Artificial Intelligence in Venture Capital

Enhancement of the venture capital investment process through hybrid human-AI models for pitch-deck evaluation

Julian de Klerk

Delft University of Technology

TU Delft

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by

Julian de Klerk

Student Name	Student Number
J.N. de Klerk	4849965

First Supervisor & Chair:	Dr. Ir. Z. Roosenboom-Kwee
Second Supervisor:	Dr. J. Gartner
Internship Company:	InnovationQuarter
Company Supervisor:	M. Theunissen
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Faculty:	Faculty of Technology, Policy & Management, Delft

TU Delft

Preface

These past months have been such a valuable and insightful experience. When I started this thesis, the intersection of Artificial Intelligence and Venture Capital was both exciting and unfamiliar. Looking back, it's remarkable how much I've learned, not only about the thesis topic itself, but also about working in a professional setting and learning about funding innovations in practice.

I would like to sincerely thank my supervisors, Dr. Ir. Zenlin Roosenboom-Kwee and Dr. Johannes Gartner, for their feedback, encouragement and clear direction throughout this process. Our meetings provided me with a good reflection, structure and academic rigor, elevating the quality of this thesis.

I'm also grateful to the UNIIQ team at InnovationQuarter for making this research possible. The flexibility and freedom given to me allowed me to take ownership of the project while receiving valuable guidance where needed. Special thanks to Mike Theunissen and Jasper Geselschap for their guidance and the insightful discussions that helped shape this thesis and my learnings at InnovationQuarter.

Finally, the Master's programme has been a rewarding journey, which taught me to connect technology, strategy and business. I'm grateful for the experiences and insights gained along the way and will carry these forward into my professional career.

Julian de Klerk
Delft, June 2025

Abstract

The pitch-deck evaluation is a crucial first step in the Venture Capital (VC) investment process, where investors assess a startup's potential in the first screening of the startup. Traditionally, this relies solely on manual human judgement, making the process time-consuming, subjective and prone to bias. With the rise of Artificial Intelligence (AI), new opportunities emerge to support the decision-making with data-driven insights. However, due to the qualitative nature of early-stage startup evaluations, implementing AI in this context remains challenging due to its quantitative and data-driven nature.

This research therefore explores the potential of hybrid human-AI models (combining human judgement with AI support) in early-stage VC pitch-deck evaluations. A case study was conducted at Innovation-Quarter using the AI tool 'Deckmatch'. Through a combination of interviews, a pilot experiment and a follow-up workshop, this study investigates how hybrid models can impact the effectiveness and efficiency of pitch-deck evaluations. This aims to answer the following research question:

How can hybrid models, combining artificial intelligence and human judgement, improve the effectiveness and efficiency of pitch-deck evaluations in early-stage venture capital?

Throughout the research, data was obtained with guidance from the Technology Acceptance Model (TAM) and Behavioral Decision Theory (BDT). The interview dataset consists of six interviews with VC professionals and their perceptions prior-usage of hybrid models within pitch-deck analysis. This was followed by a pilot experiment and workshop including both seven participants. During the pilot experiment the efficiency and efficacy was measured, in addition to the user experience. Afterwards, perceptions on hybrid models after experience with hybrid models was gathered.

It was expected that the hybrid models would enhance both the efficiency and efficacy of the evaluations, leading to a positive attitude towards use. The actual findings suggest that hybrid models show potential to increase the effectiveness or efficiency of pitch-deck analysis depending on the hybrid model used. Here, the sequential and interactive search models show the potential for improved effectiveness, at a slight decrease of time efficiency. On the contrary, the autonomous search model shows the potential for an improved time efficiency at a lower effectiveness. For the usage and preference of hybrid model type, the trust and transparency in the AI output is highlighted to be of importance. These findings contribute to the real-world understanding of human-AI collaboration in VC decision-making and offers further practical insights for VC firms, developers and entrepreneurs.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
BDT	Behavioral Decision Theory
DL	Deep Learning
LLM	Large Language Model
ML	Machine Learning
TAM	Technology Acceptance Model
VC	Venture Capital

1

Introduction

The Venture Capital (VC) industry, essential for financing high-risk innovations, still relies on manual, time-consuming and subjective workflows throughout the investment process (Röhm et al., 2022). The sourcing, screening and due-diligence processes are done largely through manual work, where Gompers et al. (2016) indicate that the average deal takes 83 days to close and the average firm spends 118 hours on due diligence over that period. This time-intensive process originates from the struggle for investors to identify exceptional firms within highly uncertain contexts, introducing inefficiencies throughout the process to obtain reliable but costly information (Retterath & Braun, 2020). As a result, VCs spend most of their time attracting and evaluating deals, additionally allowing biases to form within the decision-making (Gompers et al., 2016; Röhm et al., 2022).

Meanwhile, many sectors are automating decision-making and workflows through the use of Artificial Intelligence (AI). This increasing usage of AI is fueled by the characteristics of rapid pattern recognition, objective data-driven scoring and handling large datasets, resulting in efficient data-driven decision-making methods. Thereby, this raises the expectance for AI to reshape many of the current industries, economies and daily interactions (Vinothkumar & Karunamurthy, 2023). In 2024, already 72% of businesses reported using AI in at least one function, up from 55 % in 2023 (Singla et al., 2024).

However, while more industries adopt AI to automate decision-making and workflows, the VC industry has been relatively resistant to this automation due to the complexity of the decision-making (University of Oxford, 2024). This complexity arises from the nuanced, and context-rich judgements that current algorithms struggle to replicate (Gompers et al., 2016). Therefore, the attention can shift from full automation with AI, towards hybrid decision models that combine the AI insights with human expertise. These hybrid models thereby highlight the potential to shorten the due-dilligence and subjectivity within the investment-process, without removing the contextual reasoning where human judgement remains essential (Raisch & Fomina, 2024).

In this chapter, further context is supplied to understand the current state of the Dutch VC industry and AI technology progress. Additionally, the research is further explained through the problem statement, research objective and the research questions determined for this study.

1.1. Venture Capital Industry in the Netherlands

The Netherlands is an important country within the VC industry, as it ranks within the top 15 countries worldwide for VC investments (Dealroom.co, 2025). This is further highlighted by the deal worth of 2.4 billion euros in 2023, across 516 made deals (PitchBook, 2024). The deal worths over the years of 2014-2024 are shown in Figure 1.

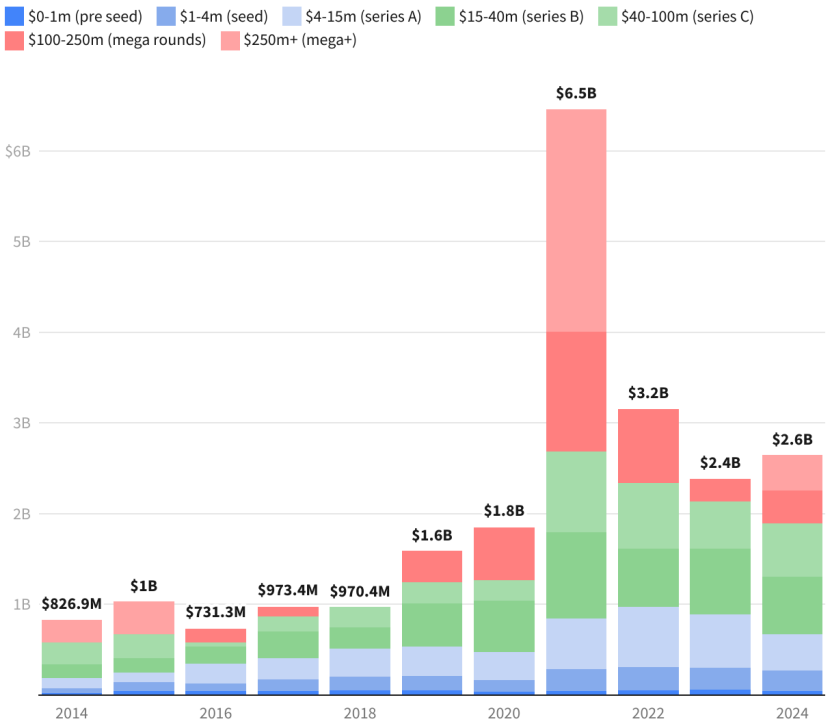

Figure 1: VC investments in the Netherlands, ranging from 2014-2024 (Dealroom.co, 2025).

As seen in Figure 1, in general an upwards trend in VC investments is obtained in the Netherlands. A spike in VC investment increases was seen in 2021 accounting to a total of 6.5 billion euros, mostly due to an increase of mega-round investments attributed to the global post-COVID financing boom (Bank, 2021; Wijngaarde, 2021). Following 2021, the funding volumes dipped as the mega-rounds disappeared. However, the absolute level of the Dutch VC investments remains to show an increasing trend, thereby also highlighting an increase in the deal flow.

While late-stage investments have heavily decreased over the last years, the amount of early stage funding, such as in pre-seed, seed or series A, have remained roughly equal. This highlights the importance of the deal flow within early-stage investments, which account for 33 % of the total deals performed in 2024 (Mensink, 2024). These large amount of early-stage companies bring limited data, and an uncertain and risky context for investors. The number of early stage deals, in combination with the limited information available at this stage, highlights the need for an improved screening process.

On top of this, the Netherlands lacks behind other countries for the investments and innovation culture in AI, especially compared to the US (Techleap et al., 2024). Founders experience a generic lack of AI-technology knowledge amongst Dutch VCs. This highlights a need for Dutch VCs to further use and incorporate AI, to maintain a competitive position compared to other countries. This underscores the further practical importance for the Dutch VC industry to explore AI applications.

1.2. Artificial Intelligence

The technological advancements with AI result in the upcome and potential within many companies to apply the technology for improved and more efficient processes. Here, the definition of AI relates to the possibilities for tasks associated with human intelligence to be executed through computational systems (NASA, 2019). However, AI is considered a broad term, made up of other techniques such as machine learning and deep learning. To further understand these techniques, a categorisation of these terms is shown in Figure 2.

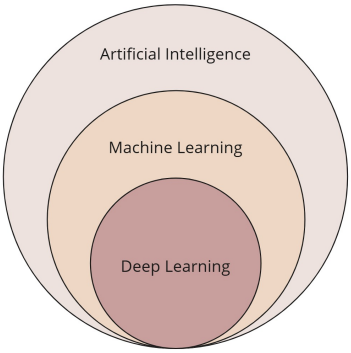

Figure 2: AI encompassing machine learning and deep learning, adapted from John and Moser (2024, p. 19).

The first subset of AI is considered Machine learning (ML), which uses data to set up systems, which automatically learn from the data and thereby can make predictions. There are three general machine learning methods, namely:

- *Supervised learning:* During supervised learning, the model is trained on labeled data. Thereby, for each input there is a correct output. An example of supervised machine learning is spam detection emails, where the email is recognized as spam through labeled spam-emails.
- *Unsupervised learning:* During unsupervised learning, the model has a dataset without providing labeled data, thereby relying on the model to find patterns in the data. This is done with for instance movie recommendation systems, where patterns from the user are detected.
- *Reinforcement learning:* This method trains a model through trial and error. Thereby it receives feedback as a reward or penalty, over time improving the model. This is for instance the case in self-driving cars, thereby interacting with the environment to make driving decisions.

Additionally, deep learning (DL) is in turn considered a subset of ML. This consists of using neural networks, allowing the model to make decisions based on the given data. Hereby this adds a different layer to the machine learning context, as deep learning extracts data from large data sets through multiple layers of extraction. Thereby it can perform well in complex tasks such as image recognition or text generation.

The come-up of these AI techniques, specifically relating to Large Language Models (LLMs), allows developers to build third-party AI tools depending on these models. These third-party AI tools can be used within the general capacities of LLMs to create specific use cases for different industries, allowing for industry-wide improvements on the efficiency or efficacy of workflows, which is also the case for the VC industry.

1.2.1. AI in Venture Capital

Integrating AI in the investment decision-making processes can assist to improve current processes and workflows, through their data analytics and pattern recognition. However, the research from Röhm et al. (2022) highlights the finding that most venture capital firms do not yet leverage AI. Currently, VCs mainly only use data-driven tools in the sourcing process. Academic research from Arroyo et al. (2019) does highlight the possibilities for machine learning algorithms to assist in the baseline screening for venture capitalists, to improve returns. This indicates that applications with AI in VC firms could enhance the practical workflows.

However, as VC investments are also related to qualitative factors, such as the founders leadership potential, team dynamics and adaptability (Gompers et al., 2016), the use of AI can be limited and hu-

man judgement could remain essential to effectively evaluate these strengths and weaknesses. Within VC, the importance of these complementary strengths is therefore the case, thus combining human judgement and AI to create an improved investment decision-making process. This combination of AI insights together with human insights and judgements is considered a hybrid model.

1.2.2. Hybrid Models

Through the use of hybrid models, humans and AI work together to come to a final decision. Here, the AI provides an output, for the human to interact with and base a decision on. Hybrid models thus present an opportunity to combine both strengths of AI and human judgement. This can utilize AI for efficient and scalable data-driven analysis, while relying on human judgment for nuanced qualitative assessments. Such hybrid models have the potential to overcome inefficiencies and reduce biases, potentially improving the decision-making process (Hu, 2023).

Hybrid models emphasize the use of humans to stay involved in the decision-making process. Keding and Meissner (2021) found that the perceived performance of AI plays a crucial role in the adoption of AI-generated insights. Specifically, managers are more likely to accept AI-based recommendations for objective and analytical takss, where AI is expected to outperform human judgement. This underlines the importance of technology acceptance in successfully integrating AI-driven insights into decision making workflows.

1.3. Problem Statement

Currently, VC investors struggle to identify high-quality firms through the screenings due to the inefficiencies that arise around sourcing information and performing due diligence, resulting in a time-consuming and subjective process (Röhm et al., 2022). The importance of the deal selection is highlighted as the most important driver of returns, by 49% of venture capitalists according to Gompers et al. (2016). Thereby, this underscores the importance of the screening phase to evaluate start-ups efficiently and effectively, as this significantly affects the downstream investment quality and eventual portfolio performance. The earliest stage, of pitch-deck evaluations, is of high importance for the further investment qualities as all start-ups that are sourced have to pass through this initial stage. Currently, the pitch-deck screening process is mostly performed through human efforts, thereby relying mostly on intuition, experience and pattern recognition. However, current AI models are promising for processing large amounts of data in an objective manner. Here, AI therefore highlights the possibility to enhance the capabilities of humans for data gathering to further understand contextual factors. The combination of AI and human judgement, through hybrid models, thus underscores a promising addition to improve the investment decision-making process.

However despite the promising addition of hybrid models, research from Keding and Meissner (2021) highlighted the importance of perceived performance of the AI for humans to adopt the actual technology. Therefore, in addition to the actual investment process enhancement capabilites, the perceived performance for the venture capitalists themselves on the hybrid model is of high importance for the eventual usage and adoption of the technology.

1.4. Research Objective

The goal of this research is to explore the use of hybrid human-AI models for pitch-deck analysis in venture capital. This is done through a single case study within venture capital firm, to obtain an in-depth understanding of the processes and perceptions involved in a real-life setting. These processes and perceptions are captured through the Technology Acceptance Model and Behavioral Decision Theory, by performing interviews, a pilot experiment and a follow-up with a workshop. Based on these techniques, the research provides an exploratory nature to the actual use of hybrid models, thereby combining both qualitative (interviews, workshops) and quantitative (pilot experiment) techniques.

In a practical sense, this research will further assist venture capitalists in their knowledge and decision-making to implement AI for their own processes. For the research a small sample size is obtained due to limited resources and time available. Therefore, a limited number of interviews, pilot experiments and workshops have been performed with participants in this single case study design. Thus, this further enhances the pilot nature of this research. However, despite the limited sample size, the research aims to contribute to the current research gap of hybrid models within venture capital, especially focusing on early-stage pitch-deck analysis.

1.5. Research questions

Based on the problem statement and literature gaps identified in the literature review, this research aims to answer the following main question:

How can hybrid models, combining Artificial Intelligence and human judgement, improve the effectiveness and efficiency of pitch-deck evaluations in early-stage Venture Capital?

Sub-questions include:

1. *What are the key factors that define a high-quality pitch deck in VC decision making?*

   This sub-question builds further on the (grey) literature identified on pitch-deck qualities and contextual factors. It allows for experimental pitch-deck creation based on the important factors.

2. *What perceptions do venture capitalists have on the usefulness and ease-of-use of hybrid models prior to adoption?*

   This sub-question builds further on the research of Keding and Meissner (2021) on the effect of perceived effectiveness on the decision-making. Thereby it applies the Technology Acceptance Model, originally developed by Davis (1985) and the Behavioral Decision Theory from Einhorn and Hogarth (1981) as theoretical framework to obtain important constructs.

3. *How do hybrid models perform compared to human only approaches in VC pitch-deck evaluation?*

   Through this sub-question, the knowledge on hybrid models in real-life settings is expanded. Current research focuses mostly on purely human judgement or purely AI models within VC. Therefore, the research gap identified is within the use of hybrid models applied to a real-life case setting within VC. This thereby builds further on research of AI on the investment decision-making process in VC by Röhm et al. (2022). Additionally, research of hybrid model types from Raisch and Fomina (2024) is applied.

4. *How does experience with hybrid models influence investor perceptions?*

   With the last sub-question, the perceptions after experience with the hybrid models is evaluated. Thereby, pre-and post experience perceptions are gathered to identify changes after experience with the tool. Again this is done through the Technology Acceptance Model and Behavioral Decision Theory, to test for the effect before and after adoption. This will add to the current research gap of limited knowledge on the influence and outcome of hybrid models on the perceptions of hybrid models on pitch-deck evaluations in venture capital. This also further researches the effects of experience on bias and trust within the hybrid model pitch-deck evaluations.

1.6. Outline of the thesis

This thesis begins with this introduction chapter, providing the background and further context of the research topic. In this introduction, the role of hybrid models for pitch deck analysis decision-making is further explored. Additionally, the introduction contains the problem statement, research objective and the research questions for this thesis. This is based on the literature review, where the current state of the literature is explored. It analyses the current research on venture capital decision-making, AI based decision-making and hybrid models. Additionally, key theories and knowledge gaps are defined. Based on the research questions, the methodology and research design is determined in the following chapter. This is followed by the results section, where the findings to the research questions are presented. The result topics, chapter numbers and their related sub-questions are shown in Figure 3.

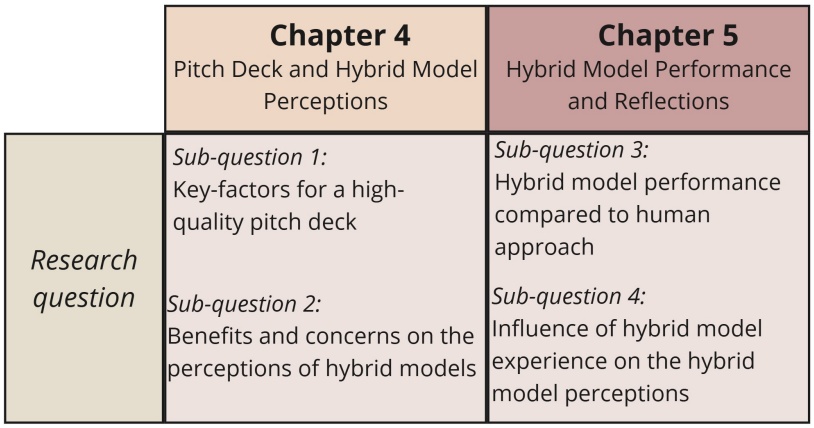

Figure 3: Results chapters addressing the sub-research questions.

As shown in Figure 3, the results will contain two chapters, relating to a specific research sub-questions. Following the results, the discussion further interprets these results and compares them with the existing literature. At last, a conclusion is provided, to reflect on the research performed, and future research topics based on this study is highlighted.

2

Literature Study

This literature review examines how AI and human judgement can be integrated to improve VC-startup screening, particularly the analysis of pitch decks, which is critical as first investment decision. Within the current literature, a growing body of research further explores the use of AI within venture capital, however limited research is available on hybrid applications combining both AI and human judgement. Thereby this introduces a research gap, which is addressed in this thesis.

To clarify the presence of this gap, the review progresses in four sub-sections. First, the literature on the VC investment-decision workflows and current practices in pitch-deck assessment is examined. Secondly, the cognitive and behavioural factors that shape human judgement in venture capital are explored. Third, the literature on the state of AI, through prompt engineering and ethical implications is obtained. Fourth, the literature on hybrid models are evaluated, blending the insights from AI to the human judgements. At last, the theories of the Technology Acceptance Model (TAM) and Behavioral Decision Theory (BDT) are further explored to provide a theoretical background for use in this thesis.

2.1. Investment decision making process

To arrive at a final investment decision, venture capitalists follow a structured decision-making process, evaluating potential investments based on a variety of criteria. This process involves multiple stages, including deal sourcing, initial screening, due diligence, investment selection, and final approval. Each stage is designed to assess the startup's potential for high returns while mitigating risk. Several models of this investment decision-making process have been set up, of which two are shown in Figure 4.

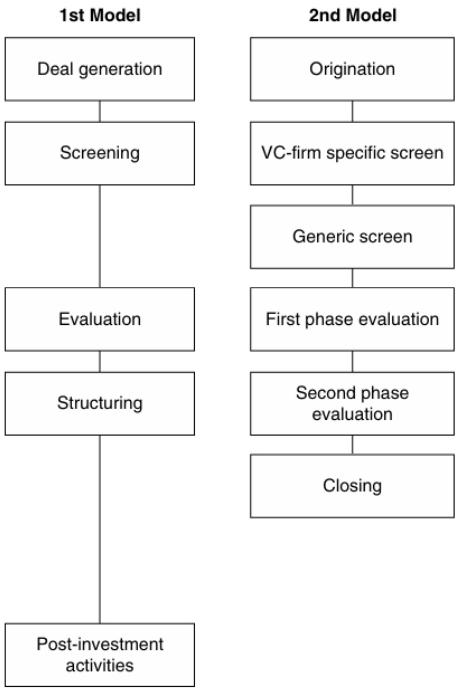

Figure 4: Investment models, first model described by Tyebjee and Bruno (1984, p. 1053) and second model by Fried and Hisrich (1994, p. 31).

Tyebjee and Bruno (1984) made the first investment model, depicting five main phases in the investment process. The first step begins with deal origination, which describes how venture capitalists become aware of potential investments. The second step is a screening process, where the venture capitalists only focus on a manageable set of potential deals. This is then followed by an evaluation step, where the potential return and risk of a deal is evaluated. After a positive evaluation, the venture capitalists enter negotiation to structure a deal for the investment terms as the fourth step. At last, the post-investment activities is the fifth step, which includes consultation, and further protecting the investment until an exit.

Additionally, a second model is described by Fried and Hisrich (1994), building on the first model. This model similarly starts with origination. This is then followed by a VC-firm specific screen, caused by the firm-specific criteria set up by a venture capitalists on for instance investment size, industry and location. Continuing after the firm specific screening is the generic screen, where the venture capitalists evaluate the firm based on general criteria on the business plan and knowledge from the VC. If the firm passes this stage, a first phase evaluation is performed, where this is generally led with a meeting with the principals of the company. Additionally, reference calls are made to existing and potential customers, and VCs further talk to each other. During the second evaluation phase, venture capitalists develop an emotional connection to the firm, thereby increasing the time spent dramatically. In this phase, the obstacles for the investment are determined and how they can be overcome, compared to earlier whether there is a serious interest in the deal. At last, the closing phase is reached where the details of the structure are finalised and further legal documents are checked.

Pitch-Deck Analysis

Essential for the original screening and applicable to all venture capital firms is the pitch-deck analysis. The pitch-deck is considered essential as the initial screening decisions rely heavily on brief, high-level material. This is further explored by Petty and Gruber (2009), where longitudinal research within a venture capital firm shows that 60% of the 3631 proposals within a VC firm were rejected on the initial screening phase. Thereby the vast majority of startups are rejected after this initial screening, highlighting the pressure on the venture capitalists to select pitch-decks worthy of deeper investigations.

The pitch-deck originates from the explosion of venture capital in the 1970s, where the investment banking industry found itself with an increasing number of potential deals (Baehr & Loomis, 2015). Additionally, entrepreneurs found out business plans are not ideal for start-ups, as the start-ups iterate quickly, thereby quickly making the previous business plan obsolete. The presentations known as pitch decks therefore became the norm for the investor to quickly assess a company and for the entrepreneur to quickly change business aspects to externals.

According to Baehr and Loomis (2015), a pitch-deck includes ten essential slides to cover a company. This includes:

- *Overview:* The overview describes the problem and how it will be solved, thereby providing a small insight into the company that further invites the reader.
- *Opportunity:* In the opportunity slide, it is essential to describe the industry, the major trends and market size.
- *Problem:* The core of the proposition is about solving a problem, and why this problem is painful to the target customers. A deep understanding of the problem is of high importance.
- *Solution:* The solution addresses how your company will tackle the problem for the customer earlier described in the specific industry.
- *Traction:* The traction slide serves as evidence to the story and assumptions told up until now. This will therefore further convince the reader of the idea's success.
- *Customer/Market:* The customer/market slide further highlights the in-depth knowledge on the customers and market segment
- *Competition:* The competition slide highlights the current solutions already in use for the problem described. This highlights the importance of the differentiating factor and the unique advantage.
- *Business Model:* The business model further highlights the financials. Therefore important aspects such as customer acquisition costs, customer lifetime value and runway. If a start-up is still in a pre-revenue stage the importance of financials such as revenue, EBITDA, burn rate and cash flow are of importance to project.
- *Team:* The team is essential to further provide the domain expertise and culture, providing the answer as to why this team is the right fit for the job.
- *Use of funds:* At last, a clear ask is of importance to convince the investor of the use of their money. This slide therefore provides further clarity and milestones for money usage.

Additionally, Chan and Park (2014) highlight the importance of the design elements within business plans for venture capital decision-making. The research shows that the design elements, such as the product imagery and colour choices, can shape the investor's screening judgements. Chan and Park (2014), noted that product photographs act as memorable cues to stand out amongst others. Furthermore, colours affect an individual's cognition during screening decisions, where red decreases and blue increases the favorability of a judgement. Thereby, these findings show that investors rely on heuristic processing at this screening stage, where design elements can influence whether a start-up progresses to the next stage.

2.2. Human Judgement in Venture Capital

To evaluate and screen the incoming companies, human judgement is essential in venture capital. Often in venture capital, human evaluators rely on qualitative insights, such as leadership qualities, market dynamics, adaptability, and team cohesion (Gompers et al., 2016). These factors are often subjective and cannot be easily quantified, making human evaluation essential for assessing these aspects of investments. Human decision-making also incorporates emotional intelligence and ethical

considerations. Blohm et al. (2020) highlight the effect of experience on decision-making and biases with business angels and an AI model for investing. The research showed that experienced business angels outperformed the investments originating from their AI model. This therefore highlights the additional input human judgement has on investment decision-making, however also highlights the influence of human biases. This research emphasized the effect where experienced business angels were able to suppress their cognitive biases more compared to inexperienced business angels resulting in an increased performance, underlining the importance of experience and heuristics.

Human biases

Blohm et al. (2020) further emphasize the importance of (suppressing) biases for human judgement in the decision-making of investments, to obtain high-quality investments. According to research conducted by Sachs and Unbescheiden (2024), 15 different biases were found that influence venture capitalist investments. These biases and the effect based on the research from Sachs and Unbescheiden (2024), are shown below in table 2.

Table 2: Effects of biases on venture capitalists, adapted from Sachs and Unbescheiden (2024, p. 7-9).

Bias Type	**Effect on VCs**
Anchoring Bias	Anchoring bias results in VCs maintaining initial expectations, thereby undermining efforts to reassess expectations.
Self-serving Attribution	Self-serving attribution causes VCs to attribute failures to external factors instead of internal factors or acknowledging poor funding decisions.
Availability Bias	Availability bias results in VCs being more optimistic (or pessimistic) in evaluations if it resembles a past success (or failure).
Continuation Bias	Continuation bias causes VCs to provide follow-on investments as the benefits of new information are overestimated.
Escalation of Commitment	Escalation of Commitment refers to VCs continuing investments instead of terminations even though the company is failing.
Gender Bias	Gender bias affects VCs through favoring their own gender or miscalibrated beliefs, ultimately leading to disadvantaging female founders.
Herding Bias	Herding bias causes VCs to follow the actions of other VCs, leading to a consensus view on funding. This results in funding of less viable organizations, overvalued companies, and excessive competition.
Information Overload	Information overload creates overconfidence for the VC and thereby lowers decision accuracy.
Introspection Illusion	VCs have limited introspection into their own decision-making, impeding learning and reducing portfolio performance improvements.
Local Bias / Home Bias	Local Bias causes VCs to be more likely to invest in start-ups close to them.
Overconfidence	Overconfidence is caused by a reduced information search, leading to a decrease in VCs' decision accuracy.
Overoptimism (Technooptimism)	Overoptimism causes a company to be overvalued by a VC.
Similarity Bias / Homophily	Similarity Bias causes VCs to positively assess founders more similar to them.
Status Quo Bias	Status-quo Bias causes VCs to maintain their previous decision.
Visual Cues	Visual elements affect screening decisions, such as the color red negatively impacting evaluation.

2.3. AI and Decision making

To further enhance the investment decision-making process in venture capital, AI can be utilized. Röhm et al. (2022) highlight the potential regarding adoption of AI in the venture capital investment decision-making processes, possibly enhancing the efficiency. However, from this research currently a limited amount of venture capital firms already apply AI in their processes, due to resource scarcity for time, people and money dedicated to the integration of AI. Röhm et al. (2022) further highlight the future catalyst for adoption within venture capital firms, based on third party AI tools that will continue to emerge. Examples of current tools existing to enhance the venture capitalists workflows are:

- *Deckmatch:* An AI platform that extracts and presents information from pitch-decks, helping investors evaluate propositions.
- *Beacon AI (SignalFire):* Monitors data feeds to predict start-ups and their traction to align with the investment fund.
- *Motherbrain (EQT):* AI system that analyses company datapoints to flag outliers and recommend investment targets.

AI Prompt Engineering

These third party tools can be made specifically for the venture capital investing process, and can also include the use of general Large Language Models (LLMs), such as ChatGPT. To understand the usage of the LLMs, prompt engineering is essential for venture capitalists to assist in the pitch-deck evaluations with high-quality, relevant and efficient outputs.

The concept of few-shot prompting was introduced by Brown et al. (2020). This introduces the importance of structuring prompts for improved performance of the AI LLMs. According to few-shot prompting, the prompt should start with a task description. This is followed by demonstrations of the mentioned task (few-shots), and at last a final input should be given where the model can give a response. Reynolds and McDonell (2021) add to the few-shot prompting principle, by addressing the efficacy of zero-shot prompting, if the prompts are well designed. It introduces structured and clear reasoning prompts to guide models step-by-step. At last, Wei et al. (2022) introduce chain-of-thought reasoning, building further on the previous prompting techniques. With the chain-of-thought reasoning, the importance of intermediate reasoning steps is highlighted to improve the ability for the LLM to perform complex reasoning. Therefore, based on the literature the structure of a prompt to obtain a high-quality output is as follows:

1. Ask a clear and concise question to the LLM.
2. Provide a step-by-step guide to notice the LLMs chain-of-thought.
3. Provide a final input where the model can put it's response.

Based on these prompting techniques, venture capitalists can be guided through the origin of the information shown by the LLM. Thus, this can assist the investors in further logic-based screenings enabling investors to enhance transparency within the AI output.

Ethical Implications

Similarly to biases formed based on human judgment, there are still challenges and implications relating to the adoption of AI in the investment decision-making process in high-stakes environments. These challenges are further highlighted by Rossi (2023), which describes ethical challenges arising from potential AI adoption. These challenges are:

- *Historical Biases:* Historical biases can be introduced into AI models, as these are trained on known data. Thereby, previous biases occuring within these training datasets can therefore cause the AI model to further reinforce these biases in the future recommendations and decions. Therefore, AI models trained on AI models can reflect past biases and discriminations in the future,

affecting the investments made and potential demographics (World of Conferences, 2024).

- *Lack of transparency:* A lack of transparency is present with AI models, due to their "black box" nature. This black box nature originates from a lack of deep understanding of the underlying nature of the model, as the focus is put on the input and output of the AI models. This lack of transparency can reduce the trust in its recommendations and create an environment where accountability is elusive (World of Conferences, 2024).

Therefore, to overcome these challenges arising with the come-up of AI, transparency, and fair and representative algorithms are of high importance. These challenges also highlight the need for human investors to stay in the loop of the investment process. Therefore this highlights the future possibility of augmenting decision-making through hybrid models (Röhm et al., 2022).

2.4. Hybrid models for Decision-Making

The current literature highlights the use of AI within VC-driven decisions, yet most studies either focus on purely using AI-driven solutions, or human judgements within VC. This therefore leaves an underexplored research topic, where the two approaches intersect. Additionally, this intersection is uniquely suited for venture capital decision-making, as this contains many contextual factors and nuances. Thereby, the AI can provide data-driven outputs, combined with a nuanced judgement from human input. Thereby, this hybrid human-AI model research within venture capital can add to the further understanding of hybrid models for decision-making within venture capital.

Recent emerging literature on hybrid human-AI models highlight different hybrid approaches that combine AI and human inputs, thereby leveraging data-driven insights, while retaining contextual understanding (Jarrahi, 2018; Raisch & Fomina, 2024). According to Raisch and Fomina (2024), hybrid problem solving is a process undergone in several stages, visualised in Figure 5.

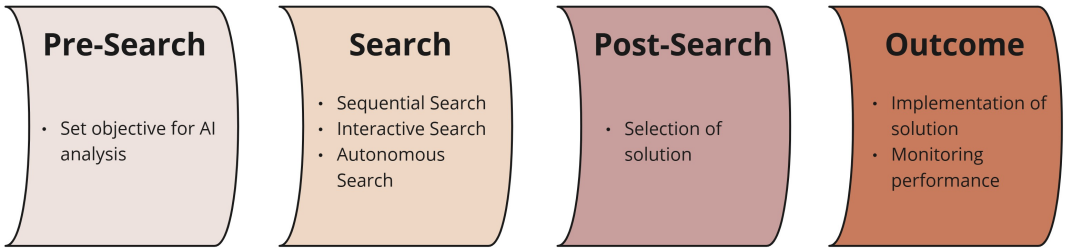

Figure 5: Hybrid Problem Solving Process, adapted from Raisch and Fomina (2024, p. 46).

As highlighted in Figure 5, in the pre-search stage humans first engage to set an objective or target of the AI analysis. Here, humans also have the responsibility to provide input information to align with the objective. This is then followed by the search stage, where either predictive AI or generative AI can be used. Predictive AI is used in the problem definition as this helps define the problem and identify potential solutions based on existing data patterns. Generative AI is used to actively create new solutions by generating novel possibilities. Further, the post-search stage follows, where humans are again responsible for the selection of the final solution. At last, in the outcome stage the solution is implemented and humans monitor performance to improve future AI solutions.

Raisch and Fomina (2024) highlight three types of hybrid search models:

- *Sequential search:* Sequential search can be used, where AI provides initial insights followed by human refinement. This uses predictive AI for the problem definition, however uses humans for the solution search. Therefore this is used to benefit from AI's prediction capabilities while also

maintaining human capabilities.

- *Interactive search:* Interactive search can be applied, which enables human-AI collaboration. During interactive search, the human and AI agent work together on both the problem definition and solution search. Thereby, this is used to combine both human and AI agent's learning skills.

- *Autonomous search:* Autonomous search can be used, which is AI-dominant. This requires an AI agent to perform an entire task (both problem definition and solution search) by using both predictive and generative AI. This is followed by selection of the solutions proposed from the AI by the human. This autonomous search process thereby minimizes human input and biases in the search process.

2.5. Theory

To further investigate the research question set up, a theoretical framework is desired for the research to build upon. As the decision-making is dependent on the perceptions and eventual usage of the technology, the Technology Acceptance Model (TAM) is explored. Additionally, the Behavioral Decision Theory (BDT) is taken to further understand and explain the human behavior relating to the TAM. Thereby, these theories form an important base for framework to assess hybrid models.

2.5.1. Technology Acceptance Model

To further analyse the implications of factors on the use of the hybrid models within pitch-deck analysis and the decision-making effects, the Technology Acceptance Model (TAM) is used. The TAM is a theoretical framework, originally developed by Davis (1985), to understand the factors that affect the acceptance of technologies. This model is visualised in Figure 6.

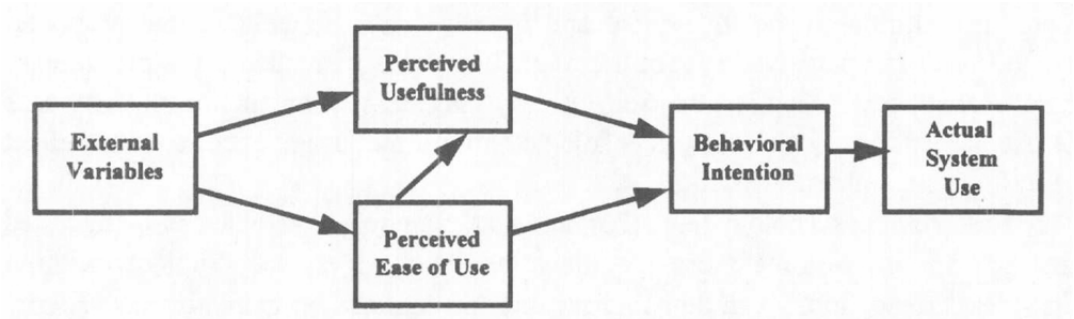

Figure 6: Technology Acceptance Model originating from Venkatesh and Davis (1996, p. 453), adapted from Davis (1985) to remove the attitude construct.

Through Figure 6, the different factors that play a role on the technology use is shown. These are highlighted below:

- *External Variables*: The external variables represent contextual or individual factors (such as prior experience, training and technology design) that influence the user's perception of the technology. This directly influences both the perceived usefulness and perceived ease of use.
- *Perceived Ease of Use*: The perceived ease of use is the degree to which a user believes that the system is effortless to use. It is affected through the external variables and influences both the perceived usefulness and behavioral intention.
- *Perceived Usefulness*: The perceived usefulness regards the extent to which a user believes that the technology enhance the performance. It is influenced through the external variables and perceived ease of use, and directly influences the behavioral intention.

- *Behavioral Intention*: The behavioral intention regards the intention of the user to actually use the technology. Through the perceived usefulness and perceived ease of use, this behavioral intention predicts the actual system use.
- *Actual System Use*: This refers to the final outcome regarding the adoption of the technology.

In the earliest model of Davis (1985), the perceived usefulness and perceived ease influence first the attitude towards using, which in turn influences the behavioral intention. However, as the perceived usefulness also directly influences the behavioral intention, following research regarded this factor as insignificant to the model, hence this factor was left out of the TAM from Venkatesh and Davis (1996), however can still be applied.

Following the TAM from Davis (1985), researchers have continued to expand on TAM, through further extensions and modifications on the TAM. King and He (2006) thereby expand on four major categories of TAM modifications, shown in Figure 7.

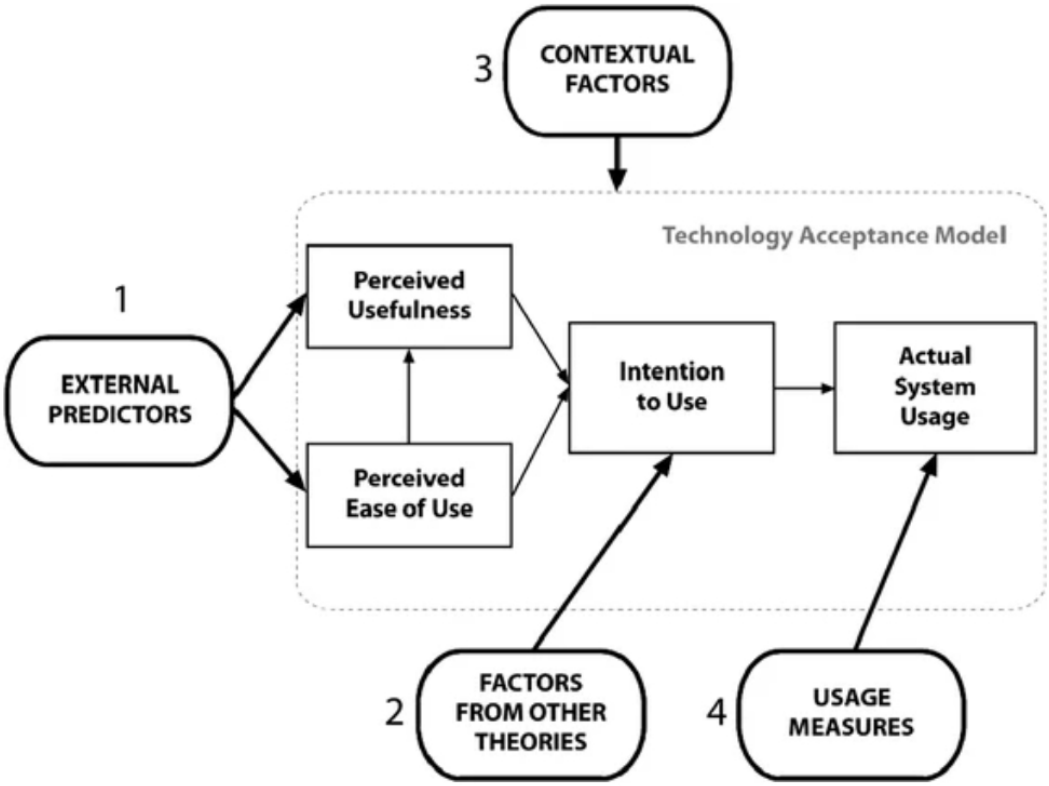

Figure 7: Technology Acceptance Model (Marangunić & Granić, 2014, p. 90).

As seen in Figure 7, this further expands on the original TAM. This does so in four categories:

- *External Predictors*: These external predictors highlight the effect on the perceived usefulness and perceived ease of use, determined by the technology and user itself.
- *Factors From Other Theories*: Factors from other theories apply as additional modifications based on increasing the predictive validity of the TAM, such as trust and risk factors.
- *Contextual Factors*: Contextual factors can further modify the TAM, through factors such as gender, cultural diversity or technology characteristics.
- *Usage Measures*: At last, the usage measures are used to modify the TAM, with measures such as the usage perception and actual usage of technology.

TAM History

The TAM is derived from the Theory of Reasonable Action (TRA) developed by Ajzen and Fishbein (1980) and Theory of Planned Behavior (TPB) developed by Ajzen (1985). Ajzen and Fishbein (1980) made the assumptions that humans are mostly rational and use the available information, on which they developed the TRA to predict and understand behaviors and attitudes. According to the TRA, the main predictor of human behavior corresponds to the behavioral intention. The TPB builds on the previous theory, by extending the theory with the concept of perceived behavioral control. This is done, as the original TRA is limited by the little control over actual behaviors and attitudes. However, the main limitation for TPB is that it relies on the assumptions that humans act rationally, with systematic decisions based on all available knowledge. This does not include unconscious motives and further biases present in humans.

2.5.2. Behavioral Decision Theory

When extending the Technology Acceptance Model to the venture capital context, the Behavioral Decision Theory (BDT) offers a complementary perspective. While the TAM assumes that decision-makers rationally assess technologies based on the perceived usefulness and ease-of-use, the BDT accounts for human psychological realities of decision-making under uncertain contexts. In high-stakes and time-constrained environments such as in venture capital, the decisions are therefore often influenced through intuition and heuristics rather than purely rational evaluations.

The BDT builds on the bounded rationality theory (March, 1978), which notes that human evaluators compensate for limited information and time constraints through intuition and pattern recognition. Thus this allows humans to handle complex situations and uncertainty. Thereby, these cognitive shortcuts are effective within these contexts, however also introduce heuristics and biases. The behavioral decision theory builds on this by identifying how these heuristics can lead to biases in decision-making. Thereby, the BDT explains how decisions deviate from rationality through for instance overconfidence and availability biases (Einhorn & Hogarth, 1981).

Blohm et al. (2020) demonstrate that suppressing cognitive biases in the VC investment process, improves the decision quality through a maximisation of the return on investment. Therefore, incorporating the BDT into the TAM-based research enables a more practical analysis of how venture capitalists adopt and evaluate new technologies.

Prospect Theory

The Prospect Theory offers an additional view on the VC decision-making heuristics and behaviors. It builds on the Expected Utility Theory, which assumes a rational evaluation of uncertain outcomes. Hereby it separates risk attitudes, from preferences over the timing of when the uncertainty is resolved. The Prospect Theory deviates from this by describing how humans actually behave under risk, thereby including pyschological biases (Kahneman & Tversky, 1979). A central concept is related to the loss aversion, which suggests that individuals evaluate outcomes relative to a reference point, and perceive losses more intensely than equal gains. Thereby, this framing can cause VCs to act more cautiously when evaluating risky propositions. In addition, the theory explains how decision-makers distort probabilities, often overweighing rare but extreme outcomes. This is reinforced through heuristics, which may lead to VCs overvaluing high-impact opportunities based on earlier reference successes. Thereby, this may lead to overconfidence biases from the VCs in similar deals. Additionally, these heuristics may create pattern-matching biases, favouring similar deals. These effects may thereby create herding behaviors and reduce the diversity in investment decisions. Gompers et al. (2016) further highlights the real-world presence of these biases, where many VCs rely on intuitive, pattern-based screening for their decision-making.

BDT and Hybrid Models

The skewed venture-capital judgements explained through the behavioral decision theory, could potentially be limited through hybrid human-AI models. Here, biases can be mitigated through use of

objective, data-driven outputs within the decision-making process. Thereby, data-driven insights can complement the human judgement to limit the heuristics and intuitions within a venture capital context. Current research supports this effect of bias limitation, where Duan et al. (2019) argue that decision systems which augment human judgement with AI support outperform purely human outputs. Thereby this underscores that the most reliable outcomes arise through the synergy between AI and humans, instead of supplementing one for eachother. Within the high-uncertainty and high-stakes context of venture capital, this could be further applied to limit biases and obtain reliable outcomes.

2.5.3. Theoretical Synergy: TAM and BDT in Hybrid Models

While the Technology Acceptance Model (TAM) and the Behavioral Decision Theory (BDT) are often treated as separate frameworks, the value lies in their integration within the venture capital hybrid model decision-making context. Here, the TAM explains the intention to adopt potential hybrid model AI tools, by focusing on perceptions such as the perceived usefulness and ease-of-use. This thereby explains the decision of potential users whether to adopt the technology. The BDT further contributes to the understanding on the tool usage after adoption. Thereby the BDT accounts for biases that influence the investor's trust in practice. Thus, the BDT captures deviations from the rational behaviour of the TAM model, to obtain a more complete understanding of hybrid model usage within venture capital pitch-deck analysis context.

2.6. Conclusion

To conclude, this literature review highlights the significant role of human judgement and AI in the investment-decision making process, with the interplay between rational decision theory and behavioral decision theory. The integration of AI in venture capital is promising to further enhance the efficiency and reduce biases. However this literature review also highlighted the challenges that arise from incorporation of AI into the decision-making process, such as ethical considerations and assessment of contextual factors.

This literature review reveals a gap in the current research, which mainly focuses on the roles of AI and human judgement in venture capital decision-making. However, limited studies have explored the interaction between those, with the use of hybrid models. Therefore, the use of hybrid models on the decision-making process within venture capital emerges as an important theme for further research.

Additionally, the use of hybrid models can be applied to pitch-deck analysis, as this remains underexplored. This can require intensive use of data-driven and contextual insights to come to a decision, thereby providing a prospective case for implementation of hybrid analysis.

At last, current existing literature either remains theoretical or focuses on large-scale quantitative analyses. Therefore real-world applications within venture capital firms remain limited, highlighting the research need to research the understanding in a practical case within a high-stake, early-stage startup investments.

3

Methodology and Research Design

3.1. Case Study Design

To answer the research question and sub-questions, a detailed methodology is of importance to come to a valid research. With the aim to explore real-world application of hybrid models within venture capital, this research applies a case study as methodology. This chapter therefore describes the case study overview, and how the quality of the research is upheld.

3.1.1. Case Study Rationale

A single-case study design was chosen, thereby exploring the adoption of hybrid models within the pitch-deck analysis process in venture capital. This design contributes to answering the research question, as the case study design contains an exploratory nature in a real-life setting. The case was selected based on the case study approach of Yin (2014), where the selected case consists of the AI tool 'Deckmatch' applied within the company InnovationQuarter. This case study thereby provides unique insights into the adoption of hybrid models in a real-life setting, thus allowing for an in-depth understanding of the dynamics and potential barriers involved in the implementation of hybrid AI models in venture capital.

3.1.2. Theoretical Framework

The case study is built on the Technology Acceptance Model (TAM) (Davis, 1985) and Behavioral Decision Theory (Einhorn & Hogarth, 1981). The TAM hereby provides a framework in order to understand the perceived usefulness and perceived ease-of-use of the venture capitalists on the hybrid model. Thereby evaluating their eventual willingness to adopt the technology itself. The Behavioral Decision Theory complements this research further by researching the roles of biases, trust and heuristics within the human judgement itself. Thereby these theories further guide the development of the data collection setup and further analysis.

3.1.3. Case Selection

The case study is performed within the venture capital firm InnovationQuarter. This is a regional economic development agency and venture capital fund based in South-Holland. Within its venture capital activities, InnovationQuarter focuses on technology-driven companies, to stimulate regional innovation. The investment process is highlighted in Figure 8.

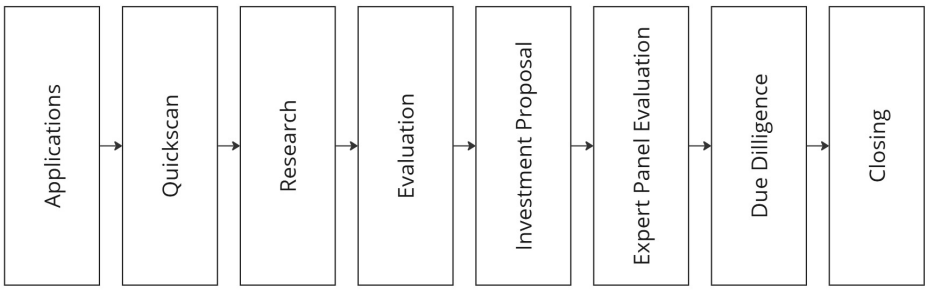

Figure 8: The investment process of InnovationQuarter.

As shown in Figure 8, the investment process is similar to the earlier described process from Fried and Hisrich (1994) shown in Figure 4 with a difference in the extension of the evaluation process. The case focuses on the early 'application' stage for pitch-deck analysis within the investment process, there highlighting similarity to literature higlighted from Fried and Hisrich (1994).

Within the case, the hybrid model originating from the company 'Deckmatch' is applied. This AI-software tool supports the evaluation of pitch-decks. This is done through natural language processing and machine learning to analyse different pitch-deck elements. Hereby the tool is able to provide information (sequential search), interact through a chatbot (interactive search) and obtain AI-based outputs and decisions based on prompts (autonomous search). Within the case study, Deckmatch is integrated into the pitch-deck analysis workflow to explore the effects of hybrid model decision-making for pitch-deck analysis in a real-world venture capital setting.

Case Selection Rationale

The case follows the rationales determined by Yin (2014), to justify the single-case study design under certain conditions. This highlights the following rationales that can be applied to this case:

- *Representative case:* The case itself applies to the single-case rationale based on the representative aspect of the case, where the case itself represents a typical project of pitch-deck analysis within the venture capital industry.
- *Revelatory case:* Access to real-world implementation of the hybrid model allows for the exploration of under researched phenomenon.
- *Theoretical relevance:* The case highlights the theoretical relevance, through application of the Technology Acceptance Model and Behavioral Decision Theory.

To add to the rationale from Yin (2014), InnovationQuarter offers an ideal context for the implementation of hybrid models. This is the case, due to the organisational wilingness to adopt AI tools, thereby providing an open approach to implementation research. Furthermore, its investment focus on early-stage ventures (ranging from Seed to Series A stages) highlight the information assymetries and decision uncertainties, that further strenghten the case and applications with hybrid models. Thus, as one of the first real-world pilots of hybrid pitch deck analysis in venture capital, this study enables insights into the practical adoption dynamics and potential barriers in hybrid model adoption.

3.1.4. Unit of Analysis

Based on the selected case, the unit of analysis is determined. This is chosen based on identification of the primary phenomena to answer the research question. This is therefore related to the pitch deck evaluation process. Within this unit of analysis, the pitch decks are evaluated based on the AI and human generated insights. Based on further insights from Yin (2014), the case study benefits from a subunit of analysis, to strengthen the flexibility of the research. This sub-unit of analysis within the case study is highlighted based on the individual decision-makers, which is examined through the contact

with these individuals throughout the case.

Importantly, the individual decision-making dynamics shape the way in which hybrid models are adopted at an organisational level. Thereby, if individual evaluators distrust the AI insights, the potential benefits of the hybrid model are undermined within the organisation. On the contrary, when individuals recognize the strengths and limitations, hybrid models are more effectively integrated. Thus, by capturing the individual-level interactions the study provides an understanding on how hybrid models influence decision-making across both individual and organisational layers for hybrid model adoption within the embedded single case study.

3.1.5. Preparing for Data Collection

To prepare for the further data collection within the case study, a protocol is determined. This protocol is determined for an interview, pilot experiment, and workshop and is visualised in Appendix A. Additionally, consent forms were created for the participants including a letter of introduction. This is visualised in Appendix A and Appendix B.

3.1.6. Data Collection

The data collection for this case study is done according to the principles of data collection from Yin (2014).

- *Triangulation:* The first principle highlights the use of multiple sources of evidence, for triangulation. This indicates the use of different sources to obtain the data. This is done through alignment of the literature review with the semi-structured interviews followed by an evaluation with the pilot experiment and the workshop.
- *Database:* Additionally, the second principle highlights the necessity to create a case study database. This aims to create a clear organisation of the collected data. Through the primary data collection in this case study, recordings are collected that are transcribed. The information obtained is stored on a safe web environment, namely the TU Delft Onedrive. After storage of the transcripts, the recordings are deleted. Additionally, the information stored on the OneDrive is removed following the end of the research project.
- *Chain of evidence:* The third principle dictates the need to maintain a chain of evidence. The core principle here is to allow an observer to trace the entire process from the initial research questions up until the conclusion of the case study, to increase the reliability of the research. In this research, such a chain of evidence is maintained through the links between the research questions and data collection methods. Additionally the reproducibility is maintained through clear documentation and guidelines throughout the research.

The data is collected through multiple methods, targeting different aspects of the research question to obtain a robust outcome. This is highlighted in an overview, where four phases are highlighted each corresponding to another sub-question. This is shown in Figure 9.

	Phase 1 Pitch Deck Insights	**Phase 2** Hybrid Model Perceptions	**Phase 3** Hybrid Model Performance	**Phase 4** Hybrid Model Experience on Perceptions
Research question	*Sub-question 1:* Key-factors for a high-quality pitch deck	*Sub-question 2:* Benefits and concerns on the perceptions of hybrid models	*Sub-question 3:* Hybrid model performance compared to human approach	*Sub-question 4:* Influence of hybrid model experience on the hybrid model perceptions
Methods	• Literature study • Interviews	• Interviews	• Pilot experiment	• Workshop

Figure 9: Research design, correlating the research questions to the methods used.

Phase 1: Pitch Deck Insights

First, the aim is to addresss the first sub-question, by identifying key factors for a high-quality pitch deck. This begins with a literature review to obtain the current state of knowledge on pitch deck evaluation criteria. During the literature review, Google Scholar was the main search engine that was used. Important keywords that were used are: venture capital, decision-making, investment process, pitch-deck analysis, AI, hybrid models, human judgement and ethical considerations. Additionally, Google was used to obtain grey literature, regarding pitch-deck analysis.

These insights are used to build upon in a semi-structured interview, which explores how venture capitalists currently analyze pitch decks in practice. Semi-structured interviews are chosen to balance the structure in the interview with flexibility. This allows for comparisons between the interviews, while still obtaining in-depth insights from participants. This approach thus increases the replicability while reducing the researcher bias (Ruslin et al., 2022). Additionally, the combination of desk research and practical evaluations aim to obtain a reliable understanding.

Phase 2: Hybrid Model Perceptions

Following the pitch decks insights, the second sub question is focused on to obtain the benefits and concerns of venture capitalists through hybrid model perceptions. This is again done in a semi-structured interview, thereby gathering insights into the perceived effectiveness and ease-of-use of hybrid models for pitch-deck analysis. The interviews are designed to obtain key constructs from the Technology Acceptance Model relating to the perceived usefulness and perceived ease of use. Additionally the Behavioral Decision Theory is included through the bias and trust topics. Thereby these semi-structured interviews obtain the data relating to the perceptions of hybrid models within pitch deck analysis.

In phase 2, the gathered insights from the previous phase are analysed and used to prepare for the following experiment. This is done by setting up three experimental pitch-decks based on the gathered knowledge, and implementing the hybrid AI tool 'Deckmatch' together with engineering prompts as an input for the model.

Phase 3: Hybrid Model Performance

The third sub-question focuses on the hybrid model performance compared to the manual human approach. An insight into this sub-question is obtained through a pilot-experiment. An overview of the pilot-experiment order is shown in Figure 10.

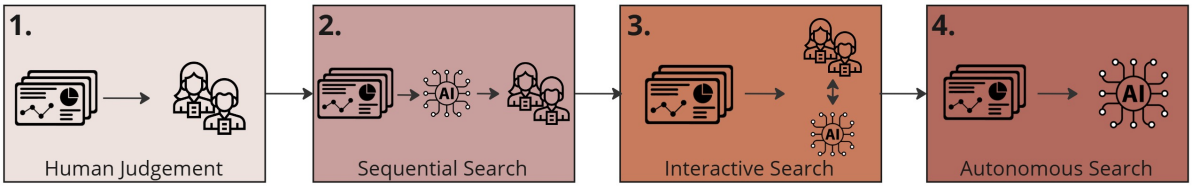

Figure 10: The experimental order, first applying human judgement to the pitch-decks, followed by the three hybrid model types; sequential search, interactive search and autonomous search.

As highlighted in Figure 10, participants first evaluate a pitch deck without any support of AI. This is followed by analysis with the use the different hybrid AI models (sequential search, interactive search, autonomous search). The pilot-experiment relates these pitch-deck approaches as independent variables that are controlled (Quin et al., 2023). Additionally, the AI tool used (Deckmatch) is also considered an independent variable. The dependent variables of the pilot-experiment are measured during or after the experiment. These are related to:

- *Time efficiency:* The task completion time is taken as a dependent variable, measured in minutes and seconds during the pitch-deck analysis. The pilot experiment is timed based from the start of the analysis until the final judgement. After 8 minutes, the participants were asked to form a judgement, to limit time constraints later in the experiment.
- *Evaluation efficacy:* The efficacy of the evaluation was measured as dependent variable after the experiment, based on the completeness of analysis from the participant on a Likert scale of 1 to 7, with 1 meaning incomplete and 7 fully complete.
- *User experience:* The user experience was measured as dependent variable in a post-experiment survey, where the confidence, trust and perceived helpfulness were measured. These were again measured on a Likert scale of 1 to 7.

The pilot experiments were mostly performed in-person, with the exception of two participants where it was performed online. This was done on a one-on-one basis with the participants set up in a meeting room. Thereby, the participants sat across from the interviewer. Furthermore, the participants had no material of their own, accessing the pitch deck for human analysis on paper, and hybrid analysis on Deckmatch on the laptop of the interviewer. The physical setup of the pilot experiment is shown in Figure 11.

Figure 11: The experimental set-up, both offline and online.

The pitch decks were given to the participants in a randomized order, to limit potential learning effects within the experiment. Additionally, the pitch-decks were created experimentally, based on the earlier findings obtained from literature and the semi-structured interviews. This thereby provides a foundation to create the experimental pitch decks. To reduce the influence of cognitive biases such as availability bias, pitch-decks are created according to criteria to limit bias formation (Einhorn & Hogarth, 1981). Based on Hsu et al. (2016), standardized structure and content, and obtaining control variables are of importance. Therefore, the pitch deck design and slides are kept similarly across the different pitch decks. Additionally, the pitch decks are created within a similar industry to limit additional effects.

Phase 4: Hybrid Model Experience on Perceptions

At last, the influence of experience with the hybrid model on the perceptions is gathered through a workshop. This was done directly after the pilot experiment with the participants, under similar conditions. During the workshop, questions were asked on the Technology Acceptance Model, relating to the Perceived Usefulness, Ease-Of-Use, Attitude Towards Usage and Intention to Use. Additionally, perceptions about bias and trust were asked based on the Behavioral Decision Theory. The questionnaire of the workshop is shown in Appendix B. These questions act as an evaluation after the pitch-deck analysis, focusing on possible altered perceptions regarding the technology adoption for potential future implementations.

Sampling Strategy

The interviews, pilot-experiment and workshop are based on non-probability sampling, where purposive and convenience sampling occurred to obtain information from experts. Purposive sampling is chosen to target venture capitalists within the case study boundaries. As the thesis is written in collaboration with InnovationQuarter and a case study is performed on their investment decision-making processes, the participants originate from this company. Additionally, convenience sampling is used to obtain the desired number of participants and results. However, as described by Emerson (2015), this type of sampling introduces unexpected or uncontrolled factors due to the bias of availability.

The participants that are asked to perform in the research, originate with a background in venture capital investing. For the exploratory interviews to set up experimental pitch decks, six venture capitalists were interviewed ranging from junior investment analysts to investment managers. Furthermore, for the pilot experiment 7 participants were obtained to research the effect of hybrid models on the pitch-deck analysis. At last, the workshop focuses on the effect of the experience with hybrid models on the participants perceptions, for which again 7 participants contributed. Due to time and resource constraints, the experimental research design can therefore be considered as an initial exploratory pilot to research the effect of hybrid models. The final list of participants, and their roles are found below in Table 3.

Table 3: Overview of participants per method, their job functions, gender and experience

Participant	Job function	Gender	Experience (yrs)
Interview			
1	Investment Manager	Male	4
2	Investment Manager	Male	4
3	Investment Analyst	Male	2
4	Investment Analyst	Female	1
5	Investment Analyst	Male	1
6	Junior Investment Analyst	Male	0.5
Pilot Experiment			
7	Senior Investment Manager	Male	18
8	Investment Manager	Male	10
9	Investment Manager	Male	4
10	Investment Analyst	Male	2
11	Investment Analyst	Female	1
12	Investment Analyst	Male	1
13	Junior Investment Analyst	Male	0.5
Workshop			
14	Senior Investment Manager	Male	18
15	Investment Manager	Male	10
16	Investment Manager	Male	4
17	Investment Analyst	Male	2
18	Investment Analyst	Female	1
19	Investment Analyst	Male	1
20	Junior Investment Analyst	Male	0.5

3.1.7. Data Analysis

For the data analysis, four principles are applied based on Yin (2014), to maintain high-quality research. First, the data analysis will show that all the evidence is attended to. Additionally, the analysis should address major rival interpretations. Third, the most significant aspect of the case study is addressed. At last, expert knowledge is used within the case study, demonstrating awareness on the case study topic.

For the research, transcripts are considered and analysed through the thematic coding tool called *Atlas.ti*. According to Yin (2014), there are different analytical strategies to be applied. In this research, the frequency of events is first tabulated as an analytic manipulation technique to provide a preliminary order. Following the preliminary order, is the strategy for the analysis itself. Based on the preliminary order, the themes are characterized according to Hill et al. (2005). Here the method is mentioned to classify the themes according to a major and minor frequency. Here the minimum threshold for a major theme includes is set at 50% of the highest theme frequency. Furthermore, pattern matching is applied, thus relying on the theoretical proposition, following the Technology Acceptance Model and Behavioral Decision Theory that led to this case study. It can be applied by comparing empirical findings from the data with the original predicted patterns derived from the theory. Alignment of these patterns thereby additionally results in a strengthened internal validity. The constructs and expected theoretical patterns are shown in Table 4

Furthermore, the pilot experiment data was analysed according to the likert scale-data obtained. Here, the data is analysed according to the averages obtained, and the standard deviation corresponding

to the results. This thereby provides a general overview for the pilot experiment, indicating potential interesting arguments.

Table 4: Theoretical Constructs and Expected Patterns

Construct	Expected Pattern
Technology Acceptance Model	
Perceived Usefulness	Users are more likely to adopt the AI tool if they believe that it increases their efficiency and efficacy of analysis.
Perceived Ease-of-Use	The adoption of the technology is more likely to occur if it is considered as intuitive.
Attitude Towards Use	Positive perceptions of the usefulness and perceived ease-of-use result in a positive attitude towards use.
Behavioral Intention	If users perceive the AI tool as useful, easy-to-use, and develop a positive attitude, they will intend to use it in future decisions.
Behavioral Decision Theory	
Bias	Hybrid models are expected to reduce existing human biases, but additionally introduce new biases as venture capitalists remain susceptible to heurstic-driven judgements obtained from the AI output.
Trust	Trust in AI is expected to remain complementary to human judgement, with hybrid models supporting but not replacing human intuition, especially in complex and uncertain investment contexts.

Following the setup of theoretical patterns, the interview data itself is coded according to thematic analysis based on Braun and Clarke (2006). This highlights six important phases within the analysis process:

- *Phase 1 - Familiarisation with the data:* This highlights the need to transcribe and read through all the data itself.
- *Phase 2 - Generating initial codes:* During this phase, coding is done systematically throughout the entire dataset. Here, interesting features of the data are identified and kept.
- *Phase 3 - Searching for themes:* Related codes are grouped into themes and extracts are obtained for each theme.
- *Phase 4 - Reviewing themes:* Themes are reviewed in relation to the coded data and full dataset, and further refined by merging, splitting or discarding them.
- *Phase 5 - Defining and naming themes:* The different themes are defined according to what it entails, and the narrative that each theme explains regarding the research question.
- *Phase 6 - Producing the report:* At last, the themes are related to theory and research questions to produce the final report.

Validity and Reliability

The internal validity refers to the extent to which a study establishes a relationship between the independent and dependent variables. Therefore, this is of high importance throughout the research process to make in the end make valid conclusions. Throughout the research, the internal validity is ensured, first of all through control of confounding variables. This is done through random assignment of the participants to the different experimental pitch-decks. Furthermore, the procedures are standardized, thereby increasing the replicability of the research.

Furthermore, potential biases in the research are mitigated, thereby further increasing the internal validity. This is shown in Table 5.

Table 5: Potential biases, their effects and mitigation strategies.

Bias	Effect	Mitigation
Confirmation bias	The researcher may interpret data in a way to support the hypothesis	Using the coding software Atlas.ti and employing pattern matching
Observer bias	The presence of the researcher may lead to influence the participant response	Use neutral phrasing for questions
Selection bias	The sample of participants may not be representative	Use a diverse sample based on experience levels and backgrounds
Response bias	Participants may answer based on expected and socially acceptable answers	Ensure anonymity and confidentiality
Instrumentation bias	Differences within the three pitch-deck may affect the evaluations	Standardize the materials to ensure the pitch-decks are formatted similarly
Sampling bias	Participants from a limited pool may result in lower generalisation	Use participants with diverse backgrounds
Learning effects	Participants who analyse multiple decks may improve their evaluation skills	Randomize pitch deck order

The external validity highlights the generalizability of the research to a broader application. In this case study, the external validity is considered through focus on the pitch-deck analysis as part of the investment process, as this is considered standard amongst venture capital firms. Additionally, purposive sampling is applied, where a range of experience levels is taken to be representative in other venture capital firms.

The reliability of the research refers to the consistency and replicability of the research. First, for the consistency of the data collection, standardized procedures are conducted for both quantitative and qualitative components. Furthermore, the replicability of the research is viable due to a clearly defined case study selection criteria, sample selection criteria and protocols to improve the replicability.

Limitations

The main challenge in the data collection is regarding the time and resource constraints. Due to these limits, a limited number of participants are gathered for the pitch-deck and hybrid-model insights. However, even though the number of participants is limited, the research still contributes to a further understanding of the research topic. Thereby acting as an exploratory research to gain intial understanding in the use of hybrid models within venture capital decision-making processes.

Ethical Considerations

Throughout the thesis, the HREC (Human Research Ethics Committee) guidelines of the TU Delft are accounted for. To pass the HREC guidelines, an HREC checklist, data management plan and consent forms have been set up for approval. This indicates that the data is obtained through a recording, which is transcribed and anonymized. Therefore, both commercially sensitive information and information regarding participants is limited. Based on the consent forms, shown in Appendix A and Appendix B, the participants acknowledged their understanding of the study's purpose, potential risks and data usage, and thereby provided their consent to participate in the research.

4

Results: Investor Perceptions on Pitch Decks and Hybrid Models

This chapter presents the insights obtained from the semi-structured interviews with venture capitalists within the case study, performed according to the methodology described in Chapter 3. The interviews were designed to gain an in-depth understanding into both the current pitch deck analysis of venture capitalists and their perceptions on hybrid models. To obtain this understanding, first the interview starting point is defined. Following the starting point, the data is collected and analysed according to a thematic analysis, as discussed in Chapter 3. Hereby, the frequency of events is provided for these perceptions, to obtain a preliminary order for further discussion. Furthermore, the pitch-decks for the pilot experiment are created and shown. At last, the hybrid model perceptions are discussed and matched relating to the expected patterns in Table 4.

4.1. Key Pitch Deck Evaluation Criteria

4.1.1. Interview Starting Point

The semi-structured interviews aim for an increased contextual understanding, for which a starting point is first defined to determine the interview questions and relate back to. This starting point is obtained from the knowledge obtained within the literature review on pitch-deck insights. Based on these insights, a further in-depth understanding of critical pitch-deck sections is desired. Additionally, the contextual factors of quality of design emerge as topic within the literature review, for which a further context is determined as starting point. At last, additional contextual factors relating to the start-up stage were asked to add to the contextual understanding. Therefore in the semi-structured interview, pitch-deck related questions asked were:

- *Typical pitch deck analysis* - What pitch-deck sections are considered most critical?
- *Quality of design* - How does the design and quality of the pitch-deck influence the analysis?
- *Dependency on start-up stage* - How are critical pitch-deck sections dependent on start-up stage?

Furthermore, questions related to the hybrid model perceptions were determined based on the theory and thereby the expected patterns in Table 4. Thus, this resulted in the Perceived Usefulness, Perceived Ease-Of-Use, Biases and Trust to be the starting point for this interview.

4.1.2. Theme 1: Critical Pitch Deck Sections

A further in-depth understanding of the critical pitch-deck sections is obtained during the semi-structured interviews, thereby emerging as the first theme. The data was analysed according to a thematic analysis described in Chapter 3. The frequency of the pitch-deck sections from the thematic analysis are

first tabulated and shown in Table 6.

Table 6: Frequency of events tabulated for the thematic analysis of the pitch-deck sections. Sample size: n = 6.

Pitch-deck sections	Number of times mentioned	Frequency Relative to Highest (%)
Solution	15	100
Team	12	80
Problem	12	80
Customer/Market	8	53.3
Competition	5	33.3
Use of Funds	5	33.3
Traction	4	26.7
Opportunity	2	13.3

Based on the frequency of events, the major themes that emerge are further discussed. To determine the major themes, the relative frequencies to the highest frequency event are taken. This is further shown in Figure 12.

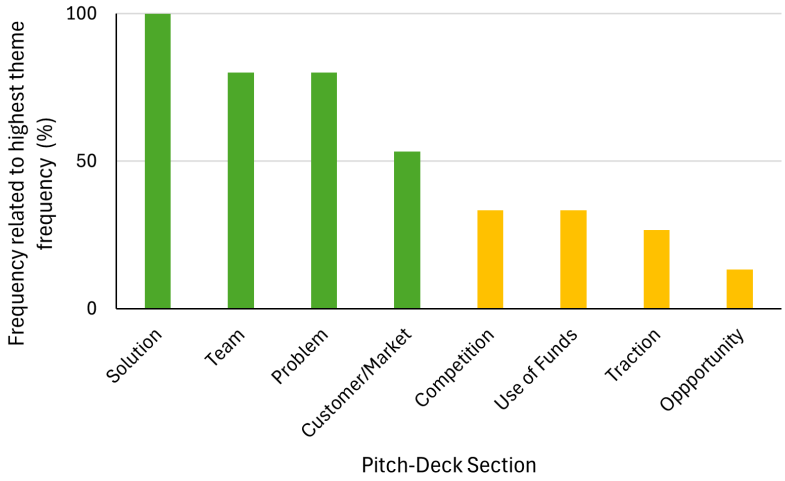

Figure 12: The frequency of events, related as a percentage to the event with the highest frequency (solution).

The themes related to more than 50% emerged as a major theme, thus relating to the solution, team, problem and customer/market.

Solution

First, the solution is considered a major theme as a critical pitch-deck section. From the interview it emerged that this pitch-deck is considered critical, as the importance is highlighted for the need of the solution to be valid. The technical credibility is hereby evaluated, further explained with a consideration from Participant #5: *'It has to be technology that works. It has to be better than the current technology'*. This was additionally echoed by Participant #1. Thus the technical workings and credibility of the solution as an improvement compared to the current state is raised as an important criteria.

Additionally, the need for the solution to align with the scoping of the fund is mentioned. Thereby, Participant #4 stated: *'If it's not really innovative or technical then it falls out of scope'*, signaling that the fund-scope alignment is additionally important before further evaluation of the entire pitch deck. Thus, the credibility of the solution and the fund scope are important factors within the solution as critical pitch-deck section.

Team

In addition, the team emerges as a major theme to evaluate pitch-decks. This is the case, as investors ultimately invest in the people behind the company. This is further explained by Participant #1: *'It's the team you invest in and not the company. Presumably there will be pivots.'*. Thereby the instability of start-investing is shown, as there are many unreliable factors that can alter. However, as highlighted the team remains essential to handle potential instabilities and unknowns at the current stage of the company. Participant #1 and Participant #5 noted that the conviction for the team section is present in the trust in the leaderships abilities to execute on the proposition. This is further specified by Participant #3, with specific traits such as their drive, ambition and experience. As a result, these reflections show that a strong and resilient founding team is important to mitigate future risks and thereby classifies as a major theme within the pitch-deck analysis.

Problem

Furthermore, the problem is identified as a major theme within the critical pitch deck sections. Here, this is further highlighted by every participant, as the company can iterate on the solution, however cannot easily change the pain-point that it tackles. This is further explained by Participant #3: *'In the context that these companies are so young, you can always change, but you can't change the problem.'*. This therefore states the importance of the problem, and a stable factor during the highly-uncertain context of venture capital investing. The participants thereby agreed that a well-formulated and validated problem statement is important to further investigate the other pitch-deck sections. The problem statement can therefore for example highlight the potential value that it can bring, and provides the possibility to judge future pivots of the solution. This is therefore considered a major theme, to build on important context throughout the rest of the pitch-deck sections.

Customer/Market

The last major theme that emerged within critical pitch-deck sections is related to the customer/market section. Here, five out of the six participants highlighted that the pitch-deck must prove that there is a definable, reachable audience with a market large enough to justify the returns. Thereby the participants note the importance of knowing your customer, thereby further explained by Participant #2, noting the need to understand who your customer is, and thus thereby who is going to buy your product. Thus, An insight into the customer is important for an overview to the investor who the company is targeting at. Additionally, the market size is important as further highlighted by participant #5, clarifying the need for the market size to justify potential future returns. Therefore when naming the market, the participants highlight the importance for assessing potential returns within the proposition that is being assessed.

4.2. Contextual Factors

4.2.1. Theme 2: Dependency on start-up stage

To further add to the previous findings, the contextual information is of importance to highlight the dependency of these pitch-deck sections on the start-up stage. Within the start-up stages, important themes were identified for early and later-stage investments. These themes thereby vary in relevance, depending on the maturity of the company and investments, thereby indicating that the context of start-up stages, adjusts the decision-making within evaluation criteria.

Early Stage

In the early start-up investing stage, the importance of the team is highlighted, as noted by Participant #4 and #5. As explained during the pitch-deck sections, this is based on the importance of their ability to handle the potential instabilities and unknowns. As these unknowns become bigger at an earlier stage, Participant #4 and #5 highlight this execution importance. However, this is contradicted by Participant #1, who highlights the increased importance of team at a later stage. This is further explained through the ability to quickly add or change a team at the very early stage. Thereby, the Participants underscores the increased importance of the team over time, and therefore the decreased desire to

invest when having to change the team. This thereby highlights the additional perspective, of interchangeability of the teams at different start-up stages from the venture capitalist perspective.

Later Stage

In a later start-up investing stage, the importance of the business model and traction emerge as a major themes. First, the traction is highlighted as an important theme, where the company at a later stage needs to obtain willing and paying customers. This is further explained, as the companies are expected to generate revenue over time. Thereby, the traction is of increased importance. Additionally, the business model becomes increasingly important at a later stage as highlighted by the Participants. This is further explained by Participant #2, through the adjust-ability of the business model at an early stage. This is supported with the quote: *'In an early stage you can tweak the business model any way you like and you can change it'*. Therefore this shows the ease to adjust the business model at an early stage, compared to importance at a later stage.

4.2.2. Theme 3: Quality of Design

Additionally the contextual input of the quality of the pitch-deck design was assessed based on the importance of the quality of design for the venture capitalists. All participants acknowledged that the design quality plays an important role for the first impressions, and thus also the evaluation. Two major themes emerged, based on the link between the design quality and both the competence of the team and cognitive bias formation.

The competence of the team was further explained by the participants, as a well-designed pitch-deck signals credibility and dedication from the team. Participant #4 thereby further explains this, as the quality of the design shows the drive and amount of effort from the entrepreneurs. Similarly, Participant #5 and #6 noted the link to the execution power, and communication capabilities of the founders. Thereby the participants linked the quality of the design directly to the capabilities of the entrepreneurs.

However, even though all the participants showed the importance within this, Participants #2 and #3 additionally note that they prefer to not be influenced by the design quality as much. Thereby indicating an awareness of the influence of the design quality as a bias within the judgement. The design quality therefore additionally highlights the tension between conscious evaluation criteria and unconscious cognitive biases and heuristics. Thus, within the theme of the quality of design, major emerging themes relate to the competence of the team and the cognitive bias formation. Thereby highlighting the unconscious influence of the design on their pitch-deck analysis.

4.3. Pitch Deck Creation

Based on the groundwork provided from the literature review and interviews, the pitch decks are set up for the pilot experiment. As highlighted in the methodology, the evaluation of the pitch-decks aims to remain similar, thereby minimising biases. Therefore pitch-deck creation criteria have been determined. These are listed as:

- *Critical Pitch Deck Sections:* Limit bias formation in critical pitch deck sections. Thereby form the pitch decks around problems within the AI implementation industry. Additionally, the team has a similar experience and composition. Furthermore, the solution should highlight its credibility to solve the problem. At last, the customer/market should remain similar to minimise the influence.
- *Start-up Stage:* For the pitch-decks, an early stage startup stage has been chosen, thereby minimising the importance of the business model and traction.
- *Quality of Design:* To maintain a similar quality of design, a uniform structure is taken. Additionally, a consistent visual design is chosen and a controlled complexity is obtained with regards to the content and jargon.

This results in the formation of three pitch decks, visualised in Appendix C, Appendix D and Appendix E.

4.4. Initial Perceptions of Hybrid Models

Further perceptions of the venture capitalists on the hybrid models is gained. These are obtained without prior experience of the participants with the hybrid model for pitch-deck analysis. These initial perceptions provide a deeper understanding of the perceived usefulness, perceived ease-of-use, biases and trust regarding hybrid models. Thus, highlighting the benefits and concerns for adoption of the hybrid models.

4.4.1. TAM: Perceived Usefulness

The first theme identified from the interviews is related to the perceived usefulness of hybrid models, thereby noting the features within the hybrid model tool important for the perceived usefulness of the participants. The data was analysed and a thematic analysis resulted in factors contributing to the perceived usefulness, shown in Table 7.

Table 7: Frequency of events for the perceived usefulness of AI in the investment decision-making process. Sample size: n = 6.

Perceived Usefulness	Count	Frequency related to highest (%)
Additional Information	18	100
Time Efficiency	9	50
Information Structuring	6	33.3
Eliminate Bias	3	16.7
Judgement	2	11.1
Data Safety	2	11.1
Accurate	1	5.6

Based on the frequency of events in Table 7, the major themes that emerge are further discussed. The relative frequency for each theme is further shown in Figure 13.

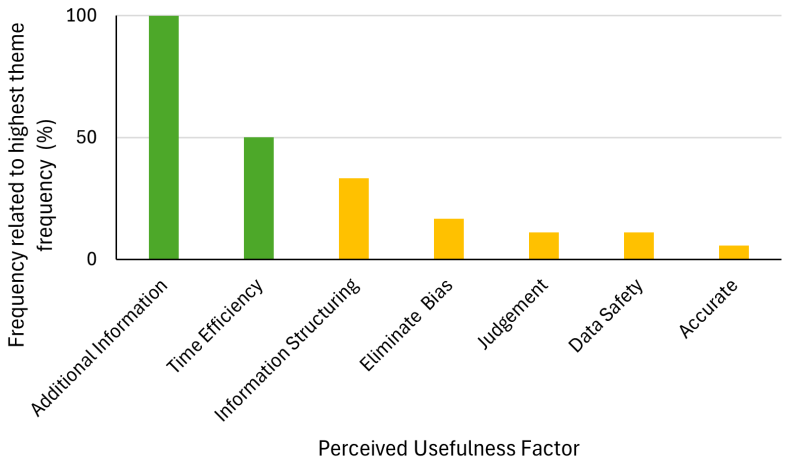

Figure 13: The frequency of events for the perceived usefulness, related as a percentage to the event with the highest frequency (Additional Information).

The themes related to more than 50% emerged as a major theme, thus relating to the additional information and time efficiency.

Additional Information

One major theme that emerged from the interviews for the perceived usefulness is related to providing the relevant additional information within the pitch-deck proposition. All participants highlighted the importance of this within the use of the hybrid model tool for pitch deck analysis. Within the perceived usefulness of providing additional background information, different applications were named for the perceived usefulness.

One important element within the perceived usefulness of the background information is on the founding team. As emphasized by Participants #3 and #6, additional information plays an important role in forming a view on the team. This is further explained by Participant #6, who noted that the information on the founding team, based on their own pitch-deck, is often very positive. Therefore, additional information on the team could provide the investor with a nuanced overview over their experiences and capabilities to judge the team.

In addition to the team background, four participants highlighted the importance of deeper background information on the startup's core proposition for the perceived usefulness. This thereby includes assistance for the context behind the problem being addressed and the proposed solution. As participant #3 noted, that he often knows the context for a proposition for roughly 70%, however missing the last additional information. Thereby, additional information from the hybrid model can be useful to understand the technical due diligence.

Additionally, participants emphasized the additional information need within the fact checking capabilities, related to the facts and figures in the pitch-deck. Already performing a fact check on these figures eventually saves the investor time, as this limits the required desk research. Besides the fact and figures fact checking, participants also note the usefulness for the market size. Furthermore, providing sources for fact checking of the investor themselves is mentioned, resulting in enhancement of the understanding of the technology and transparency.

Time Efficiency

Furthermore, time efficiency emerged as a major theme for the perceived usefulness from the interviews with the venture capitalists. Five of the participants highlight this aspect, emphasizing the perceived usefulness to create more efficient workflows. Participant #1 further reinforced this by linking it to the tool's ultimate goal, stating that *'In the end we're trying to save us time.'*. The time efficiency is important to the venture capitalists, as enforced by Participant #4, who noted that time is money within the VC industry. This is further elaborated on by Participant #1, who note that with the time efficiency, it means that it will open up the possibility to focus on the core aspects of the proposition. Thereby, the time efficiency of the hybrid model relates to an important aspect in the usefulness of the tool.

Interactions

Between these emerging themes, interactions are noted. both the additional information and time efficiency mentioned by the participants, an interaction takes place. This interaction is drawn, as the time and information are both important concepts for venture capitalists to weigh off. Finally, the venture capitalists aim to maximise the usefulness of their time spent, to obtain as much information as they seem needed to make the judgement. Therefore, providing additional information can enhance the time efficiency, or potentially enhance the decision, made within the similar timeframe with more information.

Pattern Matching

The theme of perceived usefulness is theoretically framed with an expected pattern, where users are more likely to adopt the AI tool if they perceive it as useful. Through the empirical perceived usefulness data obtained, this matches with the theoretical pattern, where background information, time efficiency, fact checking capabilities and information structuring can assist the venture capitalists to improve their work.

4.4.2. TAM: Perceived Ease-Of-Use

Furthermore the second construct relates to the perceived ease-of-use of the hybrid tool. The semi-structured interview data was again analysed according to the thematic analysis from Braun and Clarke (2006) and major themes were identified. This resulted in the following frequency of themes listed in table 8.

Table 8: Perceived Ease-Of-Use factors and the frequency of events. Sample size: n = 6.

Perceived Ease-Of-Use	Mentions	Frequency related to highest (%)
Interaction	4	100
Centralisation	4	100
Understanding of technology	3	75
Transparency	1	25

Based on the frequency of events in Table 8, the major themes are further discussed. The relative frequencies are shown in Figure 14.

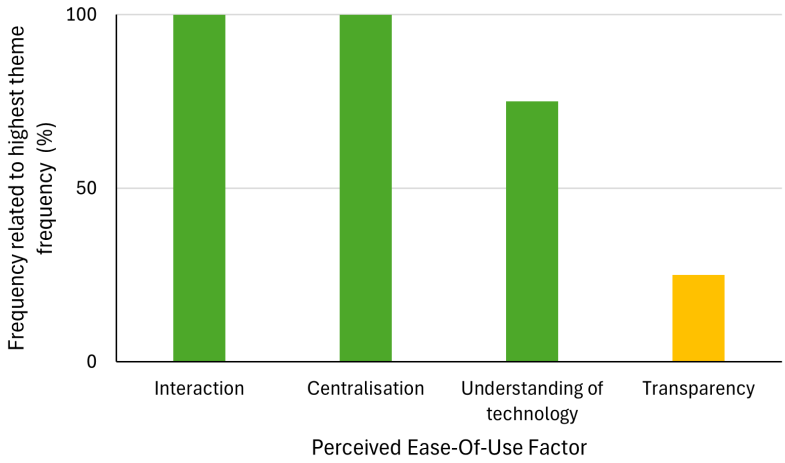

Figure 14: The frequency of events, related as a percentage to the event with the highest frequency (interaction or centralisation).

Based on Figure 14 and Table 8, the major themes within the ease-of-use are determined to be based on the interaction, centralisation and understanding of technology.

Interaction

The interaction with the hybrid model emerges as a major theme within the perceived ease-of-use. Four of the participants name the importance for the ease of use, relating it to the possibility of conversing with the hybrid model through prompting. Participant #4 further explains this, as the conversation will allow for further fine-tuning of the answers to fully grasp the topic. Thereby, the output of the hybrid model is more dependent on the investor's view and in-depth questions can be asked to inform the venture capitalists.

Centralisation

Furthermore, centralisation is considered an important theme in the ease-of-use, where the consistency of the investment process is highlighted by participants through the use of a centralised model. This is supported by three participants, all suggesting the need to obtain a fixed way for analysis. Thereby Participant #2 extends on this by noting that the investment process in an early stage can become more

professional and reformed based on this centralisation. Thus, this major theme within the ease-of use contributes to an ease-of-use in similar workings with other investors, but also result in an improved investment process.

Understanding of technology

Lastly, understanding of the technology emerged as an important theme in relation to the tool's ease-of-use. Here, Participants #1 and #3 emphasized that a clear understanding through the interface of the tool is important for the ease-of-use in understanding the presented insights. Therefore, without a clear understanding the potential of the technology may remain limited.

Pattern Matching

Corresponding to the expected pattern based on technology, the technology adoption is more likely to occur if it is considered as intuitive and easy to integrate. Therefore, based on the provided segments, the importance of the hybrid model for interaction, centralisation and understanding of the technology is raised to enhance the adoption of the technology. Thereby, obtaining a hybrid model with a user-friendly interface, encouraging interaction and a centralised overview of data contributes to the perceived ease-of-use of the venture capitalists.

4.4.3. BDT: Biases

Based on the behavioral decision theory, the theme of potential bias mitigation or reinforcement emerged. The major themes that occurred are shown in Table 9.

Table 9: Potential Bias Mitigations and Reinforcements with the use of hybrid models. Sample size: n = 6.

Bias Reinforcement	**Mentions**
Self-Reinforcing Bias	4
Confirmation Bias	1
Bias Mitigations	**Mentions**
Overconfidence Bias	2
Confirmation Bias	1

As shown in Table 9, the major themes emerging from the biases evolve around self-reinforcing bias for bias reinforcement, and overconfidence bias for bias mitigation.

Bias Reinforcements

According to four of the participants, a major theme and risk for bias is related to a self-reinforcing bias from the AI. Because the models are trained on historical data, the algorithm may systematically up-rank familiar patterns and down-rank unknown patterns. Thereby, the hybrid model can influence the biases present during the evaluation of the pitch-decks. Therefore, participants note that the use of an AI model may lead to narrower opportunities, as unconventional startups could be overlooked by AI models due to their historic representation.

Bias Mitigations

On the contrary, participants also noted the potential bias mitigations with the use of hybrid models. Here, the major bias mitigation of overconfidence bias could be limited. Overconfidence bias is caused by a reduced information search. Therefore participants noted that providing additional information from the hybrid model could improve the information obtained and thus reduce the overconfidence bias.

Pattern Matching

The participants note both perceived bias reinforcements and bias mitigations with the use of hybrid

models. Therefore, this matches with the expected pattern, where the introduction of hybrid models can result in changing investment dynamics dependent on the AI output and biases obtained because of this.

4.4.4. BDT: Trust

The trust in AI emerges as another important theme that can influence the eventual adoption of the technology. This trust in AI is drawn in question, as participants indicated a strong reliance on human intuition when evaluating the founding team and assessing the problem-solution fit. According to participants these are areas where subjective judgement plays an important role.

A nuance is introduced when asked to consider situations with human judgement and AI output conflict. Here the responses were divided, where two participants expressed a preference for their own human expertise. On the contrary, two others indicated a greater trust in AI due to its data-driven nature and time-saving potentials. At last the final 2 participants noted that their trust depends on the specific context, thus suggesting a preference for combining both the data and their own intuition to come to their evaluation.

The diversity of the views on trust in conflict highlights that the trust in the hybrid models is situational. This thereby reinforces the value of the hybrid models, that do not entire replace human judgement but complement it. Thus, these findings align with the expected pattern, where hybrid approaches may be more widely trusted, particularly in complex decision environments such as the venture capital.

4.5. Summary

In summary, key pitch deck sections are based on the solution, team problem and customer/market. Additionally, the evaluation of pitch-decks changes based on contextual factors. Here, the dependency on start-up stage causes early-stage start-ups to be evaluated more on the team, while in a later stage start-up the importance of the business model and traction is highlighted. The quality of design is also of importance as a contextual factors, where the design quality is linked to the competence of the team and thereby also bias formation within the evaluation. The initial perceptions of hybrid models, related the perceives usefulness to the factors of additional information and time efficiency. Furthermore, the perceived ease-of-use was related to the interaction, centralization and understanding of the technology for the hybrid models. At last, biases highlighted by the participants related emerging of self-reinforcing biases with AI usage, and mitigation in overconfidence bias due to the presence of additional information. Also, the trust in AI was highlighted to be situational among the participants, highlighting the potential value of hybrid models for this within the pitch-deck analysis.

5

Results: Hybrid-Model Performance and Experience-Based Reflections

In this Chapter, first the performance of the hybrid models are measured through a pilot experiment, comparing human analysis to the three hybrid model types. The pilot experiment was carried out as specified in the Methodology in Chapter 3. It thereby aims to gather an initial insight into a quantification on how the hybrid models (sequential search, interactive search or autonomous search) affect the efficiency, efficacy and user experience of venture capital pitch-deck evaluations compared to the human approach.

The chapter builds on the experimental starting point with the three created pitch decks in Appendix C, Appendix D and Appendix E. Additionally, the experiment was performed by setting up the prompt for autonomous search, shown in Appendix F. The analysis was performed using the mean and standard deviation values, obtained from the individual scorings of the participants highlighted in Appendix G. Important to note, is that the data from Participant #8 was not included in the upcoming data shown. This was done, as no limitation was set on the maximum time for analysis, leading to time constraints during the experiment and a different setup compared to other participants.

Additionally, this chapter presents the perceptions of venture capitalists after gaining hands-on experience with the hybrid models for pitch-deck analysis. Therefore, the views of the participants were assessed through a workshop, based on the Technology Acceptance Model and Behavioral Decision Theory. Thereby this includes key dimensions for the TAM such as the perceived usefulness, ease of use, attitude toward usage, intention to use. Additionally, it contains the constructs of trust and bias related to the BDT. Thus, this chapter also captures how the interaction with the tool influences the perceptions on hybrid models.

5.1. Pilot Evaluation Results

The dependent variables were related to the completeness of analysis, time efficiency and user confidence in decision. The exact measurements from the pilot experiment are shown in Appendix G.

5.1.1. Efficacy

The efficacy of the hybrid models was evaluated in terms of the completeness of analysis, thereby indicating how thorough participants identified insights from the pitch decks. Completeness here thereby acts as a construct for the depth and quality of the pitch-deck evaluation provided by the participants themselves. This measure is critical, as a more complete analysis increases the likelihood of more informed investment decisions. The average completeness of analysis for the different hybrid models and the standard deviations are shown in Figure 15.

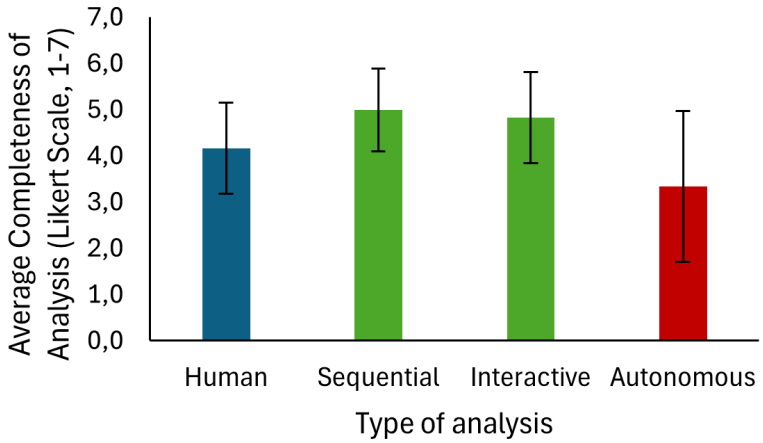

Figure 15: The average completeness of analysis for human analysis and hybrid models on a scale of 1-7. Green depicting an increase compared to human analysis, while red shows a decrease. Additionally, the standard deviation is shown with the error bar. Sample size: n = 7.

As shown in Figure 15, the human judgement scored an average completeness of analysis of 4.2. This is used as a benchmark, compared to the different type of hybrid model analyses. Here, the sequential search indicates the highest score (5), indicating the added information to the analysis of the venture capitalists. Additionally, this is followed closely by the interactive search model (4.8), highlighting its similarity for the completeness of analysis. The autonomous search scored the least (3.3), which is a decrease compared to the human analysis. Thus this indicates that the autonomous search provides the least added value in terms of efficacy of the evaluation. Therefore, these results provide an indication, that hybrid approaches can enhance the completeness of analysis and thus the efficacy of pitch-deck evaluations in VC workflows.

The results additionally highlight a stable standard deviation of the results among the participants for the human analysis, and both the sequential and interactive search. However, an increase in the standard deviation is seen for autonomous search. This indicates that while the average completeness of analysis is the lowest, participants ranged more in their evaluation completeness.

5.1.2. Efficiency

During the experiment, the time was measured starting from the beginning of the analysis until the final judgement of the participant. Here, the participants were asked to present their final judgement after 8 minutes, to limit time constraints later in the experiment. However, even though a time constraint was present, the actual time spent varied across participants, offering insights into the time efficiency of the pitch-deck evaluations. This information is shown in Figure 16.

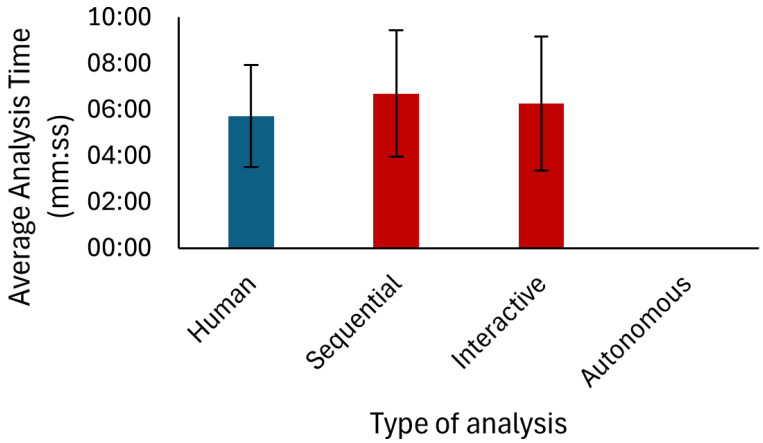

Figure 16: The average analysis time of human analysis and the hybrid model types. Red showing an increase in analysis time. Additionally, autonomous search was not measured. Furthermore, the standard deviation is shown with the error bar. Sample size: n = 7.

As shown in Figure 16, the sequential search had the highest average time (06:41) to come to the final judgement. This was followed by the interactive search (6:15) and the human analysis (5:43). At last, the autonomous search was not recorded, as the fast evaluation by the participants (due to limited information present) result in inaccurate time measurements. Therefore, the speed of the autonomous search is further highlighted by the experimental observation of the researcher, where the autonomous search provided the quickest analysis for the participants. These findings thus highlight that the hybrid models of sequential search and interactive search may introduce a less efficient evaluation process, while the autonomous search enhances the efficiency.

Furthermore, the standard deviations were determined, indicating the spread between the participants in the pilot experiment. This highlights the largest standard deviation with the interactive search (2:54), followed by the sequential search (2:44) and human analysis (2:13). The presence of these standard deviations, already present for the human evaluation, highlights the difference between the evaluation speed between the participants. This effect was further enhanced with the use of hybrid models compared to human analysis, suggesting a greater variability in how participants interact and rely on AI tools.

5.1.3. User-Experience

The user experience was further evaluated through the decision confidence from the participants in their judgement, and the perceived helpfulness of the hybrid models. At first, the confidence in the investment decision was measured by the participants on a Likert scale, thereby serving as indicator user experience of the analysis method. This is visualised in Figure 17.

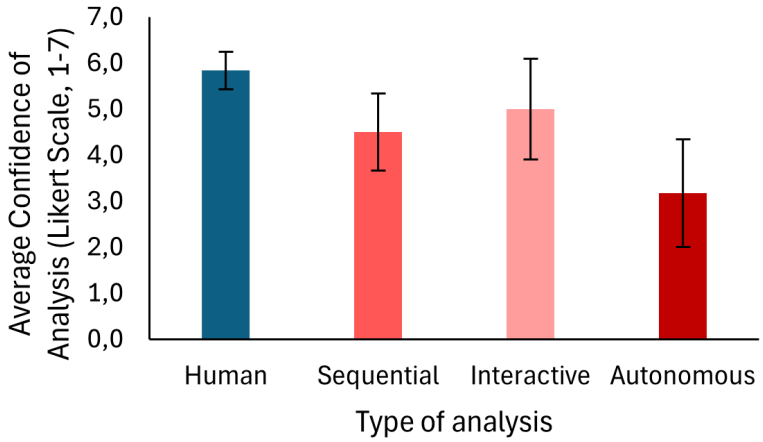

Figure 17: The average confidence of analysis among participants for human analysis and the hybrid models. Red showing a decrease in confidence compared to human analysis, with an increasingly dark colour as the confidence decreases. Additionally, the standard deviation is shown with the error bar. Sample size: n = 7.

As shown in Figure 17, the human judgement obtained the highest confidence levels in the judgement of the participants (5.8), with a low standard deviation (0.4) thereby highlighting the consistency among the participants. Among the hybrid models, the general confidence in the final judgement was lowered, with the interactive search obtaining the highest confidence level (5.0) followed closely by the sequential search type (4.5). At last the autonomous search is present with a confidence level of 3.2. This thereby highlights the confidence that is increased through the input and interaction of human inputs. The participants thus felt least secure relying solely on AI-driven recommendations. These results imply that while hybrid models may enhance the completeness of the analysis, they can reduce the confidence in the final judgement, especially when human control is limited.

Again, the standard deviations were also determined amongst the participant results. This indicated little deviation for the confidence in the human analysis, indicating a coherent high score given by the participants. However, the hybrid models score a higher standard deviation, indicating that the confidence in these models obtains a greater variability between the participants.

The use of the different hybrid models was further evaluated according to the final perceived helpfulness to the participants. The different hybrid models were again ranked according to a Likert-scale from 1-7 including a standard deviation. This is shown in Table 10.

Table 10: Average perceived helpfulness of the hybrid models (based on a Likert scale from 1-7), along with the standard deviation. Sample size: n = 7.

Type of Analysis	**Average Helpfulness** (Likert Scale, 1-7)	**Standard Deviation** (Likert Scale, 1-7)
Sequential Search	4.2	0.4
Interactive Search	5.0	0.7
Autonomous Search	2.6	1.3

The results indicate that the interactive search model was perceived as most helpful, with an average score of 5.0 and a standard deviation of 0.7. This thereby indicates a generally positive and consistent user experience. The sequential search model follows with an average of 4.2, thereby reflecting a moderate perceived helpfulness to the participants, with a consistent output dependent on the standard deviation (0.4). At last, the autonomous search model is perceived as least helpful, where it scored significantly lower (2.6) in terms of helpfulness. These findings thereby suggest that the interactive search, which obtained a high completeness of analysis but also longer analysis time compared to

human analysis, resulted in the optimal hybrid model for the participants.

5.1.4. Pilot Experiment Summary

Based on these pilot experimental findings, the three hybrid models are classified on their time efficiency, completeness of analysis and confidence in participant's judgement. An overview of the key strengths and weaknesses of the hybrid, compared to human analysis, is summarized in Figure 18.

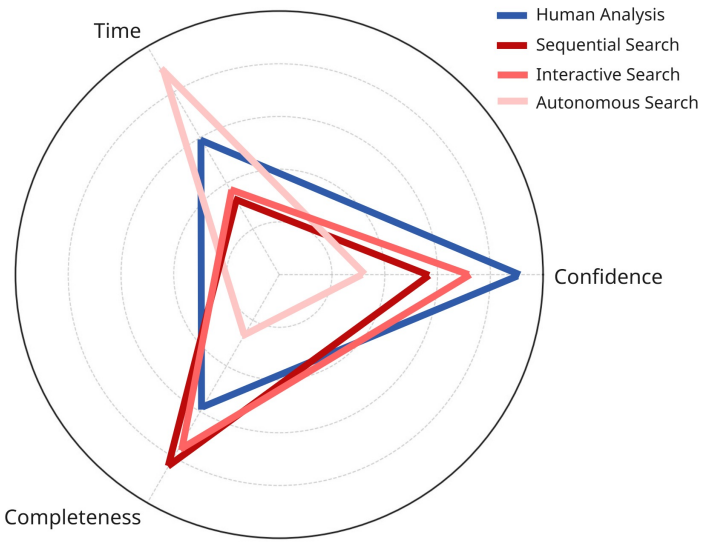

Figure 18: The spider diagram, summarizing the time efficiency, completeness of analysis and decision confidence.

As shown in Figure 18, the human analysis acts as a benchmark to compare the hybrid models to. The sequential search and interactive search show similar strengths for both the completeness of analysis. However, for the time analysis only the autonomous model considers that as a strength. All hybrid models highlighted a weakness through the decrease in the confidence levels compared to human analysis.

5.2. Post-Use Perceptions

5.2.1. Perceived Usefulness

For the perceived usefulness of the hybrid models, at first the result on their previous expectations and the most useful type of model was identified from the participant's responses. This is visualised in Table 11.

Table 11: Overview the participant's view on usefulness, and the most useful hybrid models. Sample size: n = 7.

View on Usefulness	
Positive	6
Negative	1
Most Useful Hybrid Model	
Sequential Search	5
Interactive Search	2
Autonomous Search	0

As shown in Table 11, after experience with the hybrid models six of the participants noted a positive view on the usefulness of the hybrid models. Additionally, the most useful model was related to the sequential search model supported by five participants. This is followed by two participants with a pref-

erence for the interactive search model based on the usefulness. This validates the findings presented in Figure 15, where the sequential search provided the highest completeness of analysis. At last, no participants noted the usefulness of the autonomous search model, further highlighting it's ineffectiveness for application into pitch-deck evaluation within VC.

For one participant, the expectations for the usefulness were not met. This was based on the lack of additional information obtained by the hybrid model. Specifically, the participant named the desired increase in further third party information and sources. The participant named that applying more external information sources, would increase the usefulness as: *'it would provide insight into topics not found with purely your own analysis'*. Thereby, for this participant the limited information from the hybrid models resulted in a negative view on the usefulness of the hybrid models.

Insights From The Hybrid Model

Based on the effectiveness of the hybrid models, the additional insights or patterns were assessed obtained from the hybrid model. This is highlighted in Table 12.

Table 12: Participants Additional Insights/Patterns. Sample size: n = 7.

Additional Insights/Patterns	Count
Yes	*6*
Market	3
Competitors	1
Team	1
General Context	1
No	*1*

As shown in Table 12, most participants highlighted that the hybrid models provided additional insights. These were mostly related to the market, where three participants highlighted that the hybrid model allowed for an additional information on this topic. Furthermore, Participant #19 highlighted the additional insights into competitors obtained. Participant #2 further adds to a new found pattern obtained from the hybrid model, based on the team. This thereby highlights the range of different further insights obtained by the venture capitalists, complementing the insight of Participant #15 into the general context of the proposition. One participant noted no additional insights provided, complementing the negative view on the effectiveness of the hybrid tool.

Influence on Effectiveness

These insights generally have a positive influence on the effectiveness of the tool, as new insights are highlighted to be of importance for the effectiveness during the earlier performed interviews. Furthermore, Participant #17 noted the negative influence of the additional information on the effectiveness, due to a lowered efficiency. This validates the findings earlier presented in Figure 16. On the contrary, Participant #20 noted the possibility for an increased time efficiency. This was based on the ability to fact check the market, thereby this Participant highlights the potential of the hybrid models to become more time efficient for participants on certain topics, such as the market analysis. Thus, the additional insights create a positive influence on the usefulness of the hybrid models for the participants, where the possibility is named to become time efficient on particular sections of an analysis.

Comparison To Before Implementation

Before the participants had experience with the hybrid model, the perceived usefulness was also analysed. Here, the participants highlight the perceived usefulness to be within two key concepts to provide additional information and time efficiency. During the experience however, the average time spent on analysis increased with the sequential search or interactive search models, thus potentially negatively influencing the perceived usefulness to the participants. However, as the participants remained positive on this perceived usefulness after experience with the hybrid model, this indicates the importance

of the additional information provided compared to the time efficiency.

5.2.2. Perceived Ease-of-Use

For the perceived ease-of-use, the results on the intuitiveness and the most easy-to-use model after the pilot experiment was obtained. The results are shown in Table 13.

Table 13: Overview of hybrid model ease-of-use. Sample size: n = 7.

Intuitiveness	
Yes	7
No	0
Most Easy-To-Use Hybrid Model	
Sequential Search	2
Interactive Search	3
Autonomous Search	2

As shown in Table 13, all participants noted the tool to be intuitive in usage, underscoring its ease-of-use of the hybrid models in general. However, the most easy-to-use hybrid model remains scattered among the participants. This highlights the different preferences of the participants, where some participants relate the most-easy-to use tool to the limited information shown (autonomous search), while others highlight the interactive models that offer more control over the information obtained. This diversity in the most easy-to-use hybrid model therefore highlights the importance to cater the possibility of the hybrid models to different users within different contexts.

Comparison To Before Implementation

Before the implementation experience of the participants, the perceived ease-of-use was highlighted based on interaction, centralisation and understanding of the technology. The centralisation and interaction with the tool are shown in these results with participants that highlight the sequential search model or the interactive search model to be most ease-to-use. However, additionally two participants chose the autonomous search as the most easy-to-use, as this was quick and easy to scan through due to the limited information available. This indicates a change in perception after the experiment on the easiness-to-use, where participants also include the presented information as a factor.

5.2.3. Attitude Towards Use

The attitude towards use was determined based on the response from the participants, where additional features to increase the willingness to use the tool were determined. This is shown in Table 14.

Table 14: Attitude Towards Use and desired additional features from the participants. Sample size: n = 7.

Attitude Towards Use	
Positive	6
Negative	1
Additional Features	
Fact checking	3
Assess quality of design	1
Link to own workflows	1
Portfolio-specific advice	1
Critical summary	1
Investment Proposal Writing	1

As shown in Table 14, six participants highlight their positive attitude towards use. To further increase the attitude towards use, the participants mainly noted the fact checking to further improve as a feature.

Thereby highlighting the desire for more reliable information and highlighting the understanding of the technology (transparency) of the information. This corresponds to the unmet need of the participant with a negative attitude towards use. Additionally this is based on the third-party data and fact checking capabilities, highlighting this as an important factor to potentially increase the attitude of the participants.

5.2.4. Behavioral Intention

At last, the behavioral intention was assessed, together with other parts within the investment process where hybrid models can be applied. This is visualised in Table 15.

Table 15: Behavioral Intention and the additional applications within the investment decision making process. Sample size: n = 7.

Behavioral Intention	
Positive	6
Negative	1
Additional Applications	
Writing	3
Legal Due Diligence	1
Fact Checking	1

Similar to the attitude towards use, six out of the seven participants highlight a positive intention, thereby willing to apply this further in other parts of the investment process. Again, the similar participant remained negative on the behavioral intention to use similar AI tools within the investment process, complementing the earlier negative perceived usefulness and attitude towards use. Additional applications by the participants emerged mainly related to the writing support during the investment-process, highlighting the potential for hybrid models to improve this.

5.2.5. Biases

First of all, three participants highlighted the bias within the textual output of the hybrid model. Here, the AI highlights a general neutrality about the topics. Participant #17 further explained this, as the AI model tried to end on a positive note, even when critical points are mentioned before. Therefore, this highlights the inability for the AI to have a strong opinion.

Additionally, two participants highlight further bias that can emerge from the AI output. Participant #16 here noted the possibility for hallucinations within the AI output, thus providing a misinformed analysis. Additionally, Participant #17 highlighted the dependency of the AI output, based on the input quality. Thereby he highlighted the bias, where the quality of the output is dependent on the quality of the pitch-deck. Through this bias, pitch-decks with higher qualities or more data to extract from will obtain a better AI output. Thereby these biases within the AI output can misinform venture capitalists on the actual state of the pitch deck received.

At last, two participants highlighted the biases focused on the human interpretation of the AI output. Here, the trust in the participants both highlighted the trust in the output to be of significant importance, where venture capitalists may accredit information more if the trust in the information is increased depending on the output of the AI.

5.2.6. Trust

Furthermore, all participants highlighted to have remained a similar trust in AI after the experiment. As highlighted by Participant #19, the evaluation of the data obtained from the hybrid model remains essential for the trust. Thereby, this highlights the importance of maintaining a critical perspective, and keeping a human in the loop on decision-making, to not limit the full reliance on the AI output.

5.3. Pattern Matching

To conclude, pattern matching is done to assess the findings related to the theory. Specifically, the constructs of perceived usefulness, perceived ease-of-use, attitude towards use, and behavioral intention were analyzed for their presence and consistency with the expected patterns derived from the TAM and BDT.

TAM

After experience with the hybrid models, six out of seven participants indicated a positive perceived usefulness, thereby confirming the relevance of hybrid-model evaluations. Similarly, the perceived ease-of-use was rated positively by all participants, suggesting that the hybrid models were intuitive for use. According to the TAM, these two factors are key to influence the attitude towards use. In this research, the attitude towards use mirrored the score of perceived usefulness, with six out of seven participants expressing a favorable attitude. Furthermore the TAM theory expects the pattern that a positive attitude towards use directly influences the behavioral intention to adopt the technology. Again, this was validated in the findings, where six out of seven participants indicated a positive to continue using hybrid models in their investment decision-making process. This consistency across these constructs underscores the internal validity of the findings and supports the applicability of TAM within the VC context.

Within these constructs, one participant highlights the negative perceived usefulness, reflected further in the negative attitude towards use and behavioral intention. This again corresponds with the TAM theory, however also provides valuable insights into resistance factors for use. Thereby, the participant highlights the possibilities for further fact checking as key feature to improve the perceived usefulness.

BDT

Additionally, the BDT is applied to assess the expected patterns on external factors correlating to biases and trust. The biases after the experience highlighted that, while AI tools can mitigate certain human biases, new biases also emerged related to the interpretation and over-reliance on AI outputs. This thereby aligns with the BDT and the expected pattern, where venture capitalists remain susceptible to heurtic-driven judgements based on changing biases within the AI output.

For the trust, the participants emphasized that the human judgement remained essential in the investment decision-making process. Thereby, hybrid models were perceived as supportive tools, but not as substitutes. This thereby reflects the BDT theory where trust in intuition remains, particularly in uncertain and complex contextual decisions. Furthermore the BDT validates the findings from the earlier pilot experiment, where the confidence in the judgement decreased ass the input of the humans decreased.

Overall these findings thereby validate the expected patterns derived from the BDT, illustrating how hybrid models influence the biases and trust dynamics.

5.4. Summary

Based on the results from the hybrid model efficacy, efficiency, and user experience, the findings demonstrate that the interactive search hybrid models is perceived as most helpful by the participants. While both the sequential search and interactive search score relatively similar on the efficacy and efficiency, the confidence in the interactive hybrid model is higher. Thereby, this highlights the potential influence of the confidence in the judgement on the final helpfulness.

Additionally, while the autonomous model provided a high efficiency (due to a low analysis time), the perceived helpfulness is shown to be the lowest (2.6). This thereby indicates the importance of the efficacy, where the autonomous search hybrid model scored the lowest. Additionally, the autonomous search resulted in a low confidence score, possibly influencing the perceived helpfulness to the partic-

ipants.

Thus, the pilot experiment findings highlight the potential for hybrid models to enhance the analytical depth, at the slight cost to the efficiency. Additionally, the confidence in the judgement is shown to be important, where human control results in a higher average confidence compared to AI-driven output. The results indicate that collaborative AI tools with interactive models show are promising for further integration into VC workflows, balancing the improved efficacy and user acceptance with the decreased time efficiency.

The post-use perceptions for the TAM are summarized and shown in Figure 19.

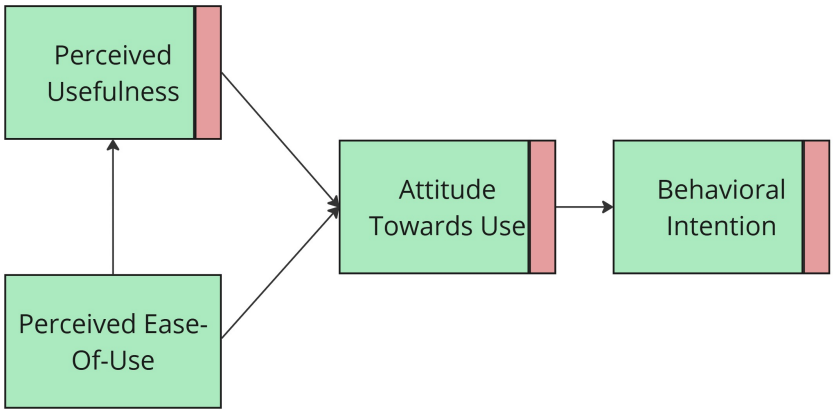

Figure 19: The summary of the TAM constructs, relating green figures to positive annotations from participants and red to negative.

Figure 19 summarizes the TAM constructs and view of the participants. Similarly to the expected pattern, the results highlight the positive view of the participants on the eventual behavioral intention. Additionally, one participants highlights the consistency within it's negative outlook on the hybrid models through the usefulness lack of additional information. This was supported by other participants noting the positive influence of additional fact checking within the hybrid tool on the attitude towards use.

At last, the biases named by the participants highlighted a shift from before the experience with the hybrid models, relating to the specific output provided by the hybrid model. Additionally, no change in trust was noted after experience with the hybrid models.

6

Discussion and Conclusions

This chapter discusses, and further integrates the findings from the interviews, pilot experiment and the workshop to answer the central research question:

How can hybrid models, combining Artificial Intelligence and human judgement, improve the effectiveness and efficiency of pitch-deck evaluations in early-stage Venture Capital?

These findings are structured through a summary of the key findings with the interpretation of the results. Furthermore, a conclusion is given to the research question(s) and at last further recommendations are given for further research.

6.1. Summary of Key Results

Pitch Deck Insights

From the pitch-deck analysis, critical pitch deck sections emerged to be related to the solution, team, problem and customer/market. Additionally, the contextual factors were further investigated, where the theme emerged related to the dependency on start-up stage for the evaluation, where the team is highlighted as important for early stage startups, and business model and traction become more important for later-stage startups. At last, the contextual factor of quality of the design emerged as a theme, where the dependency on the design as an influence on the team is noted. This resulted in further in-depth understanding of pitch deck insights adding to the literature. At last, based on the found information in the literature and interviews, the pitch decks were created for the following pilot experiment.

Hybrid Model Perceptions

Hybrid model perceptions were obtained from the interviews. Here, the TAM and BDT constructs were used to obtain information regarding these constructs. For the perceived usefulness, participants noted the importance of providing background information and time efficiency as major themes. Furthermore, for the perceived ease-of-use, the participants highlighted the importance for the hybrid models with interaction, centralisation and understanding of the technology. At last, for the biases potential reinforcements were highlighted based on self-reinforcing bias from the AI output, while potential mitigations regarding information overconfidence biases were additionally possible. At last, the participants highlighted a scattered trust, highlighting the situational perspective of the trust.

Hybrid Model Performance

Following the hybrid model perceptions, the performance was analysed in the pilot experiment. Here, the efficiency was noted, where the hybrid models of sequential and interactive search created a lengthier analysis compared to human judgement. Additionally, this resulted in a more complete analysis,

while the autonomous search analysis was short, but also incomplete. This results in the highest confidence of analysis within the sequential and interactive search, followed by human analysis. At last, autonomous search obtains the least confidence. This is again seen during the perceived helpfulness of the hybrid models, where the interactive search was highlighted to be most interactive.

Hybrid Model Experience on Performance

At last, the experience of the hybrid models on the TAM and BDT constructs was assessed. This highlighted a general positive experience on the met expectations, with participants obtaining additional insights and patterns. The perceived ease-of-use was shown to be intuitive to the participants, highlighting this ease to use. Furthermore, the perceived effectiveness and perceived ease-of-use resulted in a positive attitude towards use and positive behavioral intention of the participants. Based on the earlier perceptions of the hybrid model before experience with the tool, the most effective type resulted in the sequential search, indicating its use in the background information and other perceived effectiveness features.

6.2. Interpretation of Findings

In this section, the findings on the perceptions of hybrid models are reflected against the current literature, and interpreted and contextualized through the participant's experiences. This allows for deeper insights into the obtained results and their meanings, and placing it into a broader theoretical and practical outlook.

6.2.1. Perceived Usefulness

Effectiveness

The findings suggest that hybrid models enhance the effectiveness of pitch-deck analysis by improving the evaluation completeness, especially when human judgement is actively involved. This is supported by the pilot experiment and workshop, where both the sequential and interactive search models outperformed the human-only analysis, while on the contrary the autonomous model underperformed. These findings align with Jarrahi (2018) and Raisch and Fomina (2024), who argue that the value of hybrid models lies in active human involvement.

One potential reason for the underperformance of the autonomous model could be related to the trust of the venture capitalists in the AI generated output. Here, the results highlight the steep decrease in the confidence of the decision for autonomous models compared to others. This decrease in confidence could thus be related to the limited trust in the AI-generated decision without many validations for human analysis. This is aligned with Keding and Meissner (2021), who argue that AI is less effective in highly-uncertain domains without human oversight.

Another potential reason for the limited performance of the autonomous model compared to both the sequential and interactive models, is related to the transparency and verifiability of the outputs. Both the sequential search and interactive search show the possibilities to fact check and assess the provided information itself. However, this is not the case for autonomous model, where little transparency is obtained. The participants highlighted desire more fact checking capabilities, underscoring the importance also for the sequential and interactive search models. This is also aligned with Röhm et al. (2022), who emphasize that the effectiveness of AI tools in VC is closely tied to the ability to interpret and verify their outputs. Thus, this highlights the importance of transparency for trustworthy decision-making support.

In summary, hybrid models show potential to increase the effectiveness of the pitch-deck analysis in venture capital. However, potential reasons for the underperformance of the autonomous model highlight the importance of trust and transparency within these hybrid models. This means that the findings on the effectiveness of the hybrid models suggest that it is linked to possible verifiable outputs and thus

the degree to which the users trust the output.

Efficiency

The findings show a discrepancy between the perceived usefulness for the time efficiency, and the actual time efficiency across the hybrid models in the pitch-deck analysis. Here, the initial perceived usefulness was noted within the potential time savings, however the pilot experiment showed that both the sequential and interactive hybrid models required more time for analysis compared to the human-analysis. On the contrary, the autonomous model provided faster analysis.

Röhm et al. (2022) noted the efficiency to be a crucial aspect for the venture capitalists to interpret and incorporate the AI outputs. However, Röhm et al. (2022) also noted that venture capitalists cannot be over-reliant on the early-outputs of the hybrid models, when they are not validated. This is mentioned due to the biases and trust potentially available in these outputs. Thus, the literature highlights the need for efficiency, while remaining control over the validation of the output.

A reason for the fast analysis time of the autonomous search hybrid model, is related to the limited information output of the model. Thereby, this provides the participants with little information to gather, resulting in a fast decision. However, as the participants noted the lack of helpfulness in the autonomous model, participants prioritized the additional insights over time gains. Thus, these results are aligned with Röhm et al. (2022), where the pilot experiment showed that the efficiency is only beneficial when obtaining a certain decision quality.

This means that while the autonomous search hybrid model is efficient, it does not necessarily influence the perceived usefulness positively. On the contrary, while the sequential search and interactive search models slightly decrease the time efficiency, the output can more easily be validated. Thus, this means that the contextual factors such as trust and biases within the AI output, are important to place the efficiency wins or losses in the right context.

Synthesis

This study shows that the perceived usefulness is noted as a balance between the effectiveness and time efficiency gained. Based on this research, the effectiveness emerged as the dominant factor within the hybrid models. This is the case, as the slight time decrease shown in the sequential and interactive search models remained a positive view on the perceived helpfulness of these models. On the contrary, while the autonomous model showed an increased time efficiency, this did not necessarily result in a high perceived helpfulness. Additionally, the findings highlight the importance of trust and biases in the AI output, as this can influence the effectiveness and thus the perceived usefulness.

Overall, these findings result in a generally positive perceived usefulness of hybrid models. Here, six participants noted the positive perceptions, while one participant noted a negative view on this. One potential reason for this could be related to the participant demographic, where it can be argued that the general adoption of AI is high among young professionals. However, the limited information from the participant sample sizes only allows for speculations. This however could indicate the influence of participant demographics such as experience on the adoption of hybrid models.

6.2.2. Perceived Ease of Use

The findings show that all participants considered the hybrid models intuitive to use, thus showing a positive perception on the ease-of-use. The initial expectations for this was to have interaction capabilities, centralisation of information and technological understanding. However, preferences for the most easy-to-use model varied between participants, highlighting a potential subjectivity based on the pitch-deck evaluation styles.

Venkatesh and Davis (1996) highlight the perceived ease-of-use factors, related specifically to psychological factors such as computer self-efficacy, enjoyment and anxiety. Therefore, this underscores the subjective nature on the ease-of-use perceptions, based on the participant itself.

A further potential reason for the variation in the most easy-to-use model is linked to the nature of the different hybrid models. Here, the hybrid models offer different levels of interactivity and information density. This therefore possibly allows feature preferences within the participants to result in different final preferences. This means that while the hybrid models are shown by the participants to be easy-to-use, the usability may slightly depend on the hybrid model features and participant workflow preferences.

These findings indicate that while subjectivity may play a role in the ease-of-use for the participants themselves, the general perceptions on the ease-of-use remained positive for all participants. Therefore, the difference in the perceptions based on the subjectivity of the participants is not significant enough to heavily alter the perceived ease-of-use of the hybrid models in general.

Synthesis

Based on the TAM's proposition, the ease-of-use enhances the perceived usefulness to drive further adoption. By noting the intuitive nature of the tool, the participants show a positive perceived ease-of-use. This in turn enhances the perceived usefulness to drive adoption. Thus, the positive view on the perceived ease-of-use additionally further positively influences the perceived usefulness besides the main factors of the effectiveness and efficiency.

6.2.3. Behavioral Decision Theory

Biases

The findings indicated evolved perceptions on the biases through the experience with the AI tool. Initially before usage, the participants expressed concerns about AI reinforcing historical biases in data but also noted the potential to reduce human biases such as overconfidence. However, after interacting with the tool, concerns became more specific on the AI output tone.

An explanation for this shift can possibly be explained because of the initial perceptions from generalized notions around AI ethics, while the practical use showed context-specific limitations. The Behavioral Decision Theory (Einhorn & Hogarth, 1981) supports this notion, where biases and heursitcs are shaped by the decision context. Therefore the theory supports the change in judgement from a nuanced view to situational, through an increase in experience. This means that the perceptions on the biases within the evaluation is dynamic, where users refine views through experience with the specific context. This therefore highlights the importance of real-world testing, where users obtain both experience and shape judgements.

Trust

The results show that the trust of the participants in the AI output remained unchanged comparing before and after interaction with the hybrid models. Here, the participants noted that the output did neither increase or decrease the trust. Additionally, the participants highlighted the need for human oversight to maintain the trust in the final decision.

For trust in investment decisions, Keding and Meissner (2021) noted that in complex decision-making contexts trust in AI depends on the perceived task-fit and human validation. This is therefore especially the case when uncertainties are high, such as in early stage venture capital investing. The literature therefore supports the desire from the participants for human oversight and validation desires, however does not yet explain the unaltered change in trust.

A possible explanation for the similar trust levels is that a single exposure to the hybrid models may not provide sufficient time for the users to reassess their trust levels. A prolonged research and usage can provide repeated actions by the AI output. Therefore this means that the trust in the hybrid models is not easily gained or lost, and therefore requires prolonged use.

6.3. Implications

6.3.1. Theoretical Implications

This research advances the theoretical understanding of hybrid models, by applying them to the high-risk and qualitative setting of early-stage venture capital investing. Through the conceptualization of hybrid models from Raisch and Fomina (2024), this study applies the hybrid models in practice for pitch-deck evaluation, thus contributing to the literature with real world and case specific insights into the interaction of humans and AI.

The findings offer a deeper understanding of the collaboration between AI and human judgement, identifying key constructs for hybrid model pitch deck evaluation (effectiveness, efficiency). The results are supported by contextual and cognitive factors based on the Behavioral Decision Theory, thereby contributing to literature on an indication for performance metrics, but also highlighting contextual factors (biases and trust). This informs a future expansion of the TAM in a high-risk domain, where the trust in the output is of increased importance to the eventual perceived usefulness and thereby other TAM constructs.

Future theoretical implications can be further gathered through the long-term exposure on the BDT and TAM constructs as variables. From the prolonged exposure, the research can reliably state the effects of exposure on the constructs. Constructs such as confidence or trust can therefore be applied to further refine the theoretical models of hybrid-model decision-making in highly-uncertain contexts.

6.3.2. Practical Implications

Furthermore, the research offers practical insights for VC firms, hybrid model developers and entrepreneurs, related to the use and potential adoption of hybrid human-AI decision-making models, within pitch-deck analysis.

For VC firms, the findings suggest that the use of pitch-deck analysis hybrid models can further enhance the pitch-deck evaluation. The results offer practical insights into the trade-offs between the effectiveness and time efficiency. Thereby, enabling VC firms to make informed decisions about integrating such tools into their workflows.

For developers of AI tools, this research highlights the importance of designing hybrid models that support human-AI collaboration in a high-risk decision making context, other than full AI automation. In the context of pitch-deck analysis, the ability to fact check was highlighted to be of further importance. Therefore, developers should prioritize the features that offer complementary insights and align with the human decision-making processes. Furthermore, future possibilities for an increased time efficiency were highlighted. Thus, developers should additionally focus on seamless integration of the analysis into human workflows, to aim for both an increased efficiency and efficacy of analysis.

At last, for entrepreneurs the study highlights pitch-deck insights, based on the evaluation of venture capitalists. Thereby, this research adds to the understanding of pitch-deck sections and contextual evaluation factors, to provide a nuanced perspective for entrepreneurs.

6.4. Limitations

Furthermore limitations are addressed that arise within this research. First, the limited sample size, particularly in the pilot experiment, restricts the reliability and generalizability of the findings. Due to the time and effort constraints, only a small sample size could be taken. This results in indicative findings, on the contrary of conclusive results. Thereby this highlights the pilot nature of the study, and based on these finding potential areas for further research. This limitation can be mitigated through an increased sample size in future research.

Additionally, the research is limited by the length of the study. During the pilot experiment the participants are exposed to the hybrid models and their capabilities for a short while, to assess the perceptions before and after usage. However, this creates a limitation where the users apply the technology for the first time. Thus, an increased exposure may alter both the experimental findings and the perceptions of the participants on the hybrid models. To mitigate this limitation, future longitudinal studies can be performed to assess the long-term effects of hybrid models. This can therefore include the perceptions and experimental findings, but also incorporate changes over time.

Thirdly, potential biases within the research design arise as a limitation. The rise of biases throughout the pilot experiment is aimed to be minimized through standardized pitch-decks, however other unforeseen biases such as the experiment setup could influence the participant's evaluation results. This limitation shows the inherent challenges that arise in real-world settings.

At last, the research results can be influenced based on the presence of the researcher during the interviews, pilot experiments and workshops. Throughout the research methodology this effect was aimed to be minimized by maintaining a structured and neutral role during interactions, however the entire influence cannot be entirely eliminated again due to the nature of the .

6.5. Conclusions

Sub-Question 1: What are the key factors that define a high-quality pitch deck in VC decision-making?

Based on the literature and interview findings, key factors were identified relating to content and contextual factors.

The content factors highlighted critical pitch deck sections, corresponding to the solution, problem, team and customer/market sections. These sections are crucial to the venture capitalists to gain an understanding of the validation and credibility of these sections.

Additionally, contextual factors further shape the judgement of the venture capitalists on the start-up evaluation. This highlighted important contextual factors, relating to the start-up stage and the quality of the design. Within the early startup stage, the importance of team is highlighted due to a high uncertainty of factors. In later stages, the importance of the business model and traction increases for the assessment of the startup. Furthermore, the quality of design is of importance, as during the evaluation this is related to the founder competence and execution abilities. These evaluation dynamics highlight the incoherence in a standardized evaluation, where this understanding is important for VC decision-making.

Sub-Question 2: What perceptions do venture capitalists have on the usefulness and ease- of-use prior to adoption?

Prior to adoption, the understanding of the venture capitalist perceptions on hybrid models are gathered. Based on the Technology Acceptance Model, this is related to the key constructs of perceived usefulness and perceived ease-of-use. The Behavioral Decision Theory is also related to the constructs of

biases and trust.

For the perceived usefulness, participants primarily valued hybrid models for their ability to provide additional information and create a time efficient analysis. Additionally, for the perceived ease-of-use, participants noted interaction capabilities, centralisation of technology and understanding of the technology as key constructs.

Furthermore, participant perceptions on the biases with hybrid models related to the self-reinforcing bias that might emerge. Furthermore, bias mitigation is related by the participants to limited overconfidence bias. Additional perceptions on the trust were diverse, highlighting the situational dependence.

Sub-Question 3: How do hybrid models perform compared to human only approaches in VC pitch-deck evaluation?

The hybrid models perform differently for pitch deck evaluation. Particularly, sequential and interactive search models outperformed human-only analysis for the evaluation efficacy, however also both noted a slight decrease of the time efficiency. Here a slight difference between the two models is obtained, where the sequential search slightly outperformed in terms of efficacy, and interactive search slightly in terms of efficiency. Thus the primary value of these two hybrid models is noted in their ability to increase the evaluation completeness in the decision-making process.

On the contrary, the autonomous search model noted a steep decrease in the evaluation efficacy compared to human analysis, but also an increase for the time efficiency compared to human analysis. This hybrid model therefore highlights the potential time savings, in exchange for a lowered evaluation completeness.

Sub-Question 4: How does experience with hybrid models influence investor perceptions?

To conclude, the experience with the hybrid models positively influenced the attitude towards use and the behavioral intention to adopt these tools in other parts of the investment process. This was primarily driven by perceptions on the usefulness and the ease-of-use, based on the Technology Acceptance Model. This thus supports the use and adoption of hybrid models within the VC pitch-deck evaluations.

Furthermore, additional insights were gained on the experience with hybrid models on the biases and trust perceptions. After the experience with the hybrid models, a shift in bias type was seen from initial concerns about general AI-related biases, evolved to more practical concerns such as hallucinations and tone neutrality. Also, the trust in AI remained stable to before, highlighting the minimal encounters that significantly altered the trust. A prolonged exposure could be required to significantly alter the trust of the participants.

6.6. Recommendations

This chapter provides recommendations for future research, based on the findings of this study. Through this future research, the practical applications and theoretical development of hybrid models in venture capital can be elaborated.

Given the pilot nature of this study, thereby limited by the small participant numbers, it is recommended to replicate the experiment with a larger and more diverse sample. This will create more robust and generalizable findings, to provide a more in-depth scope. Thereby a larger sample would allow for statistical analysis, and additionally include participant subgroup comparisons. Thereby it can assist in the further validation of the hybrid model trends, and add more in-depth insights.

Furthermore, it is recommended to investigate the longitudinal impact of hybrid models within the venture capital process. This study provides a highlight of the hybrid model usage, based on immediate reactions from the participants. Thereby, the attitudes towards hybrid model usage, such as for in-

stance in the perceived usefulness or trust, possibly further evolve with longitudinal usage of hybrid models. Therefore, performing a longitudinal study on hybrid model usage, would provide in-depth insights into adoption dynamics and learning curves over time.

At last, it is recommended to expand the research scope further to other phases of the investment process within venture capital. Here, current research focused on the initial pitch-deck evaluation phase. However, the venture capital decision-making process highlights multiple stages, such as due diligence and portfolio management. Thereby, the scope of this research can be expanded to investigate the use of hybrid models in these cases. Thus, the research encompasses the full potential of hybrid model usage within the venture capital investment process, and thereby reveal phase-specific benefits or limitations.

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A

Appendix A: Interview Protocol

Interview Protocol

Interview Protocol

1. **Before the Interview**
   - Send over consent form and allow participant to sign.
   - If it is not possible, allow participant to sign at the start of the interview.
2. **Introduction**
   - Researcher explains the research purpose and goals.
   - Allow the participant to ask any questions beforehand.
   - Once questions have been answered and the consent form is signed, the recording is commenced.
3. **Personal Profile**
   - The participant is asked to give a description of their role and previous experiences.
4. **Topic-related questions**
   - The researcher has prepared questions to dive further into the topic.
5. **Interview duration**
   - The interview will last between 30-45 minutes.
6. **After the interview**
   - The researcher writes down key impressions and observations.
7. **Transcription**
   - The audio recording is transcribed within 5 days after the interview.
   - The audio recording is deleted after completion of the transcription.

Consent Form

Research Participation Consent - Interview

You are being invited to participate in a research study titled '**Venture capital investment decision-making process enhancement through human, hybrid and AI models**.' This research is done by Julian de Klerk, in collaboration with the TU Delft and InnovationQuarter, for the graduation thesis of the student.

The purpose of this study is to research the effect of AI in the investment decision-making processes within venture capital. This is done through a case study, where three experimental pitch decks are set up to be analysed with human, hybrid or AI models. Specifically, this interview is performed to explore pitch-decks qualities, and will take you approximately 30 minutes. The data will be used for the final report of the study, which will be published in the TU Delft Repository.

The interview will be recorded and transcribed, where the recording and the answers to the questions will be handled with confidentiality. The transcription will be anonymized and used to obtain an anonymous summary of the interview. The anonymous summary of this interview will be sent to you afterwards, after which you give consent in writing to further use this information for the final thesis report. Additionally, the final thesis report is shown to InnovationQuarter before publication. Even though the data is anonymized, a high risk of reidentification remains, caused by the limited possible participants at InnovationQuarter.

For administrative purposes your contact details and signed consent form will be stored on a protected OneDrive of the TU Delft. Only the researcher and his supervisor (Julian de Klerk and Dr. Ir. Zenlin Roosenboom-Kwee) have access to this information. The personal information will be terminated following the end of the research project in June 2025.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions. Thank you for your time and effort in this research. Your input is of high importance to the feasibility of this research, and therefore cooperation is highly appreciated.

Corresponding Researcher
Julian de Klerk
j.n.deklerk@student.tudelft.nl and julian.deklerk@innovationquarter.nl

Responsible Researcher
Dr. Ir. Z. (Zenlin) Roosenboom-Kwee
Z.Roosenboom-Kwee@tudelft.nl

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION		
1. I have read and understood the study information, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	☐	☐
2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	☐	☐
3. I understand that taking part in the study involves: - Partaking in the recording of audio, that is transcribed and anonymised afterwards. The data will be deleted following the end of the research project. - Answering questions regarding pitch-deck qualities	☐	☐
B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		
7. I understand that taking part in the study also involves collecting specific personally identifiable information (PII) [Name and Job Description] with the high risk for re-identification of my identity.	☐	☐
9. I understand that the following steps will be taken to minimise the threat of a data breach, and protect my identity in the event of such a breach: Data storage in a secure environment (OneDrive) at the TU Delft, only accessible to the responsible and corresponding researcher. Job descriptions will remain general and the findings are anonymised.	☐	☐
11. I understand that the (identifiable) personal data I provide will be destroyed following the end of the research project.	☐	☐
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		
12. I understand that after the research study the de-identified information I provide will be used for a graduation thesis, published in the TU Delft Repository	☐	☐
13. I agree that my responses, views or other input can be quoted anonymously in research outputs	☐	☐

I have read and understood the information above, have a minimum age of 18 years old and understand the impact of participating in this research. Hereby I consent to participate in this research and for obtained data to be further processed.

Name Participant Signature Date

Questionnaire

Personal Profile

1. What is your current role?
2. What are your previous experiences in venture capital investing?

Typical pitch-deck decision-making

1. Which sections of a pitch deck do you consider most critical?
    - Why do you prioritize these particular sections?
    - How do these sections influence your decision-making process?
2. How do the following slides weigh in their contribution on a ranking of 5 most important factors?

    Overview
    Opportunity
    Problem
    Solution
    Traction
    Customer/Market
    Competition
    Business Model
    Team
    Use of funds

    - How would your weighing be affected depending on a later/earlier start-up stage
3. How does the quality of design and presentation of a pitch deck affect your perception of the startup?
    - How does the quality of a pitch deck influence your perception in the startup's credibility or competence?

Hybrid Model Pitch-Deck Decision-Making

Technology Acceptance Model

Perceived Usefulness

1. What is required from the hybrid model to improve pitch-deck analysis and decision-making as it is?
2. How can the hybrid model influence your performance of pitch-deck analysis and decision-making?
3. Have you previously used AI tools for analyzing pitch decks? If so, what were the benefits and drawbacks?

Perceived Ease-Of-Use

4. In terms of ease-of-use, how does using a hybrid (AI-human) model compare to your current manual (human) approach?
5. What aspects of a hybrid model would make it easier or harder to use for pitch-deck analysis?

Behavioral Decision Theory

Biases

1. How do you think hybrid AI tools might help mitigate or reinforce biases in pitch-deck analysis?

Intuition

2. In what type of pitch deck elements do you feel more confident trusting your intuition over AI output?

Confidence/Trust

3. When AI analysis conflicts with your own judgement, which one do you tend to trust more, and why?

Heuristics

4. How does using AI affect your reliance on mental shortcuts when reviewing pitch-decks under time pressure?

Additional Thoughts

1. Is there anything else you would like to share about pitch-deck decision-making with AI Tools?

B

Appendix B: Pilot Experiment and Workshop Protocol

Pilot Experiment and Workshop Protocol

Pilot Experiment and Workshop Protocol

1. **Before the pilot experiment and workshop**
   - Send over consent form and allow participant to sign.
   - If it is not possible, allow participant to sign at the start of the interview.
2. **Introduction**
   - Researcher explains the research purpose and goals.
   - Allow the participant to ask any questions beforehand.
   - Once questions have been answered and the consent form is signed, the recording is commenced.
3. **Role of participant**
   - The participant is asked to give a description of their role and previous experiences.
4. **Pilot experiment and workshop setup**
   - The researcher has prepared an experimental and workshop setup for analysis
5. **Pilot experiment and workshop duration**
   - The experiment will last 60 minutes.
6. **After the pilot experiment and workshop**
   - The researcher writes down key impressions and observations.
7. **Transcription**
   - The audio recording is transcribed within 5 days after the interview.
   - The audio recording is deleted after completion of the transcription.

Consent Form

Research Participation Consent - Experiment

You are being invited to participate in a research study titled '**Venture capital investment decision-making process enhancement through human, hybrid and AI models**.' This research is done by Julian de Klerk, in collaboration with the TU Delft and InnovationQuarter, for the graduation thesis of the student.

The purpose of this study is to research the effect of AI in the investment decision-making processes within venture capital. This is done through a case study, where three experimental pitch decks are set up to be analysed with human, hybrid or AI models. Specifically, this experiment is performed to explore the effect of human, hybrid and AI models on pitch-deck analysis, and will take you approximately 30 minutes. The data will be used for the final report of the study, which will be published in the TU Delft Repository.

The experiment will be recorded and transcribed, where the recording and the answers to the questions will be handled with confidentiality. The transcription will be anonymized and used to obtain an anonymous summary of the interview. The anonymous summary of this interview will be sent to you afterwards, after which you give consent in writing to further use this information for the final thesis report. Additionally, the final thesis report is shown to InnovationQuarter before publication. Even though the data is anonymized, a high risk of reidentification remains, caused by the limited possible participants at InnovationQuarter.

For administrative purposes your contact details and signed consent form will be stored on a protected OneDrive of the TU Delft. Only the researcher and his supervisor (Julian de Klerk and Dr. Ir. Zenlin Roosenboom-Kwee) have access to this information. The personal information will be terminated following the end of the research project in June 2025.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions. Thank you for your time and effort in this research. Your input is of high importance to the feasibility of this research, and therefore cooperation is highly appreciated.

Corresponding Researcher
Julian de Klerk
j.n.deklerk@student.tudelft.nl and julian.deklerk@innovationquarter.nl

Responsible Researcher
Dr. Ir. Z. (Zenlin) Roosenboom-Kwee
Z.Roosenboom-Kwee@tudelft.nl

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION		
1. I have read and understood the study information, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	☐	☐
2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	☐	☐
3. I understand that taking part in the study involves: - Partaking in the recording of audio, that is transcribed and anonymised afterwards. The data will be deleted following the end of the research project. - Analysis of an experimental pitch-deck, through either human analysis or hybrid (human and AI) model analysis.	☐	☐
B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		
7. I understand that taking part in the study also involves collecting specific personally identifiable information (PII) [Name and Job Description] with the high risk for re-identification of my identity.	☐	☐
9. I understand that the following steps will be taken to minimise the threat of a data breach, and protect my identity in the event of such a breach: Data storage in a secure environment (OneDrive) at the TU Delft, only accessible to the responsible and corresponding researcher. Job descriptions will remain general and the findings are anonymised.	☐	☐
11. I understand that the (identifiable) personal data I provide will be destroyed following the end of the research project.	☐	☐
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		
12. I understand that after the research study the de-identified information I provide will be used for a graduation thesis, published in the TU Delft Repository	☐	☐
13. I agree that my responses, views or other input can be quoted anonymously in research outputs	☐	☐

I have read and understood the information above, have a minimum age of 18 years old and understand the impact of participating in this research. Hereby I consent to participate in this research and for obtained data to be further processed.

Name Participant Signature Date

Pilot Experiment Questionnaire

Part 3: Pilot Experimental Part – Evaluate Effect of AI on Pitch Deck Analysis

Independent Variables (Controlled in Experiment)

1. **Pitch-Deck Analysis Approach:**
    - Human Judgement
    - Sequential Search (AI-assisted with human match decision)
    - Interactive Search (Human + AI match decision)
    - Autonomous Search (AI selects match independently)
2. **AI Model Used:**
    - Deckmatch

Dependent Variables (Measured Outcomes)

1. **Efficiency Metrics**
    - Time spent on analyzing pitch decks
2. **Efficacy Metrics**
    - Completeness of analysis according to participant (How good were key factors considered, on a scale of 1-7?)
        1. Overview
        2. Opportunity
        3. Problem
        4. Solution
        5. Traction
        6. Customer/Market
        7. Competition
        8. Business Model
        9. Team
        10. Use of funds
3. **User Experience & Decision Confidence**
    - Participant confidence scores in hybrid analysis vs. human analysis (Likert scale 1-7)
    - Trust in AI-generated insights (Likert scale 1-7)
    - Perceived helpfulness of AI models in the decision process (Likert scale 1-7)

Workshop Questionnaire

Part 4: Workshop Part - Evaluate Decision-Making Implications

Technology Acceptance Model

Perceived effectiveness

1. To what extent did AI-generated insights meet (or exceed) your expectations in terms of usefulness or effectiveness?

    If your expectations were not met, how did this affect your perception of the tool's value?

2. Did AI provide any insights or patterns that you might have otherwise missed?

    - How did this influence your overall impression (or perception of the tool's usefulness?

Perceived ease-of-use

3. Which hybrid approach (sequential, interactive, autonomous) felt most useful, and why?
    - Follow-up: Which felt easiest to use and did that influence your preference?
4. How intuitive was the use of the AI tool during your evaluation process?

Attitude Towards Use

5. Would you consider using AI tools like Deckmatch in real investment decisions? Why or why not?
6. What features or changes would increase your willingness to use AI-assisted tools in pitch-deck analysis?

Behavioral Intention

7. Would you use similar tools for other tasks within the investment decision process? Why or why not?

Behavioral Decision-Theory

Biases and Trust

8. What type of bias did you feel bias in AI-generated rankings, if any? Why?
9. How is your trust in AI affected after this experiment? Why?

Additional Thoughts

10. Is there anything else you would like to share?

C

Appendix C: Pitch Deck 1

Overview

Predicting ROI before AI implementation
Helping financial institutions maximise AI investments

AI adoption in finance is accelerating, but significant value is not

Done through data obtained through customer projects and partnerships

Dross 1.

AI is an executive priority but fails to deliver...

75%	**25%**
of executives rank AI as top 3 strategic priority....	see significant value

Causing companies to *spend money on tools not going to be used* by employees

Dross From Potential to Profit: Closing the AI Impact Gap | BCG 2.

Measure the perceived ROI before costly implementation

Introducing an AI-powered implementation assessment tool for financial institutions

- **Predicts implementation effectiveness based on data on usage in similar companies**
- **Trained on perceived effectiveness effects within financial industry**
- **Recommends ready-to-use AI tools to unlock the maximum ROI**
- **Data obtained through customer projects and partnerships**

Dross 3.

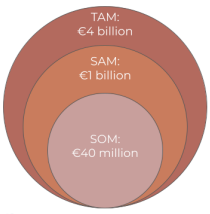
Customer

Financial institutions

Already actively implementing AI

Dross From Potential to Profit: Closing the AI Impact Gap | BCG 4.

Market



Total Available Market (TAM)
All companies willing to maximise ROI within AI implementation

Serviceable Addressable Market (SAM)
European financial institutions

Serviceable Obtainable Market (SOM)
Financial institutes actively investing in AI with 10% penetration

Dross 5.

Showing interest from financial industry

5 pilots

Collected 5 AI implementation datasets

Initial results: AI effectiveness increased by 40% according to pilot customers

Competition is expensive and not scalable

Competition	Disadvantages
Consultants	Expensive
In-house AI experts	Time-costly
	Not effective on ROI

B2B is promising

B2B SaaS Licensing
Annual license based on company size

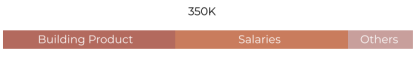
Team

CEO
3 Years Experience in Financial Institution
Digital Transformation

CTO
AI Engineer
Data Science
UX/UI

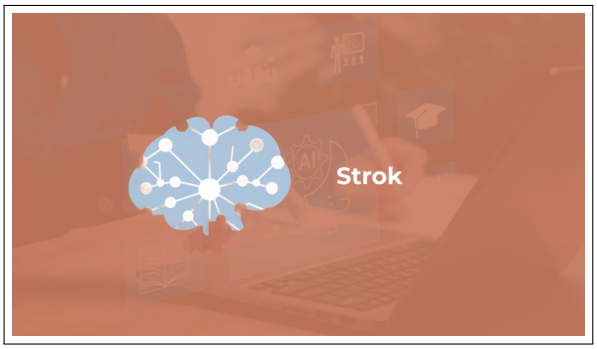
Use of funds

350K



D

Appendix D: Pitch Deck 2



Overview

Helping financial companies become AI literate

With a personalized approach and customer database

Strok 1.

Companies need to become AI literate to increase process efficiencies and adhere to EU AI Act

Enforcement:
May 2026
Every company with 30+ FTE

Strok 2.

Introducing an AI literacy platform

With a user database to track AI literacy

- **Allowing case-specific learning through datasets obtained within the industry**
- **Interactive learning tailored to role, sector and regulations**

Strok 3.

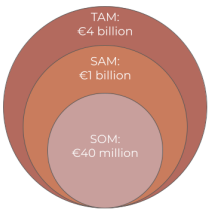
Showing interest from financial industry

5 pilots

Talks for further implementation for employees

Strok 4.

Market



Total Available Market (TAM)
All companies in EU needing to adhere to EU guidelines

Serviceable Addressable Market (SAM)
Knowledge institutes in Europe adhering to EU guidelines

Serviceable Obtainable Market (SOM)
Financial institutes with 30+ FTE, and 10% penetration

Strok 5.

Customer

Financial institutions

Already actively implementing AI

Competition is expensive and not scalable

Competition
Consultants
In-house AI experts

→

Disadvantages
Expensive
Time-costly

Why we win:
Structured
Cheaper
Faster

B2B is promising

B2B SaaS
Pay Per Employee Usage

Team

CEO
3 Years Experience in Financial Institution
Digital Transformation

CTO
Coding projects
Website building
Legal interests

Use of funds

350K

E

Appendix E: Pitch Deck 3

Overview

Financial companies currently have a hard time mapping the risks of AI

Causing vulnerabilities within the financial data

Thereby the solution is to clarify the risks and provide mitigations, saving the companies future trouble with for instance data leakage

Fessil 1.

Financial companies cannot map the risks of AI well

Which pose challenges for monitoring vulnerabilities and potential financial-stability implications

Fessil From Potential to Profit: Closing the AI Impact Gap | BCG 2.

Classify the risks of AI implementation for the specific company

With a database of every AI tool for the financial industry

- **Risks According To: Low, Medium, High**
- **Classify type of risks**
- **Risks according to company field**
- **Provide mitigations and recommendations**

Fessil 3.

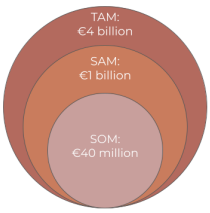
Customer

Financial institutions

Already actively implementing AI

Fessil From Potential to Profit: Closing the AI Impact Gap | BCG 4.

Market



Total Available Market (TAM)
All companies willing to maximise ROI within AI implementation

Serviceable Addressable Market (SAM)
European financial institutions

Serviceable Obtainable Market (SOM)
Financial institutes actively investing in AI with 10% penetration

Fessil 5.

Showing interest from financial industry

5 pilots

Obtained 1000+ tools in the database

Competition is expensive and not scalable

Competition	Disadvantages
Consultants	Expensive
In-house AI experts	Time-costly

B2B is promising

B2B SaaS Licensing
Annual license based on company size

Team

CEO
3 Years Experience in Financial Institution
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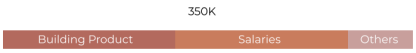
AI Engineer
Data Science
UX/UI

Use of funds



Appendix F: Autonomous Prompt

For autonomous search, an investment decision is made through a prompt within the Deckmatch environment. Based on the information provided in the tool, the investment decision is made. This is done based on the following prompt:

Final Judgement
Outline the final judgement whether to continue to invest more time or refuse the application based on the assessment of the previous findings. Do this by first assessing the previous findings. Then put all the findings together and form a final valuation from 1-10 whether to continue with the proposal. Here, 1 - 5 highlights a rejection and 6-10 a pass. Also include your reasons why it should be rejected or more time should be invested to possibly result in a final investment into the company.

The score will look like this:
Pass/Reject - (1 - 10)
Rejection Reasons: ...
Pass Reasons ...

G

Appendix G: Pilot Experiment Data

Summary of all tables

Table 16: Overview of average completeness, confidence, and time efficiency per type of analysis, including standard deviations.

Type of Analysis	Completeness		Confidence		Time Efficiency	
	Avg (1–7)	SD	Avg (1–7)	SD	Avg (mm:ss)	SD (mm:ss)
Human	4.2	1.0	5.8	0.4	05:43	02:13
Sequential Search	5.0	0.9	4.5	0.8	06:41	02:44
Interactive Search	4.8	1.0	5.0	1.1	06:15	02:54
Autonomous Search	3.3	1.6	3.2	1.2	–	–

Time Efficiency

Table 17: Time measurements per participant for each analysis type

Type of Analysis	P#7	P#8	P#9	P#10	P#11	P#12	P#13
Human	05:28	09:41	03:48	08:36	03:18	08:11	05:01
Sequential	09:20	18:04	01:51	08:06	05:21	08:28	07:02
Interactive	09:54	08:18	02:19	07:53	03:23	07:44	06:22
Autonomous	-	-	-	-	-	-	-

Completeness of Analysis

Table 18: Scores per participant for each analysis type

Type of Analysis	P#7	P#8	P#9	P#10	P#11	P#12	P#13
Human	5	3	5	5	3	3	4
Sequential	5	4	6	4	6	4	5
Interactive	5	4	6	4	6	4	4
Autonomous	6	3	4	4	2	2	2

Decision Confidence

Table 19: Evaluation scores per participant for each analysis type

Type of Analysis	P#7	P#8	P#9	P#10	P#11	P#12	P#13
Human	6	-	6	6	5	6	6
Sequential	3	-	5	5	4	5	5
Interactive	3	-	6	5	6	5	5
Autonomous	3	-	2	4	3	5	2

Trust

Table 20: Trust in Hybrid Model scores per participant

Participant	Trust in Hybrid Model (1-7)
P #7	3
P #8	-
P #9	4
P #10	4
P #11	5
P #12	5
P #13	5

Perceived Helpfulness

Table 21: Participant ratings per type of analysis

Type of Analysis	P#7	P#8	P#9	P#10	P#11	P#12	P#13
Sequential	3	-	5	5	4	5	5
Interactive	3	-	6	5	6	5	5
Autonomous	3	-	2	4	3	5	2