Supporting Entrepreneurial Logic: AI's Role in Causal, Effectual, and Hybrid Decision-Making"

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ABSTRACT,
This thesis is about how AI-driven insights support entrepreneurial decision-making in startups during the survival stage, with the focus on causal and effectual logic. Based on Sarasvathy's theory of effectuation and the Churchill & Lewis growth model, the study investigates how AI tools help founders in the survival stage and how they can be integrated. Using an abductive approach, the research connects empirical insights from eight semi-structured interviews with startup founders to existing theory. Through a structured Gioia analysis, the findings show that decision-making during the survival stage is not done strictly with either causal or effectual logic. Instead, founders tend to apply both logics this is called a hybrid approach. AI appears to support this hybrid mode by structuring uncertainty, increasing operational efficiency, and facilitating access to decision-relevant information. Particularly in tasks such as forecasting or data analysis. Every entrepreneur mentioned that AI does not replace entrepreneurial judgment but functions as a support tool which provides information on which they can decide. The study argues that hybrid decision-making should research as a third concept of decision-making approaches in future research. Moreover, as startups are getting more secure and moving on to later stages, AI's role may expand, which opens opportunities for longitudinal comparative studies.

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"During the preparation of this work, the author used ChatGPT and deepL in order to check the spelling and grammar and translate words from the native langue to English. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work."

Keywords
Artificial Intelligence (AI), Effectuation, Causation, Startup survival stage, Entrepreneurial Decision-Makin

1. INTRODUCTION

Currently, 90% of start-ups fail within the first five years (Kalyanasundaram, 2018). This high failure rate creates not only a personal and financial risk for founders but also threatens the benefits besides success for the founder that start-ups bring to a society besides the success of the founder. Examples would be innovation of technology, job creation, and economic growth in the country's or ears the start-up is from (Kofanov & Zozul`Ov, 2018). Given the role start-ups play in technological development and societal progress, understanding how to increase the chances of start-up survival, especially at the early stage, is of growing importance.

Like all other companies, start-ups go through various phases. The growth model by Churchill and Lewis was used for this study. The growth model by Churchill & Lewis (1983) describes five phases that a company typically goes through: Existence, Survival, Success, Breakthrough and Resource Maturity. Each phase is characterized by different challenges and priorities. In the existence phase, the focus is on acquiring customers and delivering products or services. In the survival phase, the company must generate a positive cash flow to sustain itself and not run out of money. In the success phase, the focus is on deciding whether the company should expand or remain stable. In the take-off phase, the company expands its business activities, which often requires delegation and financing. The last stage, the resource maturity stage is characterized by the development of formal systems and concern for maintaining the entrepreneurial spirit. The model is particularly useful for understanding how the strategic needs of a business change over time and is widely used in the entrepreneurship literature (Churchill & Lewis, 1987).

There are multiple reasons why start-ups fail. It can be a poor market fit, a limited amount of funding, or not enough manpower (Kalyanasundaram, 2018). A lot of these reasons why start-ups are failing can be summarized in the liability of newness and the liability of smallness (Gimenez-Fernandez et al., 2020). The liability of smallness explains the risk of having access to a limited amount of resources and capabilities, which creates difficulties in absorbing risks. The liability of newness is that a new company lacks established processes, financial stability, and credibility, which makes early decision-making critical (Gimenez-Fernandez et al., 2020). Another reason why start-ups might fail is the challenging business environment in which they need to make decisions. VUCA is the shortcut for Volatile, Uncertain, Complex, and Ambiguous. This is the environment in which start-ups need to make decisions (Rimita, 2019). This environment makes it difficult for start-ups to make the correct decisions because they are missing information or over- or underestimating effects in the future. Examples for the VUCA environment are political decisions e.g. trade protectionism or migration. Donald Trump is perhaps the embodiment of the VUCA world with his decisions, which are against standing agreements and diplomatic finesse (Millar et al., 2018). This process, where you don't have all the information but need to make a decision, is critical for start-ups. A positive example of good decision-making would be Netflix. They decided to change their business model from DVD rentals to streaming (Oat & Aalto University School of Science, 2013). A negative example would be Quibi, which managed to raise $1.75 billion before the launch of their platform but created a product that ignored user needs and managed to fail, even though they raised enough money from the beginning (Oladele, 2025). Quibi is a good example of how, even with enough money, it is crucial for a start-up to make the correct decisions. Talaulicar shows in his paper that a better decision-making process can increase the quality of the decisions made in a start-up. Talaulicar also shows the importance of fast and informed decisions in his study (Talaulicar et al., 2004).

A technology that potentially can help to make better decisions is Artificial Intelligence (AI). First studies have already indicated that AI can help with the optimization of the decision-making process (Schiavone et al.2022). Artificial Intelligence is a computational system that mimics human intelligence to perform tasks such as learning, problem-solving, and decision-making. It works by using algorithms, statistical models, and neural networks to recognize patterns (Russell et al., 2009). At the latest, since OpenAI had its breakthrough with ChatGPT in November 2022, AI and generative AI have been in everyone's mouth, and it is assumed that it will play an increasingly important role in the future. AI can help with better financial forecasting, market analytics, or hiring decisions. In financial forecasting, AI models such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) improve prediction accuracy by identifying patterns in historical data (Hiransha et al., 2018). In marketing analytics, AI is improving the quality of customer segmentation and campaign optimization by leveraging machine learning algorithms to analyze consumer behavior (Wang, 2022). The fields where AI can have a positive impact are vast, and it can help different kinds of entrepreneurs.

Next to the VUCA environment there are more challenges for start-ups, such as the liability of smallness and newness. Another factor influencing the decision-making of start-ups is the type of entrepreneur the founder is There are different ways for entrepreneurs to make decisions and entrepreneurs need different approaches to making decisions in such situations. They also need different tools. There is no one solution that fits all. (Sarasvathy, 2001). The paper will introduce two different types of entrepreneurs: causal and effectual entrepreneurs. The causal entrepreneur follows a predictive approach and is goal driven. They analyze the market, develop a business plan, and rely on forecasting techniques to minimize uncertainty (Dew et al., 2008). Their decision-making is similar to traditional strategic management, where clear objectives dictate the allocation of resources (Chandler et al., 2009). AI can help to deal with challenges that entrepreneurs are facing. E.g. forecasting or more accurate predictions (Antwi & Al-Dherasi, 2019). But there is a research gap about which tools are the most effective ones for causal entrepreneurs and if there are better options for a better decision-making process compared to AI powered tools.

On the other hand, the effectual entrepreneur follows a more adaptive approach. They focus more on which resources they currently have rather than setting fixed goals (Sarasvathy, 2001). To create new opportunities, they use their skills, their networks, and resources and adapt during the process. If they need more resources, they will realize that while doing. Instead of making predictions, the effectual entrepreneur is more likely to bring out a new prototype and adjust it according to the feedback (Read et al., 2016). AI could help both types of entrepreneurs to deal with the challenges of the VUCA environment. AI could help the Effectual entrepreneur to create a better analysis of the current resources and how they can be used, what possibilities the entrepreneur has. AI can also help by pointing out possible risks early to reduce the risk of failing in the process.

The potential benefits of AI usage do not come without difficulties. The adoption of AI into our work and decision-making process is something we have not fully understood yet. Many organizations face resistance from employees and decision-makers when implementing AI. People may distrust AI-driven decisions due to a lack of transparency or fear of job displacement (Bughin et al., 2018). A factor that contributes to people not trusting AI is that we often don't understand exactly how it works. AI models, especially deep learning networks, often function as “black boxes,” meaning their decision-making processes are not easily interpretable (Lipton, 2018). This lack of explainability makes it difficult for businesses to trust AI-generated insights, particularly in high-stakes industries such as healthcare and finance (Doshi-Velez & Kim, 2017). Another factor is that AI can be seen as every other technology, and we need to learn how to use it, when to use it and in which scenarios it is helpful and when we should not trust it (Carvalho et al., 2022). There needs to be a more general understanding of the technology that we start understanding how to work with its AI to create high quality outcomes. Furthermore, the technology itself still has a lot of flaws. If an algorithm is trained wrong, it can have a bias, which does not make its decision objective anymore and decreases the quality of the advice (Chen, 2023). A negative example of this would be Amazon with their algorithm which is used to decide which applicant gets the job and who doesn't. Since the algorithm was trained with old recruitment data, it also adopted these patterns, which led to men being favored over women, even with the same qualifications. Other issues are privacy and ethical concerns with AI and the amount of data the algorithm needs to be trained (Kodiyan, 2019).

The difficulties of AI must not stand in the way of the costs, which is why it is a problem that, the number of studies about AI’s influence on decision-making is growing but also fragmented (Pietronudo et al., 2022). The number of studies on the topic is increasing, but there are still many uncovered topics and unsolved questions. The paper focuses on the gaps in research on how AI can help start-up entrepreneurs make better decisions in uncertain times. The study is intended to help how AI can help to make better decisions, which should lead to future founders being able to use the AI tool in such a way that it really helps them, so that in future 90% of start-ups no longer go bankrupt in the first 5 years. It can also be used by investors to give advice to their partners without being too involved themselves. Especially the role of AI in the early decision-making stage of start-ups is largely unexplored, as this is where wrong decisions are particularly critical. First studies have shown that AI can potentially help entrepreneurs create a better decision-making progress (Schiavone et al.2022).

A lot of research has been done on the topic of AI and entrepreneurship already but there a lot of gaps as well. Much of the research is done about decision making in general and done at companies which are not in the start-up stage anymore. These companies do not face the liability of smallness and newness. These challenges are crucial and change the environment under which a decision is being made. A wrong decision can have dramatic impact at these early stages of a venture. Furthermore, the two different type of Entrepreneurs (causal and effectual) have different needs and challenges for which they potentially use the help of AI powered tools. These are also areas which have not been addressed by research today. There is a lot of research on the topics such as how AI can help with sourcing or forecasting but not in the context of causal and effectual entrepreneurship. While AI is increasingly used to support decision-making under uncertainty, there is limited empirical research on how entrepreneurs employing causal or effectual logic make use of these tools during the survival stage of a startup. Lupp (2022) explores how different types of machine learning relate to entrepreneurial decision-making: supervised learning supports goal-driven, predictive strategies aligned with causation, whereas unsupervised and reinforcement learning allow for more adaptive, experimental strategies characteristic of effectuation. These findings suggest that AI can theoretically support both decision logics, depending on how the entrepreneur interacts with the technology. In a different context, Schwab and Karlen (2019) show how causal machine learning can generate interpretable “what-if” scenarios by quantifying uncertainty in model outputs. This capacity is particularly relevant to causal reasoning in strategic decisions. However, despite these insights, no studies have examined how entrepreneurs practically use AI to support either logic in real-world early-stage environments. This study addresses that gap. The aim of this study is the following. The focus on how AI-driven insights can improve the decision-making process of causal and effectual entrepreneurs in the survival stage. The combination of the three components, plus the challenges of a start-up is a research field which has not been touched on yet. Because of that this study is answering the following the research questions.

Research question:
“How can AI-driven insights support causal and / or effectual decision-making in startups during the survival stage?"

2. THEORETICAL FRAMEWORK

Theory has been studied on the topics of start-up development stages under the model of Churchill & Lewis Growth Model (1983), entrepreneurial decision-making styles (Causation vs Effectuation) and AI and GenAI in Entrepreneurial Decision-Making.

2.1 Start-up development stages

In the Start-up development stages part the focus is going to be on the Churchill & Lewis Growth Model (1983). To define the relevant development phase for this study, I use the Churchill and Lewis Growth Model (1983), which outlines five stages of small business growth. The second stage, “Survival,” describes startups that have achieved basic viability but still face high uncertainty. The company needs to generate enough cash flow to cover ongoing expenses and decide how to allocate limited resources, in the best possible way. This model fits well with the goal of the research. The goal is on decision making during early-stage operations, where founders need to deal with uncertainty, where AI support may play a role.
Other models were considered but are less suited to this focus. The Lean Startup Model (Ries, 2011) is centered on product iteration and customer validation. Which is not the focus, it is not focusing enough on broader view of organisational development. Greiner’s Growth Model (1972) focuses on leadership styles and internal crises, this fits better for big company's which are already out od the survival stage. Compared to these, Churchill and Lewis provide a more practical framework to locate and understand the challenges founders face during survival, including the types of decisions AI might support.

The Growth Model is having 5 stages. The first stage is the existence stage. It is the earliest stage of the start-up. The characteristics are that the founders are involved in all operational processes and largely fulfil them themselves, financial resources are limited, and the profitability is uncertain. The start-up is fighting to find enough customers, and having a positive cash flow is a big challenge. The key factors are creating a clear value proposition and have a lean operation with controlled cost to create a positive cash flow, while accumulating new customers (Churchill & Lewis, 1987). The second stage is the survival stage. Characteristics of the stage are that they have a stable number of customers and revenue but not a lot. The main goal is it to stay at least break even to not create a negative cash flow and start run out of money. The founders are still heavily involved into the daily operations. Key challenges are the hiring of employees and maintaining a cash flow which is at least break even. Money is still a major scarcity factor and must therefore continue to be spent consciously and on important things. Another important step is to create business processes which can be repeated by others *(Churchill & Lewis, 1987)*. The third stage is success stage. The start-up is starts to be profitable and self-sustaining. The start-up needs to decide if it wants to stay small and stable (Success-Disengagement) or if it wants to scale up and grow aggressive (Success-Growth). This is the first time that more specific management roles are introduced, and the founders are starting to get less involved into the daily business. Challenges, are the risk of stagnation, managing a bigger Team and the decision between growing aggressive or small and steady. Success factors are a growth strategy, Sustainable financial health and access to funding for scaling and Solid organizational structure and leadership team (Churchill & Lewis, 1987). The fourth stage is the take-off stage. In the take-off stage the start-up is most of the time rapidly expanding, often with the help of external capital. The company is becoming more complex which strengthens the need for strong leadership. The founder needs to decide if they want to bring in an experienced CEO for this challenge. Another challenge is the rapid growth of the team which brings a huge increase in cost. The increase in cost can create cash flow problems. The cash flow needs to be monitored to not run out of money. Maintaining quality and customer service despite expansion is another challenge. The focus for success lies in making the right hiring decisions, choosing the right investment partnership and creating a clear growth plan for the business (Churchill & Lewis, 1987). In the fifth stage is the Maturity (Resource Maturity) Stage. At this stage, the company is a large organization with an established position in the market and efficient internal processes. These structures are also a risk, as bureaucracy can slow down the company and innovation. This is a risk for the entrepreneurial spirit. If this does not happen, competition from younger, more agile start-ups is a risk for the future of the company. The key factors for success are a balance between efficiency, agility and adaptability, continuous innovation to remain competitive and strong succession planning for leaders. (Churchill & Lewis, 1987).

2.2 Entrepreneurial decision-making styles (Causation vs Effectuation)

There are two types of decision-making approaches: causation and effectuation (Sarasvathy, 2001). Causation is about setting a specific goal and then identifying the means to achieve it. The theoretical foundation for the causation process comes from the rational decision-making process of neoclassical microeconomics (Chandler et al., 2009). According to Sarasvathy, the underlying logic is: “To the extent we can predict the future, we can control it” (Sarasvathy, 2001, p. 251). The entrepreneur follows a goal-oriented approach and tries to achieve their goals through a specific plan (Chandler et al., 2009). This approach assumes that the future is predictable and that, through careful planning, entrepreneurs can control its outcome. This is also reflected in the criteria for decision-making. In the causation approach, entrepreneurs make decisions based on their expected returns. They choose the option with the highest expected return on investment (Casson & Wadeson, 2007). Usual tools for the causation approach include a predefined business plan. The business plan is a result of the planning that causation requires. Causal logic relies heavily on forecasts, data analysis, and market predictions, and entrepreneurs try to reduce uncertainty through planning (Chandler et al., 2009). In the causation approach, entrepreneurs analyze the market, industry trends, and competitors before making moves. The goal is to position the venture optimally from the start (Chandler et al., 2009). It is also about avoiding and minimizing risks. A typical action would be forecasting, rather than embracing uncertainty as an opportunity (Sarasvathy, 2001).

On the other hand, there is also the effectual entrepreneur. The effectual entrepreneur starts with a given set of means. An entrepreneur does not start with a specific goal in mind. They think about who they are, what they know and whom they know (Chandler et al., 2009). The goal is emerging over time and as the entrepreneur interacts with the stakeholders and explores opportunity’s (Sarasvathy, 2001). In effectuation the entrepreneur is more focusing on affordable losses rather than on expected return (Sarasvathy, 2001). They invest what they can afford to lose. This leads to a development which is rather doing a lot of small steps at the time, than big upfront commitment (Sarasvathy, 2001). An example could be that a founder might launch a product prototype with minimal investment rather than securing large-scale funding before testing the market. Effectuation also relies more on business relations and strategic partnership, rather than a competitive analysis. Early partnership and self-selected stakeholders, making the future more predictable (Chandler et al., 2009). The next step is exploitation of contingencies rather than exploitation of preexisting knowledge. Effectuation models are better when there is not a lot of knowledge about a technology out there and outcomes are more random and not predicable (Sarasvathy, 2001). It also more about Controlling an unpredictable future rather than predicting an uncertain one. Entrepreneurs recognize that the future is unpredictable, so they focus on what they can control rather than trying to forecast everything. By taking action and engaging with stakeholders, they actively shape the future instead of reacting to it (Sarasvathy, 2001). An example for this could be that a new company doesn’t wait for perfect economic conditions but launches a product and adjusts based on real-world customer feedback. There is not the one fits all approach, under different circumstances, the entrepreneur needs different decision making. An example of this would be that in the existence stage it can be beneficial for the entrepreneur to use the effectuation approach and develop the business not that strict, and later when the start-up becomes bigger, e.g. in the success stage when there is more money and more to lose it can be beneficial to use the causal approach. Different approaches have different strengths and weaknesses, it can be beneficial to use both approaches in different stages of the venture. Literature is also showing that the combination of both approaches is done in practice. Read et al. found that experienced entrepreneurs rely more on effectuation in uncertain conditions but switch to causation when scaling (Read et al., 2008). Reymen et al. also found out that from the point, entrepreneurs gain more knowledge over the market they are switching from effectuation to causation (Reymen et al., 2015).

2.3 AI & GenAI in Entrepreneurial Decision-Making

AI and GenAI have huge potential to support start-ups in their development. Different use cases where and how AI can support start-ups are the following. First trend and market analysis. AI helps to process a big amount of data from social media, news etc. to identify emerging trends. Tools such as google Trends, IBM Watson or CB insights are all AI-powered and can help analysis the market and trends. AI driven tools become a core aspect of modern entrepreneurship (Schiavone et al., 2022). Generative AI is emerging as a transformative tool in market analysis and for the creation of competitive intelligence and all of this while being more efficient and accurate and old school approaches (Pattanayak, 2022).

The second aspect would be customer sentiment analysis. A study shows that AI applications in consumer research improve product-market fit and help refine business ideas (Schiavone et al., 2022). AI-driven sentiment analysis can systematically extract and interpret customer emotions, opinions, and attitudes from large volumes of unstructured data, such as social media posts, reviews, or customer service transcripts (Cambria et al., 2017). This allows entrepreneurs to gauge customer reactions to products and services more accurately and swiftly, enabling faster pivots or product iterations. According to a study by Duan et al. (2019), such real-time insights into customer sentiment significantly improve the product-market fit by aligning offerings more closely with consumer preferences and unmet needs (Duan et al., 2019).

The third is automated idea generation. AI-driven creativity tools assist entrepreneurs in brainstorming viable and scalable startup concepts, can help entrepreneurs with the creation of ideas (Uriarte et al., 2025). AI integration in idea management systems streamlines the evaluation and selection of ideas, enhancing decision-making processes and increasing the likelihood of success in competitive markets (Shaer et al., 2024). By automating the generation and assessment of ideas, AI serves as a catalyst for innovation, empowering entrepreneurs to create solutions that are both creative and strategically aligned with current and future market needs. (Shaer et al., 2024).

2.4 Impact of AI on the stage model of Churchill & Lewis Growth Model

The following part will be about the how AI can impact the different stages of the Churchill & Lewis Growth Model (1983). The first stage is the existence stage, her the venture is needs to identify market opportunity's, develop an MVP, find customers and manage the cash flow. AI can help improve all these stages It can help managing inflows and outflows, it can help scan the market and creating an MVP (Mbonigaba & Vanitha, 2018). The next stage is the survival stage. It is crucial that a startup is achieving financial stability, managing operational efficiency and customer acquisition and retention. This can all be improved with the help of AI. It can help with the management of the cash flow to improve the financial stability of the start-up (Mbonigaba & Vanitha, 2018). The next stage is the success stage the challenges are expanding market reach, managing growing teams, enhancing product development. Ai can help with the recruitment for the growing teams through algorithms, can help with the market research, through tools such as google trends Mbonigaba & Vanitha, 2018). In the fourth stage the take-off stages the challenges for the venture are the following, managing exponential growth, securing large-scale funding, expanding into new markets. Nair and Paul show in their paper that through the help of AI companies can make better decisions when it comes to their market entry decisions (Nair & Paul, 2024). that Ai with the help of Machine learning can help to increase the financial performance of a venture. As a study has shown the performance of a hedge fund could be increased with the help of AI and machine learning (Addy et al., 2024). This is no direct link to the start-ups, but it shows that next to budget allocation, AI can also make investment decisions which might help start-ups as well. This topic in general lacks shows a research gap. The last stage is the Maturity (Resource Maturity) Stage the main challenges in the stage are Maintaining innovation while stabilizing operations, preventing bureaucratic inefficiencies, risk management & crisis response. AI has proven to be a useful tool for these challenges, it is increasing the GC of company's it is used for fraud detection, reaching the ESG goals, risk management and board performance (Ahdadou et al., 2024).

The integration of Artificial Intelligence (AI) into start-up environments is increasingly discussed within the literature on innovation and entrepreneurship. Although the potential benefits of AI such as improved efficiency, data-driven decision-making, and scalability are well recognized, its implementation in early-stage ventures remains a challenge. One often mentioned barrier to successful AI adoption in start-ups is the lack of internal technical capabilities. Due to resource constraints, many start-ups do not possess employees with the necessary skills to select, integrate, and maintain AI systems effectively (Zavodna et al., 2024). In addition, a start-up's limited financial resources make it difficult to invest in AI tools or hire external experts. These limitations lead to a gap between awareness of the potential of AI and actual implementation. Furthermore, entrepreneurs may lack a clear understanding of how AI aligns with their business model. This leads to uncertainty about return on investment and slows down the decision to adopt (Jöhnk et al., 2020). Another problem is the limited availability of high-quality data. AI tools need high quality data to function properly, but early-stage ventures often lack sufficient data or struggle with poor data quality (Castillo-Martínez et al., 2024). Even when data is available, integrating it into AI systems is difficult without technical support. Legal and ethical concerns also play a role. Start-ups in Europe face strict regulations around data privacy, especially when dealing with customer information. Which is creating a problem for them. The fear of compliance and potential punishments from governmental authorizes or a destroyed public reputation because of a violation of the data privacy rights is a problem, which is preventing that companies use AI powered tools (Dwivedi et al., 2023). Another reason are cultural barriers. In small teams, decisions are often made on the basis of intuition and experience. The introduction of AI requires a shift to data-driven thinking, instead of intuition which can be met with resistance from experienced team members (Berger et al., 2019). Start-ups also work in environments with high uncertainty, where flexible, creative decisions are required. Some fear that AI could limit this flexibility or increase bias if not used correctly. In summary, the main barriers to the adoption of AI in companies are technical, financial, organizational and cultural. Removing these barriers is an essential for the implementation of AI into decision making process of Start-ups.

2.5 Propositions

The following paragraph will contain 5 propositions about AI usage in relation to effectual and causational decision making of entrepreneurs using the Churchill & Lewis Growth Model. The propositions below are grounded in the Churchill & Lewis Growth Model, which outlines how startups evolve through distinct stages. Building on this framework, the aim is it to explore how these differences influence the adoption and use of AI-powered tools. The goal is it, to test whether startups in the earlier stages (Existence and Survival) show lower levels of AI engagement due to limited resources and more immediate concerns.

Proposition 1: Startups in the Existence Stage will exhibit lower levels of AI adoption due to the perception that AI is not a critical need for their current operational and strategic challenges.

Proposition 2: Startups in the and Survival Stage will exhibit lower levels of AI adoption due to the perception that AI is not a critical need for their current operational and strategic challenges.

Proposition 3: In the Survival Stage, startups predominantly utilize AI-powered tools to support human decision-making, rather than relying on AI as the primary source for decision-making.

Proposition 4: Startups in the Survival Stage that primarily follow an effectual decision-making logic will exhibit lower overall AI adoption compared to startups in the same stage that predominantly follow a causal decision-making logic.

Proposition 5: The level of AI usage and the reliance on AI-powered tools within a startup will progressively increase as the company matures through the Churchill & Lewis Growth Model stages (i.e., from Existence to Maturity).

3. METHODOLOGY

3.1 Research Design

The research design of this study is qualitative. Qualitative research enables the investigation of a real environment, which has led to deep insights into our research context (Yin, 2011). This is done by using non-probability sampling, aiming to understand meaning, experiences, and processes in depth, not to generalize statistically (Bryman, 2016). The study uses both secondary data and primary data (interviews). Qualitative research has been chosen given the lack of existing empirical data. AI adoption in early-stage start-ups is a topic which has not yet been extensively researched. The sampling approach has been chosen for this study.

3.2 Sampling approach

The chosen approach is the purposeful sampling strategy. It is the most commonly used sampling approach in qualitative studies. It involves intentionally selecting participants. These participants are chosen based on their expertise in the topic (Palinkas et al., 2013). This method fits this type of research since the scope of this thesis is to create a general understanding of the topic of effectual decision-making in start-ups which are in the survival stage. The interviews are going to be held with entrepreneurs from different stages of the Churchill & Lewis Growth Model. There are multiple reasons for this. The first is to increase the sample size of the participants. The advantage of qualitative studies is that they don't aim to create quantifiable data, but they still need enough participants to gain insights. The second reason is that entrepreneurs who are no longer in the survival stage but in an advanced stage have additional experiences that they can use to give advice on what they would have done differently and how they would use AI to make decisions. There will also be no focus on a certain industry. The aim is to conduct interviews with different entrepreneurs from different industries. The advantages of not focusing on a specific industry are the following. First, it gives a broader insight which allows us to find patterns throughout different industries (Guest et al., 2005). The second reason is that it reduces the possibility of skewed results, which would be more likely if there were a focus on specific industries and stages (Eisenhardt, 1989). The third reason is that it increases transferability of the results. As not only one specific industry or phase is queried but several, it is ensured that the results can be used more easily by others, and they do not have the uncertainty of whether the data only applies to one industry (Eisenhardt, 1989). The fourth reason is that a broad view captures how different environments shape decision-making and AI adoption, which is a better reflection of the complex start-up environment. The above reasons have led to the conclusion that a qualitative study with purposeful sampling without focus on the industry is the best choice to answer the research question.

3.3 Data Collection

To gather the data, semi-structured interviews will be used. A semi-structured interview has the advantage that there is comparability throughout different interviews due to the existing structure; on the other hand, it also gives the possibility to dive deeper into emerging topics because of the existing flexibility (Bryman, 2016). This gives the possibility to explore the knowledge of the entrepreneur beyond the questions that were planned from the beginning. This flexibility is particularly important in this study, as entrepreneurs may hold unique, experience-based views on AI that are not easily captured through standardized questions. Semi-structured interviews allow participants to explain their thoughts in depth, describe specific scenarios, and reflect on how their decisions were made. This depth is essential for understanding not only what decisions have been made, but also how and why they were made. These insights are crucial for this study because it aims to support future entrepreneurs in their decision-making. The interview guide will be divided into three main parts. First, the questions will be about how the entrepreneur generally makes decisions. The aim is to find out if it is causation or effectuation. Second, the interview will focus on how the entrepreneur thinks about and understands AI tools if they are using them already, and if yes, which ones they are using. Third, the interview will deal with what the entrepreneur sees as barriers or helpful factors when it comes to using AI in the decision-making process. Each part will consist of open questions, with the possibility to ask follow-up questions depending on what the entrepreneur is saying. For example, if someone says they don't use AI because they feel unsure about it, there will be further questions to find out whether that's because of the cost, lack of knowledge, or doubts about its usefulness. This approach supports a flexible yet focused exploration of the research topic. It ensures that all relevant themes are covered while allowing space for insights to emerge from the conversation that have not been planned in advance.

3.4 Chandler survey

To assess whether participants tended toward a causal or effectual decision-making style, I used the framework developed by Chandler et al. (2009). Based on their validated constructs, I created a 14-item survey in which each item presents opposing causal and effectual statements. Participants were asked to indicate their agreement on a 5-point Likert scale ranging from "strongly agree" with the effectual item (1 point) to "strongly agree" with the causal item (5 points), with "neutral" coded as 3. The total score could range from 14 to 70. Scores between 14–34 indicate an effectual orientation, 35–48 a hybrid approach, and 49–70 a causal orientation. This survey was approved before the interviews.

3.5 Data Coding & Analysis

As part of the data analysis, the Gioia method will be used to identify patterns in the interview data. This makes it possible to change the raw data into usable information for the evaluation (Gioia et al., 2012). Through this process, conceptual categories will be pointed out, which can be used to develop a better understanding of how entrepreneurs think about and approach AI in their decision-making. This process is important because the goal of this study is not only to describe attitudes, but also to gather insight about how different factors shape AI-driven decision-making in early-stage ventures. In the first step of the Gioia method, the interviews will be coded based on what participants say. These 1st-order concepts will then be grouped into 2nd-order themes that reflect broader ideas, e.g., barriers to AI adoption, personal experiences with technology, or preferred ways of making decisions. In the final step of the Gioia method, these themes will be brought together into one comprehensive dimension. An example could be statements about uncertainty, fear of complexity, and lack of time being grouped under a broader dimension like "Contextual Constraints." These aggregate dimensions will form the basis for a new framework that shows how different decision-making logics (e.g., effectual or causal) relate to the adoption of AI tools. The framework will also consider how internal factors like mindset and experience, and external factors like resources or perceived risk, interact with these logics. This should help to explain under which conditions entrepreneurs are more or less likely to use AI and what are the possible use cases in this situation. To establish intercoder reliability, 3 interviews were independently coded by 2 different coders and subsequently compared to refine code definitions and ensure consistency.

The aim is not to create a fixed model, but a flexible framework that captures the variety of ways in which entrepreneurs make decisions and engage with AI. It explores how AI can help, and what the issues are that prevent it from being used. This kind of grounded theory-building is useful when studying new and complex phenomena (Corbin & Strauss, 2008), and it fits well with the qualitative and exploratory nature of this research.

4. INTERVIEW RESULTS

This section is about the empirical findings from the eight interviews, analyzed using the Gioia method (Gioia et al., 2012). The aim was it to identify how AI-driven insights support either causal or effectual decision-making in start-ups during the survival stage. With the help of the Gioia method, it was possible to cut down the original 166 first order codes and the 67 second order themes, into 36 first order codes and 6 second order themes. These where aggraded into three dimensions: causation, effectuation and hybrid. From this process four findings emerged, and the propositions could be answered. All of this is presented below and supported by direct quotes from the interview data.

4.1 Scores Chandler Survey

The scores of the chandler survey are the following:

Entrepreneur	Survey Score	Decision-Making Logic
Entrepreneur 1	44	Hybrid
Entrepreneur 2	43	Hybrid
Entrepreneur 3	46	Hybrid
Entrepreneur 4	34	Effectual
Entrepreneur 5	46	Hybrid
Entrepreneur 6	44	Hybrid
Entrepreneur 7	30	Effectual
Entrepreneur 8	40	Effectual

Figure 1.

The scores are showing the decision-making logic of the entrepreneur. Values lower than 35 means the participant follows an effectual decision-making logic, a score between 35,1 and 49 is hybrid decision making logic and a score above 49 until 70 are causal decision-making logic. The scores are made up as follows. The respondent filled out a questionnaire with 2 statements. One of them rather effectual and the other rather causal. There were 5 possible answers, and the answers were then added together. The answer that was most effectual was awarded one point and the answer that was most causal was awarded 5 points. 14 questions were included. The total number of points was then added together. The results from the Chandler survey were used in combination with the qualitative interview data and served as a form of triangulation. This approach has been chosen for a more robust understanding of the entrepreneurs' decision-making logic

4.2 AI Acts as a Real-time support tool, not a decision-Maker

The first insight is that founders didn't see AI as a tool that replaces their decision-making but rather as a tool that supports the entrepreneur in their decision-making process. In eleven quotes entrepreneurs describes AI as a tool that helps them act more confidently, through the creation or the preparation of data. It helps if there is not a lot of data available. AI-powered tools helped the entrepreneurs to understand the situation better, but not as a tool what told them what to do.

Entrepreneur5:" We love to use AI for social listening too to monitor what's trending and which brands are losing or gaining Favor online."

Entrepreneur 8: "But I never solely rely on only ChatGPT answer and most of the times it's more to understand a concept that we already saw somewhere else a bit better."

Entrepreneur 4: "For admin, yes. For anything involving coaching philosophy, we double-check everything. It's a tool, not a coach."

Entrepreneur 8: "If you only look at chatgpt personally think you always have to look at different sources to really validate like what it's saying."

Entreprenieuer3:"I would like to see it more as a supporting factor and not a factor that decides to influence me in that way, so that it sounds a bit logical."

Entreprenieuer7:" So if you encounter a problem, you can just ask one of these tools. So there these are the things. These are the parameters. Show some data. So what could be the possible reasons? Then it list out a few things."

As an example, these quotes are backed up by different second order themes. The first quote is under the theme Data-Driven Decision-Making use which is linked to causation. It reflects that the final decision remains with the entrepreneur. The second quote is under the Human Oversight in AI Use second order theme. That falls into effectuation. The founder uses AI to gather insight for his decision making but the final decision is still at the entrepreneur itself. These two examples show that AI can support both causal and effectual logic. Either by delivering structured data for long-term planning or that is adaptive that it supported the creative process as an assistant with human centered judgment.

4.3 AI Is More Useful in Structuring Uncertainty Than Eliminating IT

The second insight is that AI helps founders deal with uncertainty, but not by removing it. Instead of offering perfect answers or fixed plans, AI tools helped structure the uncertainty into a more managable siutation for the entrepreneur. In 20 quotes, founders described how they used AI dashboards, customer analytics, or other tools to better understand trends, generate hypotheses, or prioritize actions without expecting full clarity.

Entrepreneur 7:" We you we tried to use most out of it, I would say almost all of us uses AI tools for both for research and for searching, for analysis, for coding and everything else a lot."

These types of responses for example fit with the second-order theme Predictive Analytics, which is linked to causation, but also with Means Orientation and Learning by Doing, which are connected to effectuation. The founders are not using AI here with the aim of getting a total solution, but to better navigate an uncertain environment. AI is used to provide more information in order to make better decisions. Several interviewees also described how AI helped them to focus on the most important questions, even when the data was incomplete or evolving.

Entrepreneur 5: "For proposals, AI gives us a solid first draft... saves time."

*Entrepreneur 2: "*Opening *new markets is now less risky thanks to automated AI campaigns."*

This shows that the value of AI for startups in the survival stage lies more in helping to structure and respond to uncertainty, rather than having the answer to all their questions. Founders remain actively involved in interpreting results and adapting actions, which highlights how AI supports a dynamic decision-making process rather than a linear one.

4.4 AI increases operational efficeny and increases the speed

A lot of entreperurs have mentioned through out different interviews and also multiple times within the same interview that they currentl usse AI a lot to accelerate the speed of simple everyday tasks. Microsoft co-pilot was repeatedly cited as an example. In this example, *Entrepreneur 4: "We also now use ChatGPT and Copilot to streamline our admin tasks, like generating lesson plan templates and emailing parents."* In another example it is used to quickly create formal emails or to quickly create or edit Excel tables which are than used for the forcast.

Entrepreneur 5:" Copilot has also helped us a lot with cash flow modeling, invoice planning, and general forecasting."

Another example would be

Entrepreneur 2: "We train our people to use new tools and keep up with productivity improvements." And "It improves efficiency and execution of tasks."

These savings were common to all types of entrepreneurs, regardless of whether they were effectual or causal. That time saving can be used to the time that can be saved in this way can then be put back into other more important tasks.

4.5 AI-Supported Insights Contribute to Flexible Goal Development

Another finding that emerged from the interviews is that some founders did not follow fixed long-term goals but used data often supported by AI tools to shape and adapt their goals over time. This kind of flexibility was not just mentioned once but came up across different interviews in connection to user feedback, engagement metrics, or changes in the market. These adjustments align with the idea of goal flexibility within effectual logic. One founder explained:

Entrepreneur 7: "Certainly a lot of data analysis will be needed. For us also during the development and the clinical validation, there will be tons of data we are getting on board. So data analysis is a big part of it and I think we of course we can write codes to do the data analysis, but there are already trained models which can do much easier. Yeah, I think that is much better solution."

There were also cases where the long-term direction was still open, depending on how users responded:

Entrepreneur 5: "So, we're growing both sides and AI helps us to figure out which direction is the most probing one."

In these cases, AI or analytics were not only used to execute decisions but also helped in reevaluating what goals made the most sense at the time. This highlights how AI can support effectual entrepreneurs by offering new insights that lead to the adaptation of existing goals or the emergence of new ones.

4.6 Propositions

4.6.1 Proposition 1

For the first proposition the interviews didn't provide insights which are supporting these propositions. There were two entrepreneurs in the existence stage. When completing the chandler survey, both responded that they follow a hybrid decision making approach. This means that they are neither totally causal or effectual but lie in the middle, which in our case is hybrid. All of them used AI powered tools and also didn't

Entrepreneur 4: "*We also now use ChatGPT and Copilot to streamline our admin tasks.*" and "*We mostly use ChatGPT to brainstorm session plans or rewrite training content for different age groups. Copilot helps when we need to structure feedback reports or prep emails*."

Entrepreneur 8: "We use ChatGPT a lot."

Entrepreneur 8: "Almost with the certainty to say every decision that we make at least some of ChatGPT is involved."

4.6.2 Propostioton 2

For Proposition 2 the interviews didn't provide insights which are supporting these propositions. Entrepreneurs which are currently in the survival stage were using as much AI-powered tools as entrepreneurs from different stages.

Entrepreneur 7: "Since I know that you are also interested in AI, I should mention that maybe at this point, if you almost never Google things these days, we always use chatGPT or a similar kind of tools to even look for it outside of your as well as non-scientific Stuff."

Entrepreneur 5: "Copilot has also helped us a lot with cash flow modeling, invoice planning, and general forecasting."

4.6.3 Proposition 3

For proposition number 3, several statements were made in the interviews that support the proposition and show that founders in the survival stage used AI primarily as a tool that supports them rather than as a primary source for decisions.

Entrepreneur 3: "We trust AI as a first draft never final. It's a sparring partner, not a decision-maker."

Entrepreneur 3: "It is a tool to discover things that you have overlooked or that you cannot immediately foresee."

Entrepreneur 5: "We use AI to analyse audience demographics, engagement quality, fake followers, and brand fit. That helps us decide who to recommend to brands."

Entrepreneur 4: "For admin, yes. For anything involving coaching philosophy, we double-check everything. It's a tool, not a coach."

The use of AI was independet from the decision making style. Entreperuners with causal, effectual or hybrid decision making where all answering that they used AI-powered tools to support their decisions. This could be observed through every stage from every founder. They all used AI to suppored their decisions. But no one let AI-powered tools make the final decision.

4.6.4 Propostion 4

For Proposition 4 there couldn't be found evidence which is supporting this proposition. The results of the survey showed that all the 8 entrepreneurs surveyed were either effectual or hybrid, but none were causal. That makes it not possible to answer that proposition. The results have been shown that there is no difference between effectual and hybrid decision making. Both used AI-tools for the same things and also in a comparable frequency.

4.6.5 Proposition 5

The data is providing evidence which is supporting proposition 5. The founder in the Existence stage reported only use of AI tools, mainly for basic administrative tasks such as email drafting and or support of brainstorming sessions.

Entrepreneur 4: "*We mostly use ChatGPT to brainstorm session plans or rewrite training content for different age groups. Copilot helps when we need to structure feedback reports or prep emails to clubs and parents. It's practical nothing fancy, but it saves time."*

In contrast, the startup in the Survival stage demonstrated slightly more integration, particularly in data cleaning and operational support. The most extensive use was observed in the Take-off stage company, which employed AI tools across multiple domains, including forecasting, ERP systems, data processing, and customer support. They more tasks a company had to do they more opportunities arrived for the usage of AI.

Entrepreneur 2: "Opening new markets is now less risky thanks to automated AI campaigns. and" AI is used mainly in product development.

Entrepreneuer 7:"we do use some AI tools. Most of the open AI tools we use for simulations console this kind of thing, and for deciding a CAD." And "Certainly a lot of data analysis will be needed. For us also during the development and the clinical validation, there will be tons of data we are getting on board."

Proposition	Outcome
Proposition 1	Not confirmed
Proposition 2	Not confirmed
Proposition 3	Confirmed
Proposition 4	Not confirmed
Proposition 5	Confirmed

Figure 2.

5. DISCUSSION& CONCLUSION

5.1 Discussion

This research aimed to explore how AI-driven insights support either causal or effectual decision-making in startups during the survival stage. Based on eight interviews with startup founders, six key findings were derived through a structured Gioia method analysis. The results provide insights into how entrepreneurs use AI tools not only for operational tasks, but also for strategic and creative decisions under conditions of uncertainty and limited resources.

The interviews in this study showed that founders are not strictly following one or the other approach. A lot of the entrepreneurs applied a hybrid approach in their daily practice. It looks such as AI appears to reinforce the hybrid nature of their logic. Founders used AI for forecasting and planning (causation), but also for adapting their goals and exploring emerging opportunities (effectuation). The founders, who in the vast majority of cases pursued a clearly effectual approach, were also aware of the potential of AI and then used it to implement things that were more causal, into their practice. This confirms earlier findings by Reymen et al. (2015), who argued that effectual and causal logics often co-exist in practice. Another finding is that AI is more useful in helping to structure uncertainty rather than eliminate it. Instead of expecting AI to provide final answers, founders used it to better understand incomplete data, filter out not needed information, and build first drafts or get a general direction of a topic. This aligns with the term of "means-driven" experimentation found in effectuation theory (Sarasvathy, 2001). It will be interesting to see if that usage of AI will change in the future. As Rogers has shown with his diffusion of Innovation theory. The usage of technology can change over time (Rogers, 1981). Given that generative AI is still relatively new, future research could explore how its adoption and application will change the usage of AI in decision making. The data also supports the idea that in real-life environments, founders act with incomplete knowledge and use AI as a tool, that can help them process data and create a better information basis for making decisions. Today, however, they are not yet using AI to make final decisions, or they ultimately trust their own instincts rather than AI. Moreover, the interviews show that the benefit of AI is not necessarily tied to a particular strategic logic but is often seen in productivity gains. The entrepreneurs frequently stated that they use tools such as ChatGPT or Microsoft Copilot to save time and streamline administrative tasks. These tasks are essential for all founders, regardless of their decision-making logic. Future research should also focus on this if it will change based on the development how entrepreneurs will use AI in the future. Time saved on administrative or repetitive tasks through tools like Microsoft Copilot or ChatGPT enables entrepreneurs to focus on more critical activities, which is important during the survival stage of a venture. As it has been pointed out by Churchill & Lewis Growth Model in the survival stage financial constraints are a big risk of the venture. It means that founders should use as much time as possible to generate revenue. AI-powered tools can already help dealing with this challenge. This increase in operational efficiency was mentioned across interviews, independent of whether the entrepreneur followed a causal, effectual or hybrid decision-making logic. In this context, AI serves as a support tool helping with tasks such as data collection and cleaning but does not take a leading role in the actual decision-making process. These findings complicate Sarasvathy's (2001) strict division between effectuation and causation. Even entrepreneurs who demonstrate predominantly effectual logic engage in goal-oriented, forward-planning behaviors when AI tools allow them to do so efficiently. This supports the view that decision-making logics may be more fluid and situationally driven than originally theorize and supports the findings by Reyman et al. (2015)

Another insight that was observed is how AI contributes to flexible goal formation. Rather than using AI to achieve predetermined outcomes, founders used insights from AI tools to reevaluate their goals. This reflects a shift from goal-driven to goal-adaptive behavior and supports the use of effectual reasoning in uncertain and fast-moving environments. It reinforces that AI's role is not only to support execution but also to shape the strategic direction in interaction with customer feedback and evolving trends. Despite hype around AI, most founders did not expect AI to give them "the answer." Instead, they saw its main value in saving time, improving decision quality at the margins, or generating drafts or suggestions. Strategic vision and creative direction remained firmly in the hands of the founder. AI is useful, but not transformative by itself. Independent of tool or task, entrepreneurs mentioned that AI should act as a support system. This insight aligns with the findings from Jarrahi on ethical AI use and human-centered design and may indicate that trust and human control remain essential (Jarrahi, 2018). The assumption can be made that this is also the case in startup environments, especially during vulnerable phases such as the survival stage. In the current state AI-powered tools are more a support system, of the judgment of the entrepreneur itself, it is not used to make the decision itself. In every interview it was mentioned multiple times that the own judgment is important, and AI works best in combination with the human judgment. This supports the findings from Jarrahi and the expectations before the research started. What was described as "the answer" is not what the entrepreneurs are currently looking for when using AI-powered tools and also not in what AI-powered tools are currently good at. Entrepreneurs are looking for tools which help them make decisions faster and with more information without putting more time in themselves. With this research, I contribute to a growing field of entrepreneurship and digital tools in particular AI. By focusing on early-stage ventures and their real-world use of AI in daily decision-making, this study adds to the practical understanding of how decision logic is supported not replaced by technology. Next to that the findings are in line with earlier work by Reymen et al. (2015), showing that entrepreneurs shift between logics depending on the situation and stage, but also introduce AI as a new variable shaping this dynamic.

5.2 Conclusion

This research examined how AI-driven insights support causal and effectual decision-making in startups during the survival stage. Based on eight interviews with startup founders and a structured Gioia analysis, the findings show that AI is mainly used to increase efficiency, support decision-making, and help structure uncertainty, rather than to make autonomous decisions. Founders did not follow a fixed decision-making logic. Instead, most applied a "hybrid" approach in practice. They used AI both for planning tasks such as forecasting (associated with causation) and for adapting goals based on new information (linked to effectuation). Even those who tend to be strongly towards effectual thinking still used AI in ways that are typically associated with causal planning. This supports earlier findings from Reyman 2015 that decision-making logics are not static but shift depending on the situation. Across interviews, AI was described as a practical tool for saving time on repetitive and administrative tasks. In the context of the survival stage, where money is a big challenge and it is not possible to hire as many team members as might be needed, this time increment in efficiency can help to deal with one of the challenges from Winston and Churchill model. It allows founders and employees to focus more on revenue-generating work rather than operational tasks like formatting documents or checking emails for spelling mistakes. Tools such as ChatGPT and Microsoft Copilot helped free up time. AI was never used to replace human judgment. Founders mentioned that they review and check AI outputs, but trust and prefer their own judgment and haven't used AI to make decisions for them.
In response to the research question:
"How can AI-driven insights support causal and / or effectual decision-making in startups during the survival stage?"

The findings show that AI-driven insights can support both causal and effectual decision-making, depending on how the founder chooses to apply them. For causal tasks, AI provides structured information for planning, forecasting, and improving operational workflows. For effectual logic, it supports experimentation through help with brainstorming, flexible goal development, and decision-making under uncertainty as well as improving operational workflows. In both cases, AI acts as a support mechanism that strengthens, but does not direct, the entrepreneurial decision-making process. AI-powered tools are already a help for entrepreneurs and especially the improvements regarding the operational workflow and administrative tasks are a big advantage of AI-powered tools, since entrepreneurs have more time to focus on their value proposition and don't need to figure out excel or other programs.

6. LIMITATIONS AND FURTHER RESEARCH

6.1 Limitations

This thesis adds to the literature on entrepreneurial decision-making logic by exploring how AI-driven insights influence effectual and causal reasoning in startups during the survival stage. Still, some limitations need to be acknowledged. A more diverse sample especially including entrepreneurs from outside Germany, differences in gender and a broader number of different industries would help make it more generalizable. The startups interviewed had all already integrated AI in some way, which may bias the insights toward more AI-optimistic interpretations. Including startups that actively rejected AI or had negative experiences would offer a contrast and give an insight with the information from this study how and which practices these founders could use, that AI help them to overcome the challenges of the survival stage. Second, this thesis looked only at the survival stage of startups. That helped to understand how AI supports decision-making in a critical early phase, but it leaves open how AI plays a role in later stages like scaling or exiting.

6.2 Future research

Future research could further develop the concept of hybrid decision-making as an extension of the concept from Sarasvathy and building up on the research from Reymen (2015). While causation and effectuation are often presented as separate approaches, the interviews in this study suggest that founders combine elements of both in a flexible and situational way. This hybrid use becomes relevant when AI is introduced as a tool that supports both forward planning and adaptive behavior. As AI systems evolve and become more integrated into strategic workflows and founders are more familiar with AI-powered tools and their results, future studies should explore whether their role shifts from information support toward active participation in the decision-making process and also fully trust that decision making. In addition, research should be done in stages beyond the survival stage and investigate how AI usage and its influence on decision-making develop across different growth stages of a company. Comparative studies between early-stage and more mature companies could provide further insights into how the function and strategic weight of AI change as the organization grows. Practical implicants are the following. Entrepreneurs can use this finding to see AI as a tool they can use from beginning on. Not as a replacement but as a support tool for their decision making. It helps them dealing with big amount of data and bring structure into these, to make better decisions in the future. Next to that from the point on the venture hires people the founder knows that he needs to train his people with the usage of AI to make sure to get good results and use the advantages of AI.

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