traction?

Table 9: Non-optimized sustainability CSF-prompts

Impact CSF	Prompt
The company is founded with the purpose of creating a positive impact on society or the environment	Was XXX founded with the purpose of creating a positive impact on society or the environment?
The company is complying with the EU Taxonomy	Does XXX comply with the EU taxonomy?
The company is complying with the Paris Agreement	Does XXX comply with the Paris Agreement?
The company is contributing to one or several of the United Nations Sustainable Development Goals	Does XXX contribute to one or several of the United Nations Sustainable Development Goals?
Management and the organization as a whole has a commitment to sustainability and it is included in the strategy of the company	Is XXX committed to sustainability and has it included in their strategy?
The founders and management act in a purpose and passion-driven way to pursue an impact goal and not only high profits	Do the founders of XXX strive in a passion-driven way to pursue an impact goal and not only financial goals?
Public policies are in place, or will soon be introduced, that support the business and the sustainability efforts that the company is contributing to	Are there public policies in place, or that soon will be introduced that support XXX and the sustainability efforts that the company is contributing to?
The company enforces sustainability along its supply chain	Does XXX enforce sustainability along its supply chain?
Sustainability is embedded as a key part of the business model	Is sustainability embedded as a key part of XXX's business model?
The business model is scalable	Is XXX's business model scalable?

The business model is for-profit	Is XXX's business model for-profit?
The company is strategic in how it communicates its impact efforts	Is XXX strategic in how it communicates its impact efforts?
The company is addressing a relevant sustainability issue for its industry	Is XXX addressing a relevant sustainability issue for its industry?
The company's solution contributes to a transformative sustainable change	Does XXX's solution contribute to a transformative sustainable change?

B.2 Investor Profile - Northzone

Investor profile:

VC firm X is a multi-stage venture capital fund based in London, United Kingdom, focusing on investing in technology-driven companies across various sectors. Founded in 1996 by Bjorn Stray and Tellef Thorleifsson, the firm has made over 175 investments since its inception and raised a total of \$1.3 billion across eight funds. VC firm X invests primarily in European and US-based companies from Seed to Growth stages, with a focus on fintech, SaaS, e-commerce, digital health, marketplaces, and gaming sectors. VC firm X follows the Investment Strategy below.

1. Multi-stage investment: VC firm X invests from Seed to Growth stages, with typical checks between €1 million and €40 million.
2. Long-term perspective: The firm prioritizes a long-term approach to investments and aims to build sustainable, scalable companies that can become market leaders in their industries.
3. Active involvement: VC firm X actively supports portfolio companies by offering strategic guidance, expertise, and resources, often taking board seats to maintain close relationships with founders and management.
4. Flexible approach: The firm operates on principles rather than a rigid investment thesis, allowing for more flexibility and adaptability in their investments.
5. Network: VC firm X leverages its extensive industry connections to identify investment opportunities, provide introductions, and support portfolio companies in their growth journey.

Some of VC firm X's most notable investments include Spotify, iZettle, Trustpilot, Avito, Klarna, Wallapop, Lastminute.com, Pricerunner, NextGenTel, and Stepstone. In September 2022, VC firm X closed its largest fund to date at €1 billion. The increased fund size signals the firm's intent to move into the growth stages as well, allowing them to support entrepreneurs throughout their life cycle. VC firm X has offices in London, Stockholm, New York, Amsterdam, and Berlin. VC firm X primarily invests in technology-driven companies across various sectors, including fintech, SaaS, e-commerce, digital health, marketplaces, and gaming. The firm typically invests in early-stage startups, from Seed to Series A and Series B rounds, but may occasionally participate in later-stage investments. While VC firm X

predominantly focuses on companies based in Europe and the United States, they maintain a global outlook and consider opportunities in other regions.

Founding Team:

An ideal investment candidate would have a diverse founding team, which includes a balance of business and technological expertise. It is beneficial if the founders have completed academic degrees and possess industry-specific experience. Prior entrepreneurial endeavors and a history of founding companies will also weigh positively in the evaluation.

Market:

The primary product or service of the company must address a sizable market, ideally, one that aligns with current business trends, such as digitalization. The company should strive for a first-mover advantage and maintain a close relationship with its customers. I prefer companies that primarily offer software solutions and have a clear path towards profitability. Increased website traction is another positive sign.

Sustainability:

A company founded with a mission of positively impacting society or the environment holds a special appeal. Compliance with EU taxonomy, contribution towards the Paris Agreement and the United Nations Sustainable Development Goals are crucial considerations. The company must be genuinely committed to sustainability and have it ingrained in their strategy. The founders should display a passion for their impact goals beyond financial success. The company should benefit from existing or upcoming public policies that support its sustainability efforts. It should actively enforce sustainability in its supply chain and have it embedded in its business model in such a way that increased sustainable impact would be good for business. The company's business model should be scalable and for-profit. It should address a relevant sustainability issue for its industry and be capable of contributing to transformative sustainable change, like electrification and automation of cars. Lastly, the company should strategically communicate its impact efforts, ensuring that their sustainability narrative is clear and compelling to stakeholders. Each of these aspects will significantly influence my investment decision.

Appendix C - Data output

Question-based prompting without context:

<https://docs.google.com/spreadsheets/d/1yfTVFt374d2gf8nOI861edrRB4dt98zD6fNu6uRjdys/edit?usp=sharing>

Question-based prompting with context:

<https://docs.google.com/spreadsheets/d/1dn9RPeDi699NjxGnH1tqCxZiReQPOZqgl7xbZiZ0YqA/edit?usp=sharing>

Investor profile prompting without context:

https://docs.google.com/spreadsheets/d/1sa_lyO2a8FqtEAavMSBjS-dlmbRMBbhCk6LQ07VCukU/edit?usp=sharing

Investor profile prompting with context:

https://docs.google.com/spreadsheets/d/11_0zsZCpdk7LvM1-WJ6tyyKcE21RZz9C_q4WWsVOZKM/edit?usp=sharing

Appendix D - Use cases

User flow chart - Outbound Screening:

https://drive.google.com/file/d/1rV9SEFyXOz7IDUNDMTPcrfgESW6n5i4J/view?usp=share_link

User flow chart - Inbound Screening:

https://drive.google.com/file/d/1aRzCTewLwXuK8cytkTl67LC_TvYY0Uq2/view?usp=share_link