Critical Success Factors for Implementing AI Technologies in the Context of Startup Business Operations

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AFFIDAVIT

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ABSTRACT

Given the foundational technological advances made in the field of artificial intelligence (AI) over the past few years, numerous businesses have begun to explore these technologies in the context of internal process optimization, automation and efficiency increase. Given their considerable potential to reach a critical size quickly, startups may truly benefit from such technologies with regards to aspects such as team expansion, streamlined accounting or market research, to name a few.

This thesis aims to explore the necessity and feasibility of AI technologies with regards to startup processes and operations. In order to understand these two aspects, the research revolved around the analysis of different critical success factors concerning the development, implementation and adoption of such AI technologies in this context. The findings are based on insights from a secondary data analysis in the form of a review of the existing literature as well as a primary data examination subject to semi-structured in-depth interviews.

The synthesis resulted in a ranged of different affirmative and contradictory insights with regards to the overall research topic. Large-scale internally-built AI infrastructures are arguably not economically viable nor of fulfilling purpose for startups. This is mainly due to resource limitations as well as uncertain economic periods. Nevertheless, such businesses offer very favorable traits and cultural facets in relation to a successful technological business transformation. Consequently, a viable option might be to test different third-party solutions in order to define different best practices and economic approaches. Once the two aspects of resource scarcity and economic uncertainty are not as prevalent anymore, such learnings could be used to impactfully turn towards more potent internal solutions and systems. Such could help to establish a considerable competitive advantage due to the vast number of use cases and possibilities these technologies offer.

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LIST OF ABBREVIATIONS

AI - Artificial Intelligence

ML - Machine Learning

DL - Deep Learning

NL - Neural Networks

ROI - Return on Investment

AGI - Artificial General Intelligence

ASI - Artificial Super Intelligence

CNN - Convolutional Neural Networks

RNN - Recurrent Neural Networks

KPI - Key Performance Indicators

NLU - Natural Language Understanding

NLP - Natural Language Programming

CRM - Customer Relationship Management

1 INTRODUCTION

1.1 Context, Previous Research & Key Developments

Over the past few years, the field of artificial intelligence (AI) has experienced a stark increase in research, investments and deployment across various different industries due to its truly significant potential (Balakrishnan, Chui, Hall, & Henke, 2020). As a result, the number of use cases and capabilities has also exploded considerably. Numerous businesses around the globe are deploying AI technologies in order to automate, streamline or improve various business processes in an attempt to establish a clear competitive advantage (Canals & Heukamp, 2019). Such technologies are deeply embedded in the business infrastructure and require a completely different perspective or rather understanding in comparison to conventionally perceived products or services associated with AI such as smart home devices or autonomous vehicles, to name a couple of prominent examples.

As highlighted by an article in the Harvard Business Review (Davenport & Ronanki, 2018), three main types of AI can be outlined in order to define such capabilities and initiatives. The first type of AI would be process automation. It is the most common category and encompasses the automation of digital or physical tasks. Due to its affordability and easiness to implement in comparison to the latter two categories, the authors argue process automation can wield the highest return on investment (ROI) for companies. Cognitive insight is the second capability concerning such internal AI applications and revolves around using algorithms to highlight clusters and related patches in immense data sets. Given the fact that such algorithms and networks have to recognize, classify, link and store vast amounts of different data files, this category is significantly more expensive and difficult to implement efficiently as well as effectively (Halsey, 2017). Lastly, the authors define cognitive engagement as the third discipline where AI technologies are applied in business. Despite this category being the smallest when it comes to the commonality, it is arguably the one which features the most recognizable AI technologies such as natural language processing (NLP) algorithms, smart assistants as well as recommender systems for employees as well as customers. The difficulty and thus required level of sophistication here stems from the intended interaction with humans (Roukos, 2020). As showcased above, there is a multitude of different projects or use cases companies can use AI technologies for to enhance anything ranging from small processes to entire business models. The benefits resulting from such implementations or overall transformations are multifaceted that can include anything from considerable revenue increases and operating expense reductions to improved employee and customer satisfaction rates as well as more detailed insights and analytics for better decision-making across the entire business spectrum (Accenture, 2021). However, according to a recent survey by Accenture, the stakes are even higher due to the fact that 75% of executives consider going out of business within the next five years a great possibility if AI is not scaled successfully and 84% of the same pool agree to not be able to reach set growth targets without the power of AI (Reilly, Depa, Douglass, & Berkey, 2019). Businesses of all sizes will have to adapt accordingly despite the oftentimes high initial investment in such technologies as the long-term benefits and advantages far outweigh the short-term obstacles.

However, not all companies are created equally or depend on the same variables. According to Steve Blank's widely accepted definition, "a startup is a temporary organization designed to look for a business model that is repeatable and scalable" (Areitio, 2018). Whereas he describes an existing company as "a permanent organization designed to execute a business model that is repeatable and scalable" (Areitio, 2018). Startups face numerous challenges such as revenue generation, customer retention, business model validation or limited resources and funding, to name a few (Lauchengco & Wilson, 2018), in order to reach the status of an established company as highlighted by the definition above. As a result, the focus to implement various types of infrastructure to automate and streamline different complex processes is seemingly not of great importance to founders in the early stages of a startup. Nevertheless, if certain variables and metrics are successfully met, a startup can quickly move through various decisive stages and reach scalability. This is where AI technologies are are becoming increasingly crucial concerning a company's business efficiency, value proposition and thus overall competitiveness, as discussed previously. The highlighted stages in this case are existence, survival, success, take-off and resource maturity (Churchill & Lewis, 1983). According to this model, a startup could face exponential growth between the stages of survival, success and take-off. Limiting factors that are often encountered prior to this potential rapid growth phase, such as a lack of financial resources or human capital, may not apply in the not too distant future. Therefore, a proactive approach with regards to setting the company up for the potential next stage might arguably a strategically smart decision, despite the initial costs and resources used.

1.2 Research Aims & Objectives

Despite the fact that research concerning the adoption rates, the vast range of use cases and most importantly the significant benefits of AI technologies in business operations and processes has considerably increased over the past few years, startups have noticeably been left out of this consideration and discussion. This paper including its literature review and empirical research aims to answer the following key research question:

What are the critical success factors concerning an impactful implementation of AI technologies in startup business operations and processes?

The focus here lies on understanding as to whether such a significant investment in a stage prior to reaching scalability would entail a considerable competitive advantage in the long-term seeing as the business would then be able to operate much more efficiently once it reaches the point of rapid expansion. In order to thoroughly understand this issue, the literature review as well as the empirical research of this paper aims at analysing such key success factors based on staff-, business-, and technology-related contexts and decisions. Factors such as the measurability of the ROI, barriers other than financial constraints as well as the overall awareness and capabilities of teams to adopt such technologies are also embody important considerations in this research. Generaly speaking, answers to this research question and overall approach are thouroughly discussed in the literature review as well as within in the scope of the empirical research of this study. The methodology and precise structure of this qualitative analysis are thouroughly outlined in the corresponding chapter of this paper.

1.3 Structure of Thesis

In general, this thesis entails five sections. After the initial introduction to the topic and the overall research objectives, the extensive literature review thouroughly outlines the key definitions, concepts, and current as well as potential future use cases surrounding various AI technologies in the area of internal business processes and operations as outlined in the introduction of this paper. Furthermore, this section also addresses diverse aspects about startups too such as some of the main differences to established companies, frequent limitations, overall scalability and possible growth models as well as potential touchpoints with AI concerning commonly entrenched business infrastructures. Secondly, the overall structure and approach concerning the qualitative research of this study are described in the subsequent section of this paper. In this chapter, the overall research desing, strategy and methods are comprehensively highlighted. In addition, this section also determines the precise candidate pool and the further chosen criteria points concerning the selection. Furthermore, the defined interview questions are also outlined in this chapter. Thirdly, the findings and results stemming from the qualitative interviews are thouroughly discussed. This includes all patterns and key insights with regards to answering the main research question along with the set hypotheses. Lastly, all of the information gathered in this study are highlighted in the last section of the paper including any encountered limitations as well as potential future research.

2 LITERATURE REVIEW

2.1 Introduction & Topics Overview

The literature review of this paper aims to thouroughly highlight and discuss several key topics in relation to the previously outlined research questions as well as the subsequent empirical research. To begin with, artificial intelligence forms an intergral part of this study. As a result, the first part of this literature concerns the discussion of different definitions as well as a brief historic overview of this discipline of computer science and some current use cases or rather technological and economic developments. The section thereafter provides a more detailed breakdown and analysis of different AI-related fields of study. More specifically, these fields are highlighted following a narrowed-down approach from the most overarching AI layer, namely, strong and weak AI technologies, to the subcategory machine learning and its subcategory deep learning. The goal is to illustrate the status quo of this technology as well as potential use cases for businesses and ultimately startups. Subsequent to this first large topic, this paper analyses different pieces of literature concerning AI in business operations. The aim here is to highlight the dawn of a new era of digital business transformation and outline different approaches as to how stakeholders can anticipate and correspond to such. The key factor in this case concerns the human element as it is the all encompassing variable with regards to a successful anticipation, transition and evolution of this technology in a business and startup context. Lastly, three concrete success factors concerning the implementation of AI technologies in startup processes are outlined. This section also describes different factors that arguably even favour such businesses when it comes to this technological adoption. These chapters aim at establishing the underlying validation for the corresponding empirical research.

In addition to setting the foundation for the subsequent empirical research, the literature review also intends to highlight a current lack of correlating links in the current knowledge. All previously mentioned topics, namely, artificial intelligence, its potential in a business context and startups, are all thoroughly documented. Nevertheless, there are hardly any studies or pieces of literature that combine these elements. In the long-term, such technologies will undoubtedly play an indispensable role in the operating model of any business. As a result, correlating existing pieces of study in this context might provide a foundation for further research in this field.

2.2 Artificial Intelligence

2.2.1 Definition, Brief History & Key Developments

According to numerous modern day definitions, artificial intelligence forms a sub-field of computer science that encompasses various disciplines with regards to computer systems imitating human intelligence to solve a wide range of complex tasks such as visual material or speech recognition, amongst others (Marr, The Key Definitions Of Artificial Intelligence (AI) That Explain Its Importance, 2018a). Due to this approach towards human behaviour and tendencies, the field of AI is also heavily linked to areas such as psychology, biology, philosophy and linguistics (van Duin & Bakhshi, 2017). However, there is no officially agreed upon definition as the field of AI is continuously being reformulated. In addition, AI processes oftentimes differ significantly from each other and may consist of a wide range of emerging and established technologies such as multilayered deep neural networks and conventional sensors, respectively. This results in numerous domains then being termed or associated with AI which complicates the general understanding and classification of the subject (Rao, 2016). Therefore, it is more practical to refer to the extent to which AI technologies are used in any given method or initiative rather than speaking in absolutes such as "an AI" solution.

Despite the rather recent boom concerning the theory and development of AI technologies in the public eye, the concept of thinking machines has been around for decades. Besides some initial science-fiction-based approaches including works such as the *Wizard of Oz* or *Metropolis*, it was a collaborative effort of different scientists in the 1950s to truly approach this matter (Anyoha, 2017). Alan Turing, though restricted by the limitations of the technologies at the beginning of the decade, was the first to academically or rather theoretically discuss the concept of machines fulfilling human-level intelligence tasks in his 1950 paper, *Computing Machinery and Intelligence*. The term artificial intelligence was then first used by John McCarthy and Marvin Minsky in 1956 as the two hosted a cross-disciplinary conference named Dartmouth Summer Research Project on Artificial Intelligence. Despite the conference not holding up to McCarthy's expectations, the main hypothesis of AI being achievable was clearly answered positively. In addition, it also included the presentation of the first AI problem-solving program by Newell, Shaw and Simon termed *Logic Theorist*. After an almost two decade-long period of major developments stemming from various projects and the subsequent funding made available, critique from the U.S. Congress as well as a delegated report by the British Science Research Council resulted in major cuts of public backing for these projects (Haenlein & Kaplan, 2019). This was mainly due to the fact that first limitations with regards to computing power as well as to data storage concerning command memory and thus a lack of practical applications emerged. This period is now being referred to as the *AI Winter*. However, these initial limitations were overcome during the 1980s as numerous advances in technology were made. As a result, funding for such projects also saw a subsequent increase and considerable developments such as deep learning methods, which uses past experiences to learn, or expert systems, that imitate human-like decision-making processes, to name a few, were made (Anyoha, 2017). By the end of the 1990s, a large percentage of the set and then possible milestones were achieved. For instance, in 1997, IBM's *Deep Blue* AI-powered chess program beat the then world champion Gary Kasparov and a program for speech recognition was put into action on Microsoft's *Windows* (Anyoha, 2017). Seeing as computational processing power and storage have improved exponentially over the past decades (Mack, 2011), modern-day computers are now able to realize some AI use cases on a mass scale. The necessity for more processing power in the near future for more advanced solutions might not even apply as more sophisticated types of machine learning (ML) or more specifically deep learning (DL) are emerging, as highlighted in the subsequent chapters of this paper. AI technologies already form a crucial part in our everyday lives and numerous enterprises have already realized the fundamental transformation required in order to remain competitive by establishing automated decision-making procedures, data processing and storage infrastructures as well as communicating interfaces (Haenlein & Kaplan, 2019).

2.2.2 Key Concepts, Terminology & Definitions

2.2.2.1 Strong vs. Weak AI

Artificial intelligence can very broadly be classified into two categories, namely, strong and weak AI. Weak or narrow AI consists of the established forms of AI today that are designed to fulfil specific functions. Nevertheless, this category is already capable of and responsible for major innovative breakthroughs across a multitude of industries including smart assistants and self-driving vehicles (IBM Cloud Education, 2020a). As it currently stands, narrow AI is also the overarching category under which the various systems and concepts for improved business performance and streamlined operations can be classified into as highlighted in subsequent chapters of this paper. Strong AI on the other hand, can be classified into two sub-groups, namely, Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). Both of which currently only exist in a theoretical context with AGI representing machines with equal intelligence and ability in comparison to humans. This would be achieved on three levels, namely, the capacity to summarize and use vast amounts of data and information from certain domains and use such in relation to others, the capability to predict future outcomes based on past experiences and data and the competence to adjust to any given environmental change (Walch, 2019). All of the three aforementioned aspects require a fundamental understanding of such AGI technologies. Only then can the definition of a strong AI be used according to the American philosopher John Searle as otherwise they would just be a simulation. Others go even further and demand only machines with an actual conciousness be called strong AI (Walch, 2019). ASI would arguably achieve this as it surpasses human-level cognitive intelligence and ability in theory. Evidently, it is thus currently best represented by various pieces of science-fiction as it does not yet exist (IBM Cloud Education, 2020a). The previously mentioned issue concerning a lack of definition is also evident in this case and thus often times results in general misunderstandings or wrong associations. A more practical approach according to Walch (Walch, 2019), would be to avoid categorisations according to definitions and focus on a ranking of the cognitive ability of such machines to solve certain tasks ranging from simple one-dimensional challenges to such that are multi-facetted and not executionable by humans.

2.2.2.2 Machine Learning

Machine Learning (ML) is one of the key subdivisions of AI. It revolves around the concept of using algorithms fed with large amounts of data to learn and gradually improve the computed results (IBM Cloud Education, 2020c). A strong emphasis with regards to the actual processing of the data stems from statistical processes and probability calculations. Based on these classifications, clusters and predictions, the different observations can then be used for decision-making. According to UC Berkely and Dr. Michael Tamir (Tamir, 2020), three main parts with regards to the structure of the learning system of such algorithms can be defined:

1. **A Decision Process**: This aspect concerns the aforementioned predictive computations based on the classification and clustering of data. The identification of patterns is the quintessential focus in this case.
2. **An Error Function**: This analysis assesses the final prediction based on past examples. In case the result was wrong, the model aims at quantifying the degree of inaccuracy.
3. **An Optimization Process**: Depending on the result, the algorithm then incorporates the generated feedback so that the accuracy increases for the next prediction run.

This rather autonomous updating and gradual analytical improvement is what makes ML so valuable for a great number of different processes due to the vastly reduced amount of human interference. Through this continuous learning, the algorithm is then also able to highlight previously unknown insights even though its programming originally serves a different purpose (IBM Cloud Education, 2020c). The specific use cases concerning applications in business processes are highlighted later on in this paper. The way such feedback is highlighted and then implemented also depends on the type of learning model applied by the algorithm. In general, there are four specific categories, namely, supervised learning, unsupervised learning, semisupervised learning and reinforcement learning (Tamir, 2020).

First, supervised learning uses pre-defined and labelled training data sets by humans in order to determine and subsequently continuously improve the accuracy of the predictions and results. Different forms of the loss function, with which the deviation between the predicted outcome of the algorithm and the actual true result is scored, in this case are the tool to further attune the accuracy of the model over time (Sushant, 2020). According to IBM (IBM Cloud

Education, 2020d), supervised learning can generally be categorized into two groups, namely, classification and regression. Classification is the algorithm's approach to classify test data into certain groups by highlighting specific variables within the data set. Prominent examples of classification algorithms are linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbor, as well as random forest (IBM Cloud Education, 2020d). Secondly, regression helps to comprehend connections between dependent and independent variables particularly in the case of timely projections such as revenue developments. Important models are linear, logistical, and polynomial regression (IBM Cloud Education, 2020d). Both offer valuable capabilities in the areas of business analytics and forecast.

Secondly, unsupervised learning is used to dissect and group unlabelled data sets based on hidden patterns without the requirement of human interference. These capabilities make such algorithms great tools for exploratory data determination, cross-selling approaches, customer segmentation, and visual recognition (IBM Cloud Education, 2020e). Similarly to supervised learning, unsupervised learning offers different approaches, namely, clustering, association, as well as dimensionality reduction (IBM Cloud Education, 2020e). First, clustering focuses on the grouping of unlabeled raw sets of data based on certain common or uncommon variables. Clustering algorithms can be classified into different categories including exclusive, overlapping, hierarchical, and probabilistic algorithms (IBM Cloud Education, 2020e). Association rules on the other hand use a similar approach concerning the grouping of unlabelled data sets but are primarily focused about highlighting associations and trends between different elements (Wagle, 2020). The most frequently used algorithms when it comes to association rules are the Apriori algorithms. They have becoming increasingly popular through their potential concerning the understanding of consumption behaviour and have consequently been widespredily applied for recommendation engines aimed at boosting cross- and up-selling efforts (IBM Cloud Education, 2020e). Lastly, seeing as the number of variables and features in vast commercial data sets can complicate the processing and classification of algorithms, dimensionality reduction algorithms are commonly used in the preprocessing of large data sets (Gour, 2019). These minimize the quantity or range of data entry points to a manageable number while maintaining the dataset's integrity to the greatest extent possible. Prominent algorithm examples include principal component analysis, singular value decomposition or autoencoders (IBM Cloud Education, 2020e). Generally speaking, unsupervised learning algorithms provide a wide range of potential use cases as their ability to identify patters is very valuable concerning exploratory approaches in the areas of market analysis or quality assurance, to name a few. Popular areas of application include computer vision or object recognition solutions in industrial or medical environments, recommendation engines in e-commerce or market analysis tools ranging from customer persona creation to campaign automation software (IBM Cloud Education, 2020e).

Semi-supervised machine learning can be described as a practical hybrid approach between supervised and unsupervised machine learning (IBM Cloud Education, 2020c). This method is particularly useful as it uses a small section of labelled data to give the algorithms an indication on how to proceed with the grouping and classification of very large unlabelled data sets (Maxime, 2019). This can help to lower the development and operating costs of such processes significantly as labelling data sets for algorithms is time and resource intensive while also increasing the improvement rate in comparison to purely unsupervised models (Salian, 2018). Common use cases include text and visual recognition applications in product development and media as well as in scientific research and medicine.

Lastly, reinforcement learning is an approach that focuses on gradual improvements over time through feedback (Jones, 2017). More specifically, such algorithms are aiming to discover the best method for achieving a certain objective or improving their performance on a specific activity. They base their decisions on historical feedback as well as the analysis of new approaches that may offer a higher payout (Salian, 2018). The more feedback and rewards are given through reinforcement signals, the more accurate and the more agile an algorithm becomes. Reinforcement learning is generally best suited for deployment in uncertain areas where such algorithms have to make decisions by themselves. A standout example would be autonomous driving or managing inventory (Salian, 2018).

There is no best or worst approach in terms of capabilities as the aforementioned systems fulfil different needs (Jones, 2017). The crucial aspect concerns the selection of the most suited machine learning method depending on the area of application or use case (Salian, 2018). Particularly when it comes to business infrastructures and processes, all four models excel at different disciplines. Stakeholders must consequently have a holistic approach concerning the setup of their infrastructure.

2.2.2.3 Deep Learning

Deep learning can generally be classified as a subset of machine learning that describes neural networks with more than two layers. Neural networks are the building blocks for deep learning algorithms. Such networks consist of four key components: inputs, weights, a bias or threshold, and an output (Kavlakoglu, 2020). These networks use similar processing actions to that of the human brain, although far less complex, to autonomously acquire and process information. Even though a single-layer neural network, such as a more general ML algorithm, may produce quite accurate predicted outcomes, adding more layers can drastically improve the overall correctness of the results (IBM Cloud Education, 2020b). Deep learning networks and algorithms power a large number of currently established AI use cases due to their capabilities when it comes to improving process automation for businesses as well as generally executing analytical and tangible assignments without the need for human interference (IBM Cloud

Education, 2020b). Prominent examples include smart assistants in numerous areas, digital programs used for tasks such as fraud detection in retail and the finance sector as well as truly complex tasks ranging from autonomous driving to high-level simulations (IBM Cloud Education, 2020b).

In comparison to various machine learning methods, deep learning approaches do not require some sort of pre-processing as highlighted previously in the case of dimensionality reduction in order to process large unlabeled amounts of data (Marr, 2018b). Deep neural networks are made up of numerous layers of interconnected nodes, each of which improves and refines the final prediction or result. Forward propagation refers to the progression of calculations across the network. Backpropagation on the other hand focuses on the analysis and reflection of potential errors and weight calculations continuously from past computations. In combination, both help to determine crucial features for the classification of data, reflect on potential errors and improve their accuracy accordingly over time without the need for human interference (IBM Cloud Education, 2020b). This structure of multiple layers including multiple nodes and the corresponding numerous processing steps through which deep learning neural networks can be so independent and efficient is highlighted in the figure below.

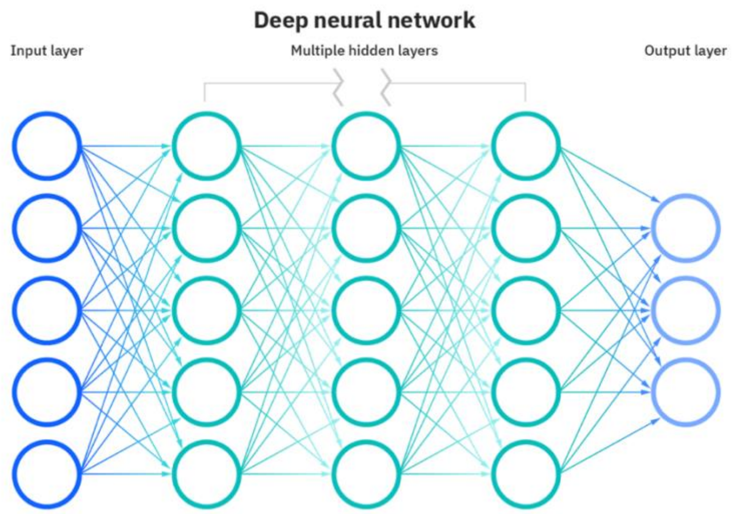

FIGURE 1 - DEEP NEURAL NETWORK STRUCTURE (KAVLAKOGLU, 2020)

Generally speaking, there are two main types of deep learning algorithms, more specifically, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). CNN is mainly used for computer vision applications and visual recognition models. RNN on the other hand is ideally suited for natural language and speech recognition use cases due to its ability to follow sequential data inputs (IBM Cloud Education, 2020b). Deep learning algorithms are generally very complex and require very large amounts of quality data to improve. Nevertheless, they can be considered as the natural next step of AGI algorithms. This is due to the fact that data creation is at an all time high and continuously increasing. Furthermore, computing power has also drastically improved over the past few years. Both factors empower deep learning networks to offer the best results for multiple use cases in comparison to simpler machine learning models (Marr, 2018b).

Overall, all of the aforementioned definitions and terminologies overlap in numerous areas and must be considered as an interconnected entity. This is why some examples and business use cases applied in different categories. Generally speaking, these disciplines can best be described or categorized in a Matryoshka doll as showcased in the figure below. AI is only the broad terminology for all of them and consequently can be broken down into these various fields of study and practice.

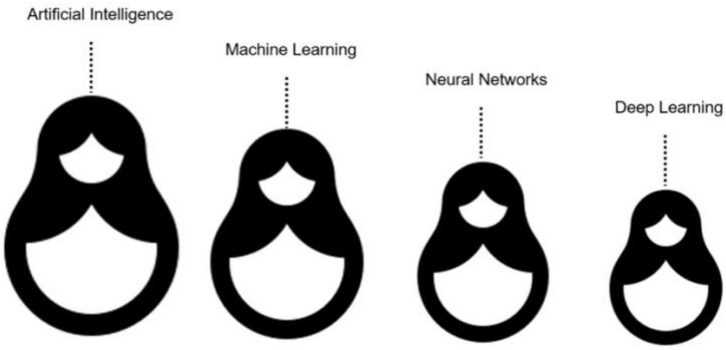

FIGURE 2 - AI LAYERS (KAVLAKOGLU, 2020)

The more powerful computing power becomes and the more use cases due to a drastically increasing amount of data creation emerge, the more resources and time will be invested in the development and applicability of more refined AI algorithms. Deep learning neural networks are currently the most advanced state with regards to overall capabilities and proximity to AGI. Due to the technology's incredible potential, numerous companies are already deploying AI solutions across a multitude of use cases. This crucial next step of digital transformation is further highlighted in the subsequent chapter of this paper.

2.3 AI in Business Processes & Operations

2.3.1 A New Era of Business Transformation

Despite some previously established use cases and examples, the majority of companies is still trailing behind when it comes to the widespread adoption of AI technologies across the entire business spectrum. As stated in the introduction of this paper, this next phase of digital transformation is already an inevitable reality for businesses, regardless of size, industry or location. Due to their ability to significantly reduce costs and increase revenues through various process optimizations, it is believed that such AI technologies and solutions will contribute $13

Trillion to the economy by 2030 (Fountaine, McCarthy, & Saleh, 2019). According to a poll of thousands of executives about the deployment and organization of AI technologies in their firms, only 8% of companies engage in fundamental methods that allow universal adotion as most companies so far have only conducted pilot programs or used AI in very one-dimensional and isolated use cases (Fountaine, McCarthy, & Saleh, 2019). This is due to a number of different issues ranging from an misinterpretation of the true scale of this technology and an excessive amount of inbound reasoning to an evasion of responsibility of decision-makers, too broadly defined goals concerning the term AI transformation and digitization as well as incrementalism with regards to the actual commitment when it comes to funding and resources allocated towards such projects (Pettey, 2020).

One of the most considerable misunderstandings by managers and decision-makers is to regard AI as a ready-to-use solution with instant yields. Companies often invest immense sums of money in data infrastructure, AI software and data analysis tools as well as model improvement initiatives after deciding to focus on a handful of individual projects (Fountaine, McCarthy, & Saleh, 2019). Some of these ventures are able to achieve minor successes in specific areas but fail to establish some sort of true cross-discplinary and -departmental impact hoped for by these executives. Companies often encounter issues during the transition from pilots to business-wide systems and, more importantly, perspective-wise, shifting from concrete business challenges, such as an improved campaign analysis to enhancing the customer journey as a whole (Fountaine, McCarthy, & Saleh, 2019). Leaders are also prone to oversimplifying AI requirements. While disruptive technology and expert human capital are essential, a corporate culture, structure, and the established working methods must also be aligned to promote an expansive AI adoption across the entire firm. Conventional attitudes, processes and routines, on the other hand, are incompatible with an overarching AI transformation (Fountaine, McCarthy, & Saleh, 2019).

In order to overcome this issue as well as the more broadly defined ones highlighted in the section above, three initiatives concerning the overall attitude and approach of companies wanting to make this change can be outlined. First, corporate departments have to move from working in silos to interdisciplinary cooperation (Fountaine, McCarthy, & Saleh, 2019). This approach would help enterprises to not only develop AI solutions that span across different business disciplines but it would also foster an overarching understanding and perspective of employees. That way, certain requirements and business-specific particularities for such AI solutions could be anticipated early, saving development resources, while also increasing adoption rates (Fountaine, McCarthy, & Saleh, 2019). In light of the three highlighted business dimensions of this paper, namely, staff-, business-, and technology-based contexts, this would facilitate the transition on all levels. People would be more educated and involved in during the conceptualization, roll-out and improvement phases. This in turn improves the overall experience and adoption rate, costs could be reduced as potential bottlenecks can be anticipated early and the technology itself could be tailored to the specific demands of the business as each company differs drastically in terms of numerous variables.

Second, it is imperative for companies undergoing such a transition to move from experience-based to data-driven decision making (Fountaine, McCarthy, & Saleh, 2019). This factor is essential during the implementation of such technologies as it would, on the one hand, foster a more proactive approach from the leadership side, as well as, on the other hand, reduce costs significantly in the short- and long-term once AI infrastructures using big data have been deployed (Stobierski, 2019). As soon as the initial implementation phase has been completed, employees at all levels will supplement their own acumen with algorithmic recommendations. This machine-human collaboration in itself is more effective than either of the two alone. However, in order for this to work, employees at all levels must have faith in the algorithms' recommendations while also being empowered and encouraged by the leadership to make decisions. Consequently, it is indispensable to depart from a vertical hierarchy and decision-making (Fountaine, McCarthy, & Saleh, 2019). When it comes to the three dimensions, this aspect most affects the staff-related contexts as it requires a company-wide structural change. Upon a successful completion of this transition, the other dimensions would also experience a shift with cost reductions and more efficient processes from a business perspective as well as a more effectively communicated and implemented development of the technologies applied.

Lastly, in addition to changing the overall decision-making, a company's mindset and approach concerning risk aversion also has to evolve towards a more agile, flexible and experimental approach (Fountaine, McCarthy, & Saleh, 2019). Due to their nature of improving over time through more iterations and feedback, AI algorithms and particularly more complex structures, are hardly ever fully efficient and functional from the beginning. This process requires time and would in the meantime probably lead to some miscalculations and misinterpretations. Employees have to be encouraged to proactively understand this process in order to continuously collaborate with each other to minimize any initial errors that could affect the business. Nevertheless, such will most likely happen in the beginning of such a transition. However, this must not lead to a complete disregard and discontinuation as the long-term benefits are more important than smaller initial setbacks. Consequently, this factor affects all three dimensions as a failure culture must be clearly communicated and encouraged amongst the workforce, smaller setbecks with reagrds to the business performance must be considered as necessary hurdles in the short-run from a business perspective and the technology must be proactively supported in order to yield the desired efficiency and long-term benefits for the company.

These three factors apply for companies of any size and industry concerning such a technological transition as all three dimensions are heavily affected. Large coporations might encounter more issues with regards to the intangible factors such as data-driven decision making, staff empowerement and risk tolerance due to the established culture. Changing such can also result in high monetary and resource costs. Startups on the other hand, are by their experimental nature, as discussed in the last section of this literature review, much closer to these required structures. Furthermore, team sizes are drastically smaller and more dynamic. This could consequently imply a more significant long-term success with regards to an AI business transformation as any cultural barriers or setbacks, caused by internal resistance, would not apply in comparison, even upon reaching scalability. Nevertheless, despite these clear recommendations and required action steps, there is still a large gap between the current state of affairs and the desired boost concerning operational effectiveness, creativity and productivity as well as financial efficiency.

2.3.2 Bridging The Gap

As highlighted in previous sections, both sides, namely, the human element as well as the algorithm aspect, stand out with very important but unique traits. Humans are obviously more creative, impromptu, judgemental and social while machines excel more at accuracy, processing speeds and scalability. In order for this overarching transformation to work, companies will have to focus on embracing the strengths of both parties as none of the aforementioned business benefits can be achieved by one fraction alone. This symbiosis is what will redefine working positions, processes and business approaches in an entirely new way. All too often, companies focus solely on the technological aspect of such a transformation but seeing as this spans across all three dimensions, namely, staff-, business- and technology-related contexts, a broader perspective and approach is required. In their book *Human + Machine*, authors Paul R. Daugherty and H. James Wilson (Daugherty & Wilson, 2018) further highlight a gap that describes the complementary elements that each side can additionally contribute to the overall benefit of the business as shown in Figure 3 below.

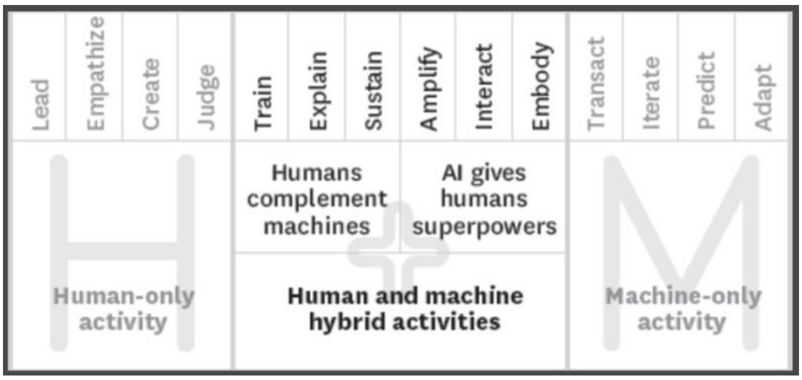

FIGURE 3 - THE MISSING MIDDLE (DAUGHERTY & WILSON, 2018)

Referred to as "The Missing Middle", the authors highlight this intersection of disciplines and abilities perfectly as such fundamental AI transformations enable both sides to not only fully focus on their respective strengths but also collaborate extremely effectively in a completely new layer which drives overall improvements across the entire spectrum (Daugherty & Wilson, 2018). This in turn creates numerous new tasks for existing positions and will create a number of new roles across a multitude of different disciplines. Six main areas arise that will have to be covered by staff with high expertise in different disciplines such as accounting, marketing or human resources as well as by new roles that focus entirely on the technological aspect and its execution. In the case of startups, these roles will also have to be covered though various resource-related barriers will undoubtedly arise in comparison to large companies. Nevertheless, by setting the foundation with initial pilots and the right structural as well as cultural approaches, such companies can subsequently deploy a successful and more widespread approach upon overcoming these resource-specific hurdles in the beginning.

To begin with, the training aspect with regards to the implementation and maintenance of these algorithms has to be highlighted. Indeed, there has been a shift from people having to adapt to machines to now machines learning how to best serve humans. Nevertheless, to get to an efficient and effective level of collaboration, initial rigorous training as well as continuous maintenance is absolutely key (Daugherty & Wilson, 2018). From a technological standpoint, this training comes in the form of active and passive ML approaches tailored to the required tasks. From a human perspective and depending on the scope of AI technologies deployed across different business disciplines, different roles are required concerning this continuous training. For instance, in the case of a chatbot solution as an additional customer service touchpoint, this can range from simple objectives such as NLP fine-tuning to truly complex AI tasks such as mimicking human behaviour and showing empathy (Daugherty & Wilson, 2018). Two areas are crucial with regards to the trainer element, namely, interaction modelling and data wholesomeness (Daugherty & Wilson, 2018). Interaction modelling or design in this case refers to the implementation and continuous interation of the overall technology infrastructure as referred to later on in this paper. Data wholesomeness on the other hand, describes the aforementioned discipline of using filtered and consequently proper data with regards to the specific use case. When it comes to startups, resources are not as readily available. As a result, such companies have to focus on the essential elements of their business structures or value offering, depending on which area the focus lies. By deploying initial AI trainer pilot initiatives in the form of hiring new staff or empowering and enabling existing team members, best practices and methods can be tested early which in turn provide a solid foundation for more graduated systems upon the company reaching scalability. This is also in line with the previously highlighted cultures prominent in most startups due to their experimental nature. When it comes to the training element of this gap, the staff-specific dimension is arguably the most important one as it sets the foundation in startups for the respective technologies and the corresponding sophistication deployed which ultimately affects the business-related dimension in the mid- to long-term.

Secondly, the interpretation of the working processes and approaches of the algorithms as well as the one of the actual results form the second category within this interdisciplinary framework. In a larger business environment, hiring specialists for such roles is a clear cut solution though a general understanding of these workings will be essential for employees across all positions. Similarly to the training category, two main task objectives stand out, namely, an algorithm analysis and interpretation strategy (Daugherty & Wilson, 2018). The first position fulfils overlapping tasks with trainers as errors are highlighted and corrected though this role primarily focuses on understanding the fundamental workings of the corresponding algorithm and why a given error happened in the first place. The interpretation strategy on the other hand not only focuses on analysing the results but also on how AI systems can be best deployed for specific use cases based on the given results (Daugherty & Wilson, 2018). When it comes to startups, the latter role is arguably more crucial as the first one can theoretically be approached by trainers as well. However, understanding and anticipating which algorithm best fits for each dedicated business application is a vital role as iterations and late pivots can be quite costly. Due to the resource constraints of startups, this is a vital factor. The staff dimension again has to be in the spotlight by decision-makers in this case as the right appointments affect any technology-related outcome and ultimately the business performance as a whole.

Thirdly, sustaining positions would be responsible for the proper execution and running of these algorithms (Daugherty & Wilson, 2018). They are the controlling element on a multitude of levels ranging from the checking of input and output data, flagging errors as well as setting limits and discussing any legal or ethical issues with the leadership team. Overall, their task is to establish a solid trust foundation in these technologies by all internal and external stakeholders. Trust is one of the main challenges when it comes to adoption rates of such technologies, due to factors such as intrusion, a lack of familiarity as well as a lack of general regulation (Gillespie, Lockey, & Curtis, 2021). Such barriers must be overcome in order to accelerate overall adoption and acceptance levels. One factor that could prove vital in this case is ethics compliance. This would include aspects such as the avoidance of biased and discriminating interaction between the machine and certain social groups as well as the monitoring and analysis of ethical business pracices. If sustainers manage to adequately address such issues from the beginning, it would increase trust levels in such systems in general. Furthermore, sustainers also have to keep track of the scaling of such solutions. This could be described as an inter-relationship management discipline between humans and machines aimed at understanding and influencing the non-economic impact during large automation processes to avoid any shifts in acceptance levels (Daugherty & Wilson, 2018). Lastly, this also includes performance assessment tasks of machines as opportunity areas must be highlighted in order to drive business performance. Similarly to the previous roles in relation to start-ups, sustaining roles and positions might not be realizable at first with especially deployed staff members due to the aforementioned financial barriers. Nevertheless, if occupied successfully by existing employees or leadership team members, the business can be set up in the right way until such barriers can be overcome. Again, this transformative element focuses primarily on the staff dimension with any technological or business-related impacts being subsequential chain reactions. Despite this, such can be detrimental for start-ups upon scaling up as it would drive business efficiency and operational effectiveness as well as initially establishing the cultureal foundation for a collaborative interaction between humans and machines.

The previously three highlighted roles focus more on sustainably improving the various AI systems in place to continuously drive performance way beyong the point of sole implementation. The second part of the proposed bridging of this gap by Daugherty and Wilson (Daugherty & Wilson, 2018) aims at highlighting how working systems based on their fundamental capabilities can already elevate the performance of employees on a multitude of levels. First, the outlined amplification element (Daugherty & Wilson, 2018) is arguably the most commonly perceived and already deployed discipline. Despite a vast number of potential future use cases and areas of opportunity, amplification tasks already provide significant support for various tasks. One example would be generative design suggestions for campaign and business assets based on previously used shapes and styles as well as similar ones from other parties (Daugherty & Wilson, 2018). Another example would be the analytical determination of customer reviews and corresponding action suggestions. Reviews are immensely important for product or service information research as 94% of online customers read such prior to making any purchasing decisions (Anderson, 2018). Thorough analyses as well as constructive interactions with customers through comments, both of which AI also assists with and assumes, businesses can truly elevate their customer relationship management (CRM) efforts. There are numerous other examples ranging from enhancing quality control performances in production lines to improving accuracy levels of diagnoses of medical personel through two factor - machine then human - analyses (Daugherty & Wilson, 2018). In the case of startups, such amplification tasks can prove inherently valuable for factors such as market and customer research with regards to time and cost efficiency and overall effectiveness concerning subsequent insights and results. Consequently, the three dimensions have to be highlighted in this case. Through continuous training that would improve the overall efficiency and accuracy of such AI solutions, the technological dimension would in the long-term significantly benefit as algorithms would more inherently understand the specific requirements and processes of a given business. When it comes to the staffing dimension, people would be less occupied with analytical processing tasks, amongst others, and can consequently pursue other more human-suited initiatives such as creative design, strategy planning as well as CRM-focused efforts. Both dimensions drive business performance in the short- and long-term. Due to this as well as due to all of the the insights and data points gathered from such a process, growth of the third dimension is innately promoted.

The second pillar of the machine-driven business and people advancement segment concerns the elevated interaction between humans and algorithms (Daugherty & Wilson, 2018). This can apply in both cases, namely, for internal external touchpoints as well as products or services in the form of chatbots, voice assistant, robo calls, request processing, training or illustration as well as numerous other applications. Depending on the given use case, startups can benefit from such functions internally when it comes to HR-specific topics as well as externally. However, it has to be mentioned that customer interaction points such as chatbots have to be deployed carefully and consequently require prioritization by the corresponding stakeholders as poorly trained algorithms in this case can negatively impact the overall customer experience (Harper, 2019). Such a focus on external touchpoints in relation with products and services might arguably be better suited for later initiatives. Nevertheless, when it comes to onboarding or training efforts as well as other HR-specific requests, such AI solutions can be of great use even for startups. The staff dimension would be the one that clearly benefits the most in this case as interaction processes become automated and less stakeholders would be required.

Lastly, embodiment stands in stark contrast to the previous two categories as it can be described as a physical extension of working capabilities (Daugherty & Wilson, 2018). This section includes well-known agents such as robots, sensors and motors in more production-centered industries. There is a commonly perceived notion that such actors drive automation and consequently autonomous working capacities, due to reduced robot prices, facilitated integrations and a continuously growing number of use cases and applications (Tilley, 2017). Nevertheless, similarly to the aforementioned collaboration opportunities, the aspect of AI embodiment could also be argued to add new layers to human means rather than just replacing them (Daugherty & Wilson, 2018). In order to improve assembly line flexibility and overall efficiency, Mercedes-Benz has been fostering such collaborative working arrangements in its plants since 2016 (Gibbs, 2016). Along with other technologies such as IoT or Blockchain this premise of AI technologies concerning flexibility, high efficiency and full transparency generally drives the concept of Industry 4.0. Manufacturers around the world have since adapted various technologies with an increased focus on the human element over the past few years. In the case of startups, this concept might not apply directly as such embodiment practices are currently mainly found in large companies due to the significant captial investment required. Nevertheless, when looking further down the line, new ways of working are already being conceived and established that could prove extremely valuable for startups. The combination of technologies such as 3D printing and AI provides more cost effective approaches to smaller and more specialized manufacturing initiatives. In such a setup, AI-powered machines could help with regards to error detection, resource efficiency and analytics (USM Business, 2019). This would again elevate the performance of the associated staff which in turn leads to quicker product pivots or general improvements. The concept of embodiment heavily influences the technological dimension as it revolves around the improvement of production or operation processes. Furthermore, it also foresees a strong collaborative basis with people to drive further advances. This ultimately also drives the staffing dimension as the right people will be required for such positions which eventually drives the overall business performance and growth.

To sum up, the highlighted gap consisting of the previously described six domains strongly outlines the required understanding and perspective of fostering healthy symbioses between humans and machines. This applies to all types of businesses and industries as AI technologies are extremely versatile with regards to different use cases and applications. This general understanding consequently requires action steps from leading stakeholders. Due to their generally dynamic and agile cultures, startups are in prime condition to adopt such structures and collaborative blueprints. Despite some probably rather limited deployment due to resource constraints, fostering such approaches could prove vital in the long run as it would set the foundation for future operations streamlining as well as human resources efforts. Bridging this gap can be viewed as the stepping stone the establishment of the right culture as such is indispensable for long-term success. The subsequent section of this paper aims at highlighting and discussing various success factors for AI-driven and scalable decision-making in startups.

2.4 Success Factors for Implementing AI in Startup Operations

2.4.1 Culture and Empowerement

Arguably the most important building block when it comes to such an impactful transition and subsequent sustaining efforts is the right cultural setup as previously highlighted in this paper. However, seeing as culture can hardly be measured by conventional key performance indicators (KPIs), it is arguably the most challenging factor with regards to a lasting transition (Walker & Soule, 2017). This is due to the fact that such a change cannot be communicated in a conventional top-down order as it has to be adopted, lived and promoted by all individual team members in an organization. Exemplified values and goals by the leadership with subsequent employee empowerment are consequently the key to establish a strong communal acceptance and support systems. Seeing as the organizational structure including an establishment of values of a startup should start to form as soon as the venture outgrows the capabilities of the initial founding team (Mandaville, 2021), previously described concepts such as focusing on inter-disciplinary collaborations and agile team setups, a strong emphasis of data-driven decision making as well as a certain embracement of failures and errors for future growth have to be communicated and lived by the leading stakeholders. One of the key points of discussion in this case is the question of decentralization and centralization. The assertion pro centralization argues that it minimizes overhead and advances decision-making efforts, while opponents argue that it might result in organizational rigidity in the long-term. On the other hand, the promotion of decentralization states that it increases ownership and responsibility amongst team members, while the assertion against it argues that it causes structural and operational turmoil in the short-term (Mandaville, 2021). This discussion heavily depends on each specific case as startups find themselves in vastly different stages with different resources and market conditions. Nevertheless, the aforementioned cultural and structural setup has to be considered and consequently pursued regardless of hyper-growth, influences from external stakeholders such as investors or product- or service-related setbacks and pivots, to name a few (Walker & Soule, 2017).

When it comes to the different initiatives concerning the implementation of such values and communication of long-term visions for the company's setup and modus operendi, three key factors stand out. First, a strong focus on recruiting is absolutely essential. However, finding and successfully hiring the right candidates in terms of cultural fit in line with the overall AI transformation aspirations can prove to be very difficult due to a number of issues. First, it is very difficult for startup leaders to outline the precise requirements for the ideal candidate as multiple factors apart from operational expertise or craft come into play (Riani, 2020). In addition to qualifications in line with the precise role requirements, elements such as personality, knowledge and interest, ambitions as well as overall goals must all be thoroughly considered (Riani, 2020). Particularly the first two points are essential with regards to the adoption levels and learning capabilities as well as cultural fit in relation to an AI work environment of a candidate. Second, startups rarely have dedicated human resources (HR) specialists (Rust, 2019). As a result, various best practices are not considered and subsequently executed when it comes to the full-cycle recruiting process (Martic, 2018). This concept describes a 360-degree approach concerning the thorough consideration of required roles, the publishing and promotion of relevant information, the application of best practices with regards to screening and interviews as well as the subsequent onboarding and referral efforts (Martic, 2018). Startup leaders have to anticipate such bottlenecks and educate themselves as well as other team members in order to improve the hiring process of the right candidates as human capital is imperative for such an organization-wide undertaking. Lastly, competitive factors often hinder startups from acquiring the best talent. Such range from less attractive compensation possibilities to a reduced amount of local talent which is often hired rapidly by large companies as well as time constraints as startups cannot afford to spend a lot of time with regards to open positions in contrast to bigger employers (Rust, 2019). Thorough preparation and consequent prioritization is absolutely key in this case. By swift operations along the full-cycle recruiting process and by spending a bit more on more urgently required roles in order to hire the ideal candidate, startups can avoid potential drawbacks or cultural misalignment in the future.

The second crucial aspect concerning the implementation and fostering of the right values and culture with regards to an AI-driven company is adequate training. Corporate training at startups reaps numerous benefits in addition to the strengthening of certain skillsets. As a result, different required coachings and practices revolving around various aspects of AI as highlighted previously in this paper would also foster team collaboration, creative engagement as well as communication (Gupta, 2019). Furthermore, training and educating team members on multiple levels ranging from functional to more interpersonal skills would also significantly improve the different skillsets available at the company and increase overall productivity levels as well as promote open communication to drive innovation (Horowitz, 2010). Lastly, strong efforts by leading stakeholders with regards to employee training also increases corresponding workforce satisfaction levels which in turn leads to higher retention levels as well as an increased attraction for new talents (Gupta, 2019). Seeing as resources are scarce at startups, this is a significant aspect worth considering.

In order for all of these aspects to come to fruition, different requirements have to be fulfilled. To begin with, leading stakeholders have to clearly define and outline the overall goals and objectives with regards to the different training initiatives. This includes desired learnings and outcomes which in the case of AI-driven motivations can range from technical trainings to more human-centred approaches aimed at fostering collaboration and the understanding of different roles. Other important objectives that need to be defined include timeframes, benchmarks and KPIs, structure and training layout as well as participants and potential cross-divisional coperations (Thomas, 2020). This also includes the selection and iteration of the right tools and methods. Seeing as trainings can be quite costly in terms of money and time, third party solutions might help to drive such efforts in the beginning and on which more sophisticated systems and sequences can later be built upon (Horowitz, 2010). By successfully anticipating such variables, the planned trainings will be more likely to have a lasting impact on the overall culture and employees' sense of empowerement.

Second, continuous learning and personal development also have to be exemplified by the leaders of a startup in the form of involvement, facilitation or assistance (Thomas, 2020). This would not only help to communicate certain expectations and values but also to track the effectiveness of different methods and approaches as well as to pivot to potentially better learning models. Furthermore, it would increase trust levels and consequently factors such as employee satisfaction and consequently retention as highlighted above (Gupta, 2019). The aspect of management involvement is also particularly crucial as educational efforts can be resource intensive and establishing certain best prectices based on rapid pivots can prove to be a garant for success in the long-term including improved management practices as well (Horowitz, 2010).

Lastly, feedback forms the ultimate requirement with regards to the successful implementation of training initiatives at startups. Leaders have to promote and engage in open communication measures in order to drive the progress of the different training initiatives as well as to better understand employees' sentiments and developments not only in relation to the overall dynamics of the transformation but also with regards to the company's culture as a whole (Klein, 2016). According to Klein (Klein, 2016), feedback measures should be tested and chosen for the long-term depending on the specific circumstances as well as team strucutres and particularities of each startup. Such can range from rea-time feedback during meetings or via online communication channels as well as individual or small group meetings on a weekly, monthly or semi-annual basis. It is imperative that this type of communication culture is also exemplified by leading stakeholders as any feedback initiatives must not be one-directional. This would sustainably and continuously improve the insights with regards to the transition process and overall sentiment of employees. By successfully executing such, certain trends and potential bottlenecks can be outlined or even anticipated quickly.

2.4.2 Lean Resource Distribution

As previously mentioned in this paper, startups face a number of different resource-related challenges ranging from monetary constraints to a more challenging position towards human capital and multiple external factors affecting operations and growth. Consequently, founders and leading stakeholders must focus on the adequate prioritization of certain areas or disciplines with regards to the allocation of resources (Alvarez, 2020). Even though resource scarcity can arguably be considered a positive enabler concerning innovation in startups due to a lack of competing initiatives and less corporate politically-driven analysis paralysis (Phillips, n.D.), investments in technology and human capital as highlighted in previous sections of this paper can without a doubt represent a formidable challenge for startups in various growth stages. Given the business promises to or even already fulfills a specific need in the market as this is the single most important key to long-term growth and overall potential (Ursache, 2018), it is imperative for founders and key-decision makers to focus on the long-term operational model and the corresponding benefits when deploying various pilots and AI initiatives. In the early stages of a startup, the actual technology should not be the primary focus as so many variables about the business might change entirely within a short period of time. Therefore, concentrating on the human element with regards to culture and team chemistry as well as making the most of singled-out and business use case relevant third party solutions concerning the technological tools is of considerably higher importance (Cohen & Eng, 2016). Through such initial pilots on a human as well as a machine level, entrepreneurs can gradually increase their investments in previously highlighted trainings or more advanced tools. The key here is to embrace uncertainty as it maximizes flexibility with regards to the openness to invest more in currently used solutions, team setups or external partnerships or to pivot to entirely new ones (Schontal, 2015). Furthermore, if startups invest valuable resources in trainings but not in various technologies themselves, the overall importance of the transition might become obsolete in the eyes of employees who then might look for alternative workplaces where their knowledge can be applied. As long as the priorities of the business, ranging from a focus on product or service to internal operations or human operations, are clear with regards to these initial pilots, the learnings will far outweigh the drawbacks.

One frequently quoted methodology that could prove a valid framework for such decision-making and continuous investments in people and technology would be the approach popularized by Eric Ries, the lean startup methodology (Ries, 2011). At the core of this methodology stands the question of relevancy versus wastefulness of different efforts. Such is answered by the continuous deployment of minimum viable products (MVPs) or initiatives in line with subsequent pivots, iterations or disposals. The key here is a focus on validated learnings based on previously defined KPIs (Globalluxsoft, 2017). According to Ries (Ries, 2011), as long as the long-term vision is clear, immediate action with potentially inefficient or not ideal models is far more beneficial than trying to implement the perfect system once a certain milestone is reached or specific results are expected. As a result, startups should outline the key areas on which they want to focus on with regards to their AI business transformation and gradually test and iterate towards the ideal solutions for them. As mentioned previously, every business drastically differs from others even to the ones in the same industry. Therefore, a clear set of overall objectives with regards to the different AI use cases in line with specifically designed KPIs to measure the process is key when making investment decisions. Based on the insights gathered from continuous performance assessments, startups can then highlight different methods and tools that will prove essential upon entering a rapid growth phase and reaching scalability.

2.4.3 Scaling Enablement

Lastly, once the aspects of the cultural level as well as the business-relevant resource allocation are considered thoroughly and implemented gradually, it is key to holistically assess any best practices in order to anticipate required scaling measures prior to larger transaction volumes, team sizes or necessary infrastructure setups. The underlying principle of this key success factor derives from the fact that successfully tested and implemented AI applications will help the business to scale vastly more efficiently and rapidly (Georgiou, 2019). However, there are a number of considerations worth highlighting when it comes to the complex subject that is rapid business growth or scaling. Generally speaking, a startup's scaling process is defined by the overcoming of six challenges, namely, factors concerning staff, shared values, structure, speed, scope and funding (Landry, 2019). Despite the fact that at such a stage, more investments in AI technologies and trainings have to be defined and executed, previously implemented tools and cultural setups can help to facilitate such challenges and accelerate scaling efforts (Georgiou, 2019).

First, the staffing challenge is indispensable not to prioritize. A team of well-recruited and trained professionals can help to accommodate numerous bottlenecks that arise during such a phase (Landry, 2019). At this stage, it is also important to grow the number specialists and avoid generalists that can fulfil a wide range of tasks (Conant, 2021). However, the cultural values have to be in line with regards to adoption rates of AI technologies in everyday workflows as well as continual feedback culture to optimize such processes. Consequently, the staffing challenge stands somewhat in correlation with the question of shared values. Open communication amongst previously- and newly-hired team members is key to continuously transmit such. Leaders have to focus on not de-personalizing the business by highlighting action steps rather than desired cultural setups (Landry, 2019). Besides these important considerations concerning the right setup of these two challenges, it is also crucial to highlight the potential of AI to assist with such efforts. This can range from automizing and consolidating recruiting systems and enhanced data security systems to various training programs (Georgiou, 2019).

Second, the challenges of structure and operational efficiency can subsequently be addressed. Overall team formats and setups as well as corresponding trainings have to be continuously assessed, as previously mentioned (Landry, 2019). Nevertheless, structure also refers to the different processes put in place to support the growth of the business. One key here is to institute AI- and data-based decision-making (Georgiou, 2019). This constitutes the foundation for operational efficiency on all levels. Clearly, previous and consequently larger investments in this area should be targeted towards the generation and preparation of the right data sets and corresponding infrastructures as previously highlighted in this paper. Depending on the stage and resources available to the startup as well as on how much the previously implemented infrastructures, best practices and proven systems have to be focused on during this phase. One model that could facilitate this priorization and analysis process is a general transformation model as highlighted in the figure below (Iansiti & Lakhani, 2020).

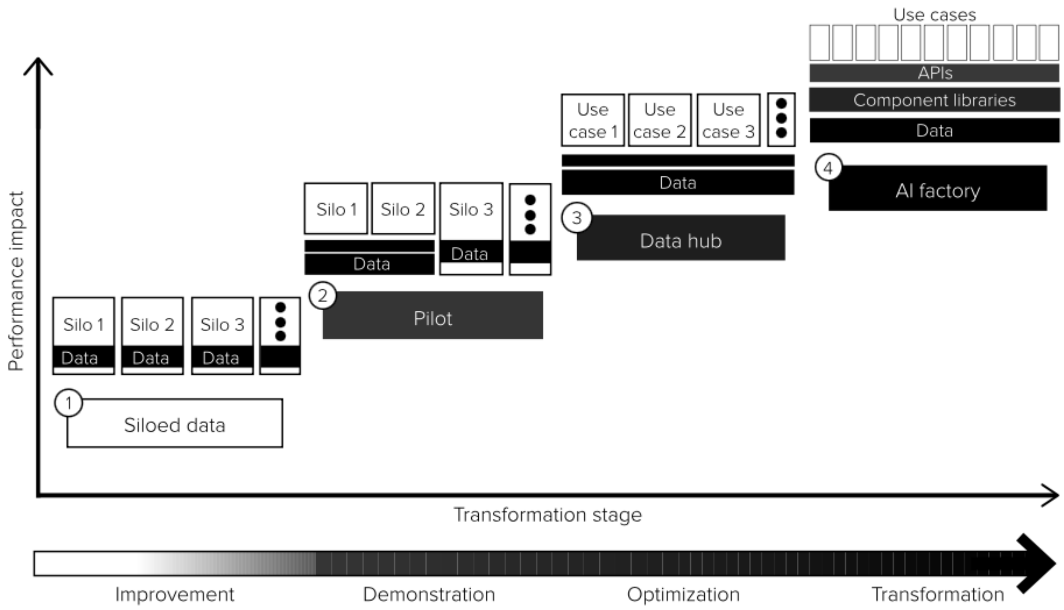

FIGURE 4 - FOUR STAGES OF DIGITAL OPERATING MODEL TRANSFORMATION (IANSITI & LAKHANI, 2020)

Figure 4 above underlines the shift established companies have to make in terms of their organizational structure and technical infrastructure from separated silos to a use case specific approach. In context, AI-powered business divisions such as marketing, HR, product development or customer service should not act independently but rather merge together in case of overlapping use cases. For instance, the customer segmentation data used during the product development can help marketers to more efficiently communicate a given product or service with customer service agents benefiting from the additional insights gathered along the way (Iansiti & Lakhani, 2020). Startups on the other hand, are already based on a flexible and adaptable setup concerning their business operations (Picken, 2017). In addition, the infrastructures supporting a larger business are yet to be thoroughly established. Consequently, startups are potentially better positioned when it comes to the scaling process. In such a case, investments should be directed towards an entire setup transformation aimed at highlighting use cases rather than business divisions as highlighted in Figure 4 above (Iansiti & Lakhani, 2020).

Lastly, scope and funding are communicating vessels when it comes to the decisive scaling factors of a startup (Landry, 2019). Scope in this case refers to business opportunities that should be focused on upon maturing in the initial markets and geographies. Similarly to previously highlighted factors, different AI applications can facilitate such market or potential product-market fit analyses enabling the business to make more effectively and efficiently transitions (Iansiti & Lakhani, 2020). Depending on the given setup, the business might rely on third party data or tools to anticipate such conversions with further investments being directed towards internal technical and organizational foundations. As a result, it is absolutely key to align a startup's financing strategy with its growth strategy (Landry, 2019). However, finding and partnering with external financing stakeholders, ranging from venture capitalists, angel investors or crowdfunding patrons, to name a few, always represents a considerable challenge for startups (Cremades, 2016). A proven AI setup can not only act as an asset concerning the organizational composition and efficiency in the eyes of potential investors but also facilitate the preparation of investment decision-forming data such as revenues and financial projections as well as market research. Such documentation efforts are often times quite time consuming due to the due diligence leading stakeholders have to fulfil (Cremades, 2016). As a result, AI can enable startups to pursue more opportunities as well as to provide a reference point of legitimacy in the eyes of possible business relationships.

2.5 Conclusion

In summary, artificial intelligence is a sub-discipline of computer science aiming at imitaging the cognitive processing capabilities of humans (Marr, 2018a). The field has experienced a fluctuating amount of research and development over the years due to technical constraints or a lack of use cases. Nevertheless, computing power and storage capabilities have vastly increased over the past few decades enabling current computers to accommodate extensive programs and applications (Mack, 2011). Seeing as we are now also witnessing the dawn of even more powerful areas of opportunity such as quantum computing, the number of potential use cases and overall efficiency will only more exponentially increase in the future. Nevertheless, the human element is the most important aspect when it comes to the implementation of AI technologies in a business context. This includes all roles ranging from a technical setup and maintenance perspective to the cultural adoption across all different business divisions including leading stakeholders as well as employees. This is also highlighted as arguably the most important success factor with regards to AI business transformations. It encapsulates considerations and mandatory action steps concerning the recruitment, training and fostering of culture across all levels. Once this foundation is set, strategic long-term investments have to be made along with a clear focus concerning the anticipation of crucial scaling factors such as staffing, organization and operational infrastructure as well as scope and financial support (Landry, 2019). More specifically, leading stakeholders have to outline areas of focus, deploy initial pilots, consistent test and iterate them based on continuous feedback and anticipate potential bottlenecks due to changing environments. These steps are important in order to shape the ideal environment for human and machine collaboration as every company is drastically different. During the scaling process, more emphasis has to be placed on guaranteeing operational efficiency in key areas and system security as well as higher investments in successful initiatives.

As previously stated in this paper, the existing literature mainly views the topics of artificial intelligence, its use in business contexts and startups quite separately. Nevertheless, there are numerous areas of opportunities for startups with regards to setting up a corresponding infrastructure seeing as the subsequent operational efficiency and data-driven processes will arguably be indispensable not only upon scaling but also for companies in general in the near future. When it comes to the current state of affairs and sentiment of leading stakeholders, the empirical part of this paper aims to thoroughly analyse such. The consecutive section of this paper introduces the methodology used in the successively illustrated empirical research in full detail.

3 METHODOLOGY

3.1 Introduction

The aim of this research is to outline and consequently verify critical success factors with regards to the implementation and adoption of AI technologies in the context of startup business operations. Such are drawn from general influencing factors concerning the growth of startups or technology adoption, to name a few, as previously stated in this paper. Nevertheless, such success factors are yet to be empirically proven. As a result, the following section of this paper introduces the methodology of this study including the data collection plan and research instrument, the target population, the sampling method as well as methods of analysis. Seeing as there is a large body of supporting literature for established companies, the research aims to test such promising areas of opportunity in the context of startups. If proven, the subsequently highlighted key success factors may serve as a design framework or rather blueprint for startups with regards to the overall capabilities, focus points as well as potential scaling opportunities when it comes to the technical adoption and business transformation involving these technologies.

Such aspects are examined through a qualitative research approach consisting of semi-structured interviews with specialized insiders from the startup scene in Austria and Vienna. The precise candidate criteria are described in more detail in the subsequent chapter. The resulting opinions and reflections of the interview candidates will provide insights from actual businesses or rather startups that further add to the findings from the literature review. Furthermore, these insights also take into consideration the truly varying environemnts, business infrastructures, team setups and experiences each startup and business in general is confronted with. Such insights are absolutely essential when it comes to the empirical research concerning the overarching research question, namely, what the key success facors are concerning an impactful implementation of AI technologies in startup business operations and processes. The following sections of this paper further illustrate the overall research plan and previously mentioned elements.

3.2 Data Collection Plan & Methodology

Seeing as startups differ drastically depending on the industry, size, infrastructure setup and a number of other factors, semi-structured interviews are the ideal mode of data collection for this research. This is due to the fact that this research method allows for a stringent degree of relevancy with regards to the overall research topic, while also providing space for responding to participants' particularities and unique positions that may provide further or even unanticipated insights concerning the field of study (McIntosh & Morse, 2015). For the sake of this research, a free expression of opinions and experiences is key. Despite the fact that such might differ in terms of context, the underlying insights concerning the overall research question are expected to be in line in order to answer such. Further reasons why this research method was chosen and the corresponding advantages are highlighted later on in this paper.

Overall, the interviews were conducted with stakeholders concerning startups ranging from current and past founders to key executives. The focus here was to exclude any external interests or biases from parties such as investors or program facilitators. Nevertheless, the target population was still kept heterogenous due to the different specialisations and industries yet it was also a coinciding group due to the similar overall environments the candidates are in This is expected to provide a more diverse set of experiences and insights about various technical requirements, infrastructures, necessary financial considerations and cultural aspects with regards to AI use cases in business. Due to the aftermath of the economic challenges caused by the Covid-19 pandemic as well as the ongoing war in Ukraine, some interviews were conducted virtually while others were held in person, given that the candidates felt comfortable and that the situation has allowed it. Various aspects with regards to the limitations of this research are thoroughly discussed in the last chapter of this paper.

Additionally, prior to every interview, an interview guide was arranged in order to help keep the conversation on track. This is due to the fact that semi-structured interviews may differ in terms of the arrangement of questions and subsequent follow-ups depending on the candidate. Consequently, all fundamental questions concerning the main research question were included in bespoke interview guide. Prior to the real interviews, different pilot tests were conducted in order to further improve the core structure of the questionnaire.

In total, seven interviews were conducted with an average length of 36 minutes. Furthermore, the interview candidates were provided with an interview guideline. Consequently, the interviewees were prepared which resulted in considerably more constructive insights and experiences shared. All of the interviews, both, virtually and in person, were recorded with a microphone for later transcription and analysis. As described in this paper, the interviewees were also provided with a consent form to indicate the desired extent of data privacy concerning any quotes or pieces of information shared.

3.2.1 In-depth Interviews

Qualitative interviews are the most frequently used method of data collection with regards to qualitative research (Jamshed, 2014). This format has proven to be very useful in a variety of methodological concepts. It is a particularly ideal form of research method when the research aims to understand subjective opinions, experiences and perspectives of different individuals in a specific domain. Consequently, qualitative interview research has the ability to outline insights from more minor groups in a given pool which would otherwise not be heard or considered. This stands in stark contrast to a generalized set of trends of a large group of people for which different quantitative methods would be more applicable (McGrath, Palmgren, & Liljedahl, 2018).

In-depth interviews are a type of qualitative interview research which focus on the exploration of different experiences and perspective of a candidate on a specific topic (Boyce & Neale, 2006). For such, open-ended questions are used in order to unveil potentially new insights which in turn create the possibility to dive deeper into the subject. Due to the fact that such interviews are arguably set in a more comfortable ambiance, candidates may feel more open to provide additional or more profound insights. Consequently, in-depth interviews provide a significantly more detailed and complete picture of a certain topic in comparison to quantitative questionnaires or surveys (Boyce & Neale, 2006).

Nevertheless, in-depth interviews may also include some limitations depending on the situation. Such can range from an inconsistent use of interview techniques to a certain interview fatigue of the candidate. Other factors include certain biases from candidates seeing as they are deeply involved in a given topic or domain or the aspect of insights not being generalizable. This is due to the fact that such research normally consists of comparably small samples without the use of any random sampling procedures (Boyce & Neale, 2006). Nevertheless, the deep insights gathered from such interviews justify such parameters. Furthermore, there is an extensive body of literature indicating that a smaller sample size is legitimized as soon as a certain level of saturation from the different insights is reached (Marshall, Cardon, Poddar, & Fontenot, 2013). Further advantages and limitations of this research methodology are highlighted later in this paper.

3.2.2 Semi-Structured Interviews

Semi-structured interviews refer to a sub-genre of in-depth interviews where the body of core questions remains the same for each interviewed candidate, but the follow-up questions might differ drastically depending on the elaboration of an interviewee. It is a set yet adaptable type of research methodology with which underlying perspectives and insights can be explored without having to adhesively follow the precise interview guideline (Adams, 2015). The key in this case are open-ended questions including follow-up questions starting with *why* or *how*, for instance. The anticipation of such follow up questions is crucial and the interviewees must be encouraged to dive deeper into a specific domain. When it comes to this particular research, semi-structured interviews allow the researcher to extensively prepare and analyse the contents and questions including potential iterations due to new insights from previously held interviews. This will be key as startups vary drastically with regards to size, structure or industry, to name a few, and the posing of standardized questions would not conclude in sufficient results. The flexibility granted with this semi-structured approach is essential in order to understand specific underlying principles in certain domains while also keeping in mind the big picture with regards to the adoption of AI technologies in a business context across industries. This approach would also allow the participant to ask questions in return to get a better understanding of the context and the research goal being analysed. One crucial element in this case is the following of a red string seeing as answers and explored topics might vary significantly as the candidates have a completely different set of experiences and expertises. Nevertheless, careful preparation and guidance during the interview can counter such challenges. Generally speaking, the benefits of this method far outweigh such potentially troublesome challenges. Further potential limitations and hurdles concerning this research approach are highlighted later on in this chapter.

3.3 Target Population

As previously stated in this chapter, the target population for this research consists of a more selected group of key stakeholders in startups in Austria with a strong focus on Vienna. This is due to its central European location, its high level of education and its continuously growing investing ecosystem (Christopoulos, 2015). However, narrowing it down to Vienna alone or broadening it to the continent of Europe would not be beneficial to this research. Furthermore, seeing as the main focus of this research aims to understand the underlying principles and dynamics in startups, only current and past startup executives and were included with regards to the semi-structured interviews. Venture capitalists, incubator or accelerator program specialists as well as publication experts, to name a few external stakeholders, have been excluded as they might introduce a distorted or biased perspective. Furthermore, it would be important to obtain purely business-focused insights from insiders. This is further underlined by the fact that founders, entrepreneurs and like-minded people often have a very contrasting set of intrinsic values, principles and motivations in comparison to interest representatives from the finance and investment sector. Correspondence prior to the interview confirmation was used to outline such candidates.

When it comes to the term startup and corresponding selection criteria, no limitations were applied with regards to the industry the startups operate in. This is due to the fact that AI technologies can be applied in a number of different processes and consequently renders the question of industry irrelevant. Furthermore, seeing as there is no universally agreed on definition of startups (Shontell, 2014), one of the most important criteria points in light of the overarching research question concerns the age of the startup. More specifically, seeing as startups reach drastically varying sizes depending on their time in existence, it would be important to focus the research on companies which are shortly before the scale-up phase. As a result, companies aged between five and ten years would be an ideal point of focus. Such businesses, given an underlying great value proposition and general potential, often times find themselves at the cusp of rapid growth and scalability. It would be at this point where the aforementioned underlying dynamics and potential plannings are made. This is due to the fact that then, a well-functioning executive team is normally already in place which could then provide insights regarding previously outlined dynamics and potential plannings rather than founders who are just starting out, amongst other non-ideal candidates. All relevant factors concerning this research are outlined below for more clarity:

- Element: Current or past startup founder, current or past startup executive
- Sampling Unit: Startups (characterized by the aforementioned criteria)
- Extent: Austria with a strong focus on Vienna
- Time: Availability between March and May 2021

3.4 Sampling Method & Approach

The sampling method used for this research is based on a convenience sampling approach. This is due to the fact that this non-probability approach provides the opportunity of gathering data from members of the aforementioned population based on convenient factors with regards to the research. Seeing as this study aims at analyzing startups which are prior to the scale up phase, several subjective criteria points could as a result be used to outline such sampling units and consequently elements as previously highlighted. The use of this sampling method is further highlighted by the fact that startups differ drastically in terms of structure, stakeholders and industry, to name a few. As a result, different forms of probability sampling methods would in comparison not take into account such differences and particularities. It is as a consequence arguably impossible to conclude in any generalizations about the chosen pool due to such differing factors. Lastly, the aspect of availability also played a key advantage role given the aftereffects of the Covid-19 pandemic as well as the current events unfolding in

Ukraine. In light of this factor, convenience sampling provided the most advantages over other sampling methods for this research.

When it comes to potential drawbacks of this sampling method, the most notable one would be the elements of variability and bias (Acharya, Prakash, & Nigam, 2013). This is due to the fact that subjectively chosen criteria points regarding the selection may already introduce certain biases based on the interview candidate's background and profile. As a result, another drawback would be the inability to draw generalizations for the entire population. However, the subjectively chosen criteria points included as many factors as possible in order to generate as much of a holistic perspective as possible based on factors such as different industries as well as varying operating models and value offerings, to name a few. In addition, the aforementioned advantages of using this sampling method for this research outweighed these limitations, as stated earlier in this section.

3.5 Defined Interview Questions

Despite using a semi-structured interview research approach, the core questions have been outlined in advance and remain the same for all candidates as required by the methodology. This is due to the previously highlighted goal of drawing overarching principles and trends from specialized view points and insights from a wide range of industries and expertises. Naturally, the questions can be categorized into interview-protocol-relevant sections. To begin with, the candidates were asked general introductory questions aimed at facilitating and classifying subsequent insights during the synthesis. Subsequently, different views on AI in business were explored in order to obtain an understanding of personal estimations regarding the potential of the technology. After that, different elements on the feasibility and potential use cases of AI in startup processes were asked. Furthermore, the following section explored potential critical success factors for the actual implementation of AI technologies in startups. Prior to the outro, general questions on startups and the Austrian market were asked. It is important to note at this point that these questions were prepared prior but the interviews were still held in a semi-structured way as highlighted above. Consequently, in case the candidates slightly diverted in terms of insights shared, the interview did not adhere strictly to every single question outlined below. Nevertheless, the overall topic groups were used as a red string with as many prepared questions asked as possible. All of the questions are described in more detail below:

3.5.1 Introductory Questions

- What is your name and background?
- When was your startup founded?

- In what industry does your startup operate in?
- What is the value proposition of your business in terms of products or services offered?
- What is the current headcount including potential projections for the near future?
- Where in Austria including potential other locations is your business located?
- How would you rate the potential of the Austrian startup scene/market?

3.5.2 Artificial Intelligence in Business

- To what extent are you familiar with Artificial Intelligence?
    - From a current trend and buzzword to a new era of technological evolution, how would you rate the potential of this technology?
    - What do your peers and colleagues think about this technology?
    - To what extent are you considering educating yourself further in this area?
- What applications and use cases are you aware of or familiar with concerning AI technologies in business operations and processes?
    - How would you rate the potential of this technology in such a context?
- For established companies, what factors would you highlight as potential bottlenecks or hurdles concerning the implementation and adoption of this technology in such a context?

3.5.3 Artificial Intelligence for Startup Operations

- In comparison to established companies, how important would you consider AI to be for startup business operations and processes?
    - In what areas (applications) or scenarios (startup phases) could you see AI to be used by startups?
    - Are you aware of any current use cases, products or solutions in the startup scene in this context?
- What would you describe as the biggest hurdles or reasons against this technology concerning the use of it in startup processes?
- What would you highlight as the biggest areas of opportunities or potential benefits as a result of startups using this technology?

3.5.4 Key Success Factors for the Adoption & Implementation of AI Technologies

- How would you describe the key success factors with regards to the successful implementation and adoption of AI technologies in startup operations from a staffing perspective?
    - What are potential benefits and long-term implications?
    - What are potential threats, bottlenecks or counter-productive elements?
- How would you describe the key success factors with regards to the successful implementation and adoption of AI technologies in startup operations from a business perspective?
    - What are potential benefits and long-term implications?
    - What are potential threats, bottlenecks or counter-productive elements?
- How would you describe the key success factors with regards to the successful implementation and adoption of AI technologies in startup operations from a technological perspective?
    - What are potential benefits and long-term implications?
    - What are potential threats, bottlenecks or counter-productive elements?

3.5.5 Startups

- What are the two/three biggest challenges startups face during a rapid growth or scaling phase?
- Scaling: To what extent do startups anticipate future events such as business infrastructure requirements or operational efficiency?
- How much do mature startups invest in terms of resources (time, money, people) in such aspects?
    - How are KPIs or the the ROI typically defined when it comes to significant technological and cultural investments in your startup?
- To what extent does your startup work in silos versus inter-disciplinary collaboration?
- How do decision-making processes look like in your startup?
- To what extent does your startup and you personally accommodate and encourage a failure culture?

3.5.6 Outro

- Do you have any more remarks or ideas concerning artificial intelligence in the context of business use cases and particularly for startups?
- Do you have any questions?

3.6 Methods of Analysis

Seeing as this research is based on qualitative semi-structured interviews, a qualitative content analysis approach was used for the determination of results. First, the recorded interviews were transcribed - a preparatory step prior to the actual analysis. An additional preliminary task included some initial notes about the gathered insights as well as subsequent introductory clusters by the researcher. When it comes to qualitative research analysis, the collected data is conventionally categorized using labels based on the core topics of the respective collection method (Forman & Damschroder, 2008). There is a disagreement in the existing literature on qualitative content analysis, with some researchers focusing on quantitative methods such as the counting of words or clusters while others solely examine the given data using qualitative assessments and interpretations (Forman & Damschroder, 2008). This research aims to outline findings by compiling the contents of the transcribed interviews in order to discover and emphasize certain key statements and insights using labels and categories. Consequently, a similar structure to that of the questionnaire with regards to the overarching topics was applied when it comes to the creation of said labels. More specifically, the labels were classified into two main categories. The first one concerned any observations and statements on AI, both, generally as well as in a business infrastructure context. Secondly, different insights and experiences shared on the topic of startups including general information as well as specific data on the Austrian market were clustered together. The red and green colorcoding referred to negative and positive observations, respectively. Orange codes highlighted general observations while blue was used to mark any statements on the personal background of the candidate, his or her current position as well as general information on the discussed startups.

As shown in Figure 5 below, the overarching genre of insights shared on AI was split into the following sub-categories. In case interview candidates mentioned any internal company use cases such as tools as well as products or services powered by AI, they were marked within the homonymous category. The sub-category *Technical Aspects* included any observations or insights made on the currently perceived potential as well as anticipated and experienced benefits. The second aspect within this sub-category involved any highlighted challenges concerning the technical development or implementation of such systems.

Artificial Intelligence	0
Company-internal Use Cases	15
Technical Aspects	0
Potential	0
Anticipated & Experienced Benefits	39
Challenges	0
Human Capabilities & Knowledge	3
Economic Feasibility	6
Legal Compliance	4
Data Privacy & Security	9
Budget	5
Machine Errors	7

FIGURE 5 - CODING LABELS ON AI - BREAKDOWN I

The sub-category *Human + Machine* concerned any cultural aspects in relation to the technological realization of this business transformation. The label *Intermediary Roles* referred to any affirmative observations made by the candidates on such required positions and tasks. The label *Transition & Adoption* included any positive remarks on different practices and perceived benefits from a cultural perspective in relation to adopting this technology. Similarly to the category *Technical Aspects* mentioned above, the *Human + Machine* category also featured a dedicated section with highlighted challenges in this context. Lastly, the two clusters *Existing Ceiling of AI* as well as *Overall Potential* included more general statements made on the currently existing limitations and generally perceived potential.

Human + Machine	0
Intermediary Roles	16
Transition & Adoption	3
Transition to more Creative Occupations	5
Testing	3
Trust in AI	8
Challenges	0
Familiarity with other Systems & Routines	4
Loss of Human Interaction	6
Explainability	6
Ethical Factors	12
Usability & Adoption	4
Fear	15
Trust	18
Existing Ceiling of AI	15
Overall Potential	17

FIGURE 6 - CODING LABELS ON AI - BREAKDOWN II

The second large cluster of labels concerned any observations made on startups as well as on the Austrian startup scene as shown below on Figure 7 and Figure 8. The first sub-category within this cluster included all of the described challenges startups generally encounter and face. Within this category is also a breakdown of the different resource limitations highlighted by the candidate. Seeing as there are several important ones, these were added. The second major category within the topic of the label *Startup* concerned the internal processes. This section aimed to highlight different dynamics and approaches by startups which could prove to be favourable concerning a technological business transformation including AI technologies as highlighted within the literature review of this paper. Important labels within this group included any notions on internally-built tools as well as the three main cultural points of failure culture encouragement, interdisciplinary decision-making and cross-departmental collaboration. Lastly, the neutral label Collaboration with External Partners included the important consideration of working with third-party solutions as well as other symbiotic business partners. As highlighted in the findings discussion of this paper, such could represent an intermediary option for startups in order to test and trial different approaches and best practices.

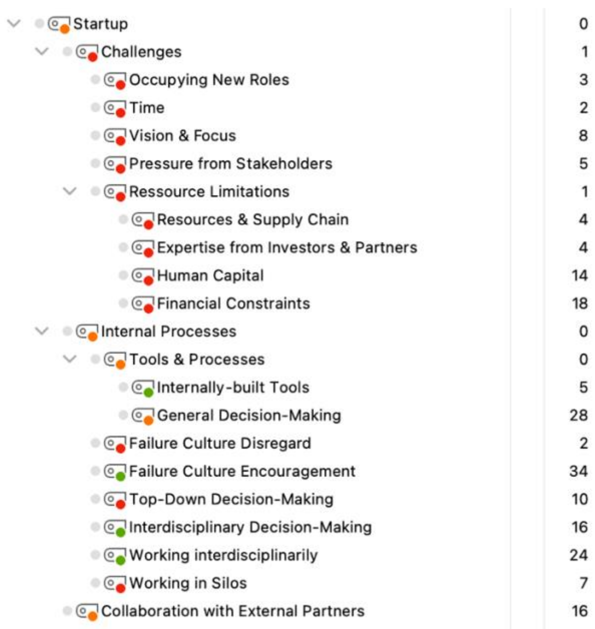

FIGURE 7 - CODING LABELS ON STARTUPS - BREAKDOWN I

Ultimately, the sub-category Austrian Startup Scene concerned any observations made on the particularities and specific features of this market. These insights were categorized into two main notions, namely, negative and positive observations. The negative aspects included highlighted challenges and demanding factors. When it comes to the positive aspects, such included described outstanding elements with regards to this sub-category which stand out and have indicated positive developments over the past few years.

FIGURE 8 - CODING LABELS ON STARTUPS - BREAKDOWN II

3.7 Methodology Evaluation

3.7.1 Limitations of the Chosen Methodology

Despite there being a number of advantages of the chosen methodology as stated previously in this paper, some important limitations must also be noted. As previously stated, certain biases can be introduced to the study during the sampling procedure. This can consequently affect the responses and insights gathered during the interviews due to the given particularities or characteristics of the candidate. Furthermore, the actual responses may be distorted due to intentionally modified answers from the interview candidate. A potential reason for such actions may stem from a certain sentiment with regards to having to answer in a socially acceptable way, for instance. In addition, interview candidates may also not understand or interpret the asked questions in a different way and subsequently answer in a counterproductive manner with regards to the research aim. However, there was an intent to overcome this hurdle by welcoming and encouraging questions of comprehension as well as rephrasing certain questions in case the candidate showed signs of uncertainty in terms of understanding.

Furthermore, certain limitations caused my the interviewer may also affect the gathered data. This could be due to the researcher asking questions with a different wording or adding altering elements to them which are either irrelevant to the research or prime the interviewee in a way that is counterproductive with regards to later answers. Similarly, certain biases may be caused by the interviewer's character, age or speech, to name a few examples. Additionally, aspects such as common contacts or past interactions may also affect the given responses. However, none of these factors deterred the results of this primary research in any way.

3.7.2 Ethical Concerns

In addition to the previously mentioned limitations of this qualitative research approach, certain ethical concerns also arise. Most importantly, such concern the confidentiality and privacy with regards to the personal data of the interviewees as well as their responses. Seeing as the findings are discussed in the subsequent chapter of this paper, such issues must be addressed accordingly during such a research process. The following steps outline the corresponding precautions.

To begin with, the entire interview procedure and research methodology was explained in detail to the interview candidate prior to the start of the respective session in order to provide them with the utmost transparency about the process. Furthermore, the later described insights and experiences are completely anonymized as confidentiality represents one of the main ethical concerns. The only time the names are mentioned in this thesis is in an overview table in the appendix of this paper. Also, the interview candidates were provided with a written consent form prior to the interview where they could explicitely state their preferred level of permission with regards to the data shared and captured through an audio recording in the subsequent session. Lastly, the researcher also guaranteed access to the respective recorded sessions and final sysnthesis of the research. It was aimed with this step to grant more transparency to the process after the interview sessions and as a result build trust with the candidates before the actual interview. This is an important element when it comes to the sharing of sensible data or private insights.

3.8 Conclusion

To sum up, the chosen qualitative research approach through the means of semi-structured interviews represented the most advantages with regards to the overall research objective. Seeing as startups differ drastically as previously highlighted in this paper, quantitative methods would not have been sufficient in outlining respective particularities or circumstances. Semi-structured interviews provide enough flexibility to explore given special insights while also following a guiding structure which is relevant with regards to the research question and subsequent synthesis. As previously stated, the sampling unit of the target population consisted of past or existing startups which have experienced or currently find themselves in the scale-up phase. The element are consequently past or current founders and startup executives as they can provide the most insights with regards to the businesses' current and anticipated dynamics and functionalities, the overall vision and how it is followed as well as people-related experiences without a sole focus on operational aspects. Lastly, convenience sampling was used for this research as this method too provides the most flexibility with regards to understanding business or industry-specific and generally varying elements as well as insights. Subsequent concerns such as variability or bias were addressed to the utmost extent as highlighted in this chapter.

4 RESULTS AND DISCUSSION

4.1 Introduction

The findings and insights gathered during the semi-structured interviews are discussed in this section. It has to be noted at this point, that the majority of interviews were held in German due to the interviewees feeling most comfortable in this language. Consequently, the citations and paraphrases used in this section are accompanied by an English translation in brackets next to the stated phrase. Seeing as the quotes are also followed by the respective names of the interviewees, the table below outlines all of the candidates including some information on their respective active years with regards to the businesses and experiences discussed during the interviews.

Name	Years	Industry	Location
Mrs. Scherzinger	2017 - Current	Retail & E-Commerce	Vienna
Mrs. Hallmann	2018 - Current	Medical Products	Vienna
Mr. Schwärzler	2015 - Current	Industrial Software	Vienna
Mr. Resch	2015 - 2018	Online Dating & Medical Products	Vienna
Mr. Mitrovic	2018 - 2021	Insurance & NLU Software	Vienna
Mr. Stangl	2015 - 2018	Online Dating & Medical Products	Vienna
Mr. Ardaiz	2018 - Current	HR Data & Consumer Products	Vienna / California

TABLE 1 - INTERVIEW CANDIDATES

When it comes to the chronological sequence of topics and fields of study, the structure of this discussion follows the same order as the interview guideline. The guideline aimed at exploring different topics while also building up on each other. As a result, the discussion follows roughly the same trajectory with regards to the two main topics which define the various success factors and challenges highlighted in this paper. Both topics include a number of sub-points which are further illustrated in each section. The two main topics are as follows:

- Artificial Intelligence
- Startups

This blend of technical, cultural and financial aspects based on insights from the Viennese and Austrian startup scene aims at answering the main research question which reads:

What are the critical success factors concerning an impactful implementation of AI technologies in startup business operations and processes?

4.2 Artificial Intelligence

4.2.1 Coding & Evaluation Approach

Figure 5 below provides a precise overview over the chosen codes and labels for each observation and respective cluster. The Code-Matrix-Browser visualization shows the number of marked observations for each label as well as each interview candidate. The section on artificial intelligence is split into two main subgroups, namely, technical considerations as well as collaboratory observations between humans and machines. Within the technical considerations group, statements on anticipated benefits were collected alongside various challenges. When it comes to the Human + Machine subgroup, the most frequently used labels included intermediary roles and various positive statements on the cultural readiness for such as technological transformation as well as various related cultural challenges. The two labels of overall potential and existing ceiling of AI aimed at highlighting more general statements made by the interviewees. Two categories are clearly noticeable in this quantitative visualization of observations, namely, anticipated benefits as well as the cultural challenges of trust and fear. Besides, the numbers of highlighted statements are arguably quite evenly distributed.

FIGURE 9 - OBSERVATION CODES & LABELS ON AI

4.2.2 Generally Perceived Potential & Apparent Existing Limitations

The first main topic that was discussed during the interviews after the description of personal backgrounds and founding experiences was the broad topic of artificial intelligence. The goal was to understand the level of education the candidates have around this topic as well as their prioritization of this technology. Furthermore, this section aimed at analysing the true applicability and subsequent real-life benchmarks concerning the overall potential as well as existing limitations of artificial intelligence. In general, the results and insights shared by the candidates for the most part reflect the previously outlined findings from the literature as highlighted below.

To begin with, all interview candidates acknowledged the probable monumental potential artificial intelligence offers with regards to business applications and use cases both product and service-related as well as internally. Nevertheless, some candidates also highlighted a particular hype around the topic which can distort the technological and societal impact in the short-term. Mr. Mitrovic elaborated on this by stating that artificial intelligence as of right now "… *ist extrem gehyped, allerdings in einigen Nischen nutzbar und in einem Teil dieser Nischen dan nauch ökonomisch sinvoll nutzbar*." [… is extremely hyped, but it can be used in some niches, and in some of these niches it is also economically viable.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). This general potential along with the fact that AI is still early in its overall adoption and applicability was also underlined by Mr. Ardaiz. He stated when it comes to AI "… we are looking probably along the same lines of what th internet has done for people or humanity, both good and bad, so it has to be taken with a grain of salt, but it really has the kind of potential to really transform a lot of things for sure in a lot of different ways." (S. Ardaiz, personal interview, Vienna, April 19, 2022). This impact with regards to people has also been highlighted by Mr. Mitrovic and Mr. Ardaiz later on during their respective interviews. Both highlighted a high probability of this technology enabling people to transition from rather mundane and routine tasks to more creative roles. This poses the aspect of people having to either up- or cross-skill or being threatened of losing their job. Nevertheless, Mr. Mitrovic aimed at introducing a positive perspective in relation to this challenge by stating: "Man kann natürlich auch ein bisschen den Perspektivenwechsel machen und das auch positiv beleuchtet und sagen okay, dann hat man keinen studierten Menschen dort sitzen der nahezu identische Texte liest. Der kann dann sein Potenzial und seine Kreativität nutzen, um kreative Lösungen zu finden, einzusetzen, zu nutzen, statt seine Zeit damit zu verbringen Verträge zu vergleichen oder was auch immer." [Of course, you can also change your perspective a bit and look at it in a positive light and say okay, then you do not have a studied person sitting there reading almost identical texts. He can then use his potential and his creativity to find creative solutions, to apply them, to use them instead of spending his time comparing contracts or whatever.] (D. Mitrovic, personal interview, Vienna, April 14, 2022).

These two notions of both, the currently existing technological ceiling of AI as well as its potential drawbacks and concerning considerations, were highlighted by all candidates. Mr. Mitrovic outlined three overarching reasons for this, namely, economic feasibility, political consideration as well as technological limitations. The factors of political implications as well as economic feasibility are discussed in more detail later on in this chapter. When it comes to technological limitations however, Mr. Mitrovic highlighted the current issue of real-life applicability of this technology. He stated: “Insofern funktioniert es noch nicht so, dass es einen echten Mehrwert bringt. Da ist nämlich das Problem, dass dieser ganze Hype Benchmark-basiert ist. Das heißt, diese coolen Zahlen kommen aus dem wissenschaftlichen Benchmarking Bereich, der absolut seine Legitimität hat. Aber die lassen sich in der Realität nicht wieder abbilden oder nur sehr vereinzelt. Deshalb sage ich, dass es derzeit einige wenige nutzvolle Nischen gibt.“ [In this respect, it does not yet work in such a way that it offers real added value. The problem is that all this hype is benchmark-based. That is, these cool numbers come from the scientific benchmarking area, which has its legitimacy. But they can't be replicated in reality, or only very sporadically. That is why I say there are these few useful niches.] (D. Mitrovic, personal interview, Vienna, April 14, 2022).

Nevertheless, the niches outlined by Mr. Mitrovic already provide a considerable amount of highly useful use cases and applications for businesses. Despite only three candidates having a technical background, all of the interviewees were able to highlight aspects such as task automation as well as text and visual recognition as initial elements that already showcase the potential of AI in routine business tasks. As highlighted by Mr. Schwärzler, such initial steps form the basis for trust and awareness when it comes to the subsequent adoption and promotion by the people within the organisations. He argued: “Das heißt, wenn das jetzt so unter der Haube so langsam reinkommt und dann irgendwo sinnvolle Vorschläge macht und man merkt es kaum, dann funktioniert es.“ [That means that if this now comes in slowly under the hood and then makes reasonable suggestions and you hardly notice it, then it works.] (B. Schwärzler, personal interview, Vienna, May 6, 2022). Apart from an adoption as well as trust and fear standpoint, which is thoroughly described later on in this section, there are several other currently evident benefits and advantages as a positive byproduct of using artificial intelligence in business processes and operations according to the candidates. Apart from the apparent aspect of task automation, other factors include new business models through newly processed and interpreted data as stated by Mr. Resch and Mr. Stangl, faster and more consistent decision-making as highlighted by Mr. Mitrovic, more efficient recruiting systems as highlighted by Mr. Ardaiz as well as less dependencies on external partnes such as legal parties due to interpretive capabilities on the part of the AI. Mr. Mitrovic further elaborated on the latter: “Man kann gewisse Tätigkeiten von Anwälten oder von studierten Juristen, vielleicht Anwälte noch nicht, aber gewisse Tätigkeiten von Juristen heute zumindest teil-automatisieren oder voll-automatisieren. Das ist bis vor 10 Jahren noch nicht gegangen. Und heute kann man das als Technologie kaufen, installieren und laufen lassen.“ [It is possible to partially or fully automate certain activities of lawyers or paralegals, lawyers perhaps not yet, but certain activities of paralegals can be automated today. That was not possible until 10 years ago. And today you can buy it as technology, install it and run it.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). These current as well as anticipated benefits continued to be mentioned throught the interviews upon exploring subsequent topics and challenges. Such are further elaborated on in the respective sub-chapters of this discussion.

4.2.3 Challenges of AI in a Business Context

4.2.3.1 Economic Feasibility

One of the most prominent challenges outlined by the candidates revolved around the aspect of economic feasibility when it comes to the implementation and maintenance costs in relation to the subsequent benefits of AI. In this regard, all candidates did not differentiate between established businesses or startups. Any investment is highly evalued based on the cost-benefit calculation. Mr. Stangl stated: "Man muss probieren, mit möglichst wenig Ressourcen sehr gute Ergebnisse zielen zu können." [You have to try to achieve very good results with as few resources as possible.] (S. Stangl, personal interview, Vienna, April 27, 2022). Seeing as with AI, it is a rather continuous process with ongoing required investments, large-scale applications may often appear to not be feasible. In this case, technological barriers are not the main challenge. With regards to a contact of his who works with Natural Language Understanding (NLU) programs and solutions, Mr. Mitrovic stated: "Ich glaube schon, dass die Jungs das technisch hinbekämen. Ich glaube einfach, dass es bei ihnen ein wirtschaftliches Thema ist, da es sich quasi nicht lohnt für nur ein paar hunderttausend Menschen, die in einem bestimmten Dialekt sprechen eine AI zu trainieren." [I think the guys could do it technically. I just think it's an economic issue for them, because it's not worth it to train an AI for just a few hundred thousand people who speak in a certain dialect.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). Nevertheless, it has also been highlighted that this factor of economic feasibility will continue to decrease due to a constant increase in computing power and a reduction in development, implementation and maintenance costs. This trend has been historically documented with regards to AI as well as computing power and data storage in general as outlined previously in this paper (Mack, 2011). When it comes to startups in particular, Mr. Stangl described a general practice which also could also very much apply to the development and implementation of AI. He argued: "In den moisten Fällen reicht es, ein schnelles Proof of Concept zu entwickeln und so sehr Ressourcen-schonend zu arbeiten." [In most cases, it is sufficient to develop a quick proof of concept and thus work in a very resource-saving way.] (S. Stangl, personal interview, Vienna, April 27, 2022). This is a very important insight given intangible success factors such as human adoption and promotion of this technology - aspects which are described in the Human + Machine section below.

4.2.3.2 Data Privacy & Security

When it comes to data considerations, the candidates highlighted two main aspects with regards to using AI as businesses and startups. First, there is the factor of data privacy and security. The second being regulatory implications. To begin with, four out of the seven candidates underlined the important consideration of data collection, processing and storage. The complexity here stems from the integration of systems from which AI algorithms can pull the data streams from. Consequently, the machine might be able to use information which should not be processed in the first place due to a multitude of potential reasons. In addition, the machine is not capable of understanding or interpreting the data in relation to its privacy, relevancy and protectability. This factor is also strongly tied to the aspect of ethical considerations based on the programming intention of a given AI system as highlighted my Mr. Ardaiz. The challenge of ethical implications is discussed in detail further on in this paper. Seeing as data is generally becoming increasingly valuable, the challenge of storing such data securely and having controllable systems will accompany this technological transition continuously. This challenge will also strongly influence the relevant aspects of trust and fear concerning the adoption levels of employees and customers alike.

Secondly, the interviewees voiced the crucial factor of legal compliance and regulatory considerations. Regardless of the origin of the given data, either from employees or customers, acceptance and transparency are key elements for any company. This compliance can also be very resource-intensive as highlighted by Mr. Resch. He argued: "… Du brauchst eigentlich immer die Akzeptanz der Personen, die die Daten hergeben. Also das sind natürlich die Regulatoren und das sind die Gesetzgebungen und das sind, ja, gesetzliche Bestimmungen, die du einhalten musst. Das ist, glaube ich ein Schritt. Das ist auch die Frage, hat jedes Startup oder haben kleinere Unternehmen diese Möglichkeiten, dem so genau nachzugehen?" [You actually always need the acceptance of the people who provide the data. So it is about the regulations, of course, and the legislatures and, yes, legal requirements that you have to comply with. That is, I think, one step. Then there is also the question, does every startup or do smaller companies have these capabilities to follow this so closely?] (B. Resch, personal interview, Vienna, April 27, 2022). Given its importance and the high amount of resources required, this topic poses a significant challenge for startups and businesses alike which might even pose the threat of discouraging leading stakeholders of investing bespoke resources in such technologies.

4.2.3.3 Human Capabilities & Budget Allocation

Another critical factor would be the combination of finding rightly skilled people as well as making the corresponding financial dedication with regards to ressources made available. One crucial factor in this case are the decision-makers as pointed out by Benjamin Schwärzler. He stated: "Man braucht ein Budget dafür und nur wenn die Entscheider glauben, dass das tatsächlich funktioniert und dann noch einen wirklichen Vorteil bringt, dann werden sie es machen. Und ich denke, das ist wahrscheinlich der kritische Erfolgsfaktor - um das zu erreichen, braucht es einen Haufen Market Education und gute Beispiele, wo es funktioniert hat, das zieht am meisten.“ [You need a budget for it and only if the decision makers believe that it actually works and then results in a real advantage, then they will do it. And I think that's probably the critical success factor - to achieve that, you need a lot of market education and good examples where it's worked, that's what attracts the most.] (B. Schwärzler, personal interview, Vienna, May 6, 2022). These exemplary use cases are becoming more prominent as highlighted in the literature review due to an overall increased awareness about the technology as well as through an ever growing number of third party products and services.

The second aspect with regards to this challenge concerns the element of human capital. As highlighted by Mr. Resch, particular roles occupied by experts were needed in order to realize his company’s aspirations with regards to the applied artificial intelligence algorithms. He affirmed: “Also bei der Implementierung waren sicher zwei Leute voll involviert, immer wieder. Natürlich gibt es Phasen, wo es auch andere Aufgaben gibt, aber das war ein Dauerthema. Und wir wir hatten zum Schluss einen Data Scientist, der nichts anderes gemacht hat als Daten lesen und interpretieren.“ [So during implementation, two people were certainly fully involved, again and again. Of course, there are phases where there are other tasks as well, but that was an ongoing issue. And at the end, we had a data scientist who did nothing but read and interpret data.] (B. Resch, personal interview, Vienna, April 27, 2022). Mr. Mitrovic added the complexity of a challenging labor market for startups when it comes to AI experts. He stated: “… aktuell hast du als Scale Up ziemliche Schwierigkeiten auf einem sehr leergefegten Markt Senior Personal im Ai Bereich zu finden. Die Leute gibt es nicht.“ [… currently, as a scale up, you have a lot of difficulties to find senior personnel in the Ai area on a very empty market. The people do not exist.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). This challenge is thoroughly described later on in this section as other candidates added to this thought. Nevertheless, it also represents an important consideration with regards to the technical realization of AI technologies in startups.

4.2.3.4 Machine Errors & Explainability

The last challenge raised by three out of the seven candidates concerned the aspect of anticipating and managing machine errors. Despite the arguably lower error rate in comparison to human decisions, the aspects of explainability and transparency, also represent considerable factors. In case errors of any nature made by algorithms occur, the question of responsibility arises. Furthemore, such events can harm intangible factors such as trust levels of employees and customers alike which in turn might negatively affect the transition of becoming an AI-powered business. Besides intermediary human roles that can be used to anticipate errors or to train the machine after an error occurred, technological possibilities are also emerging as highlighted by Mr. Stangl. He argued: “Es gibt ja auch Methoden, wo die Maschine praktisch erklären muss, wie sie zu diesem Schluss gekommen ist. Das geht in die Richtung Explainable Machine Learning. Also das wird in Zukunft sicher immer wichtiger werden.“ [There are also methods where the machine has to practically explain how it came to this conclusion. This goes in the direction of Explainable Machine Learning. So that will certainly become more and more important in the future.] (S. Stangl, personal interview, Vienna, April 27, 2022). Such technological options are however also accompanied by the previously highlighted challenges.

Another crucial element in this consideration is the aspect of human perception and capability. Mr. Mitrovic stated: “Die meisten Leute verstehen sie (die Maschinen) auch nicht. Explainability ist auch ein echtes technisches Thema, das immer mehr Bedeutung bekommt.“ [Most people do not understand them (the machines) either. Explainability is also a real technical issue that is becoming more and more important.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). Consequently, in case a given AI solution makes a recommendation, it might be offsetting for people as they often do not understand the reasoning or data behind the suggestion. Particularly in the beginning, such a fundamental understanding is however key. As pointed out by Mr. Stangl and Mr. Mitrovic, people with strong statistical and data science backgrounds are needed in order to overcome such interpretation and explainability issues. The elements of trustability and human capabilities are further explored in the subsequent section of this chapter.

4.2.4 Human + Machine

4.2.4.1 Transition & Adoption

The process of transitioning to an AI-powered business is heavily influenced by the human element. As highlighted in the literature review, it will require various forms of close collaboration during the transition process as well as afterwards. AI will in the short-term most likely not function as a standalone entity. Consequently, a crucial part of the research concerned the exploration of such forms of collaboration as well as required roles perceived and experienced by the candidates.

One key term was repeatedly outlined by all candidates in different contexts with regards to the implementation and adoption of AI technologies, namely, trust. Apart from the previously highlighted aspect of transparency and explainability, Mr. Resch, Mr. Ardaiz and Mr. Stangl all outlined the crucial factor of testing, validating and iterating in order to build trust in different types of new technologies. In addition, an open mindset also plays an important role along with the outlined notion of encouraging failures in order to learn. Mr. Resch recalled: “Die Leute haben einen sehr starken IT-Fokus gehabt. Ich kann mich erinnern, wie Stefan

(Mitgründer) mit der Idee gekommen ist, dass er diese unterschiedlichen AI Technologien einführen will. Wir haben das mit offenen Armen empfangen. Das war für uns und auch für ihn Neuland.“ [People had a very strong IT focus. I remember Stefan (co-founder) coming up with the idea that he wanted to introduce these different AI technologies. We welcomed that with open arms. It was new territory for us and also for him.] (B. Resch, personal interview, Vienna, April 27, 2022). Upon implementing such technologies, Mr. Resch described rigorous analysis phases in order to continuously improve bespoke innovations. He stated: “... diese Inhalte sind von uns vorab definiert und erlernt worden in diesem AI Tool und das ist dann später auch überprüft und validiert worden. Und diese Implementierung, dieses Testen, das ist von uns auch immer wieder vertestet, verprobt und analysiert worden ...“ [... these contents have been defined and learned by us in advance in this AI tool and this has then also been checked and validated later. And this implementation, this testing, has also been tested, tried and analyzed by us again and again ...] (B. Resch, personal interview, Vienna, April 27, 2022). Apart from continuously improving such tools, these processes build trust in the eyes of the employees or the customers. This in turn represents arguably the most crucial success factor for transitioning to an AI-powered business in the long-term as the intangible but ever so important element of trust has been outlined numerous times by all the candidates.

4.2.4.2 Intermediary Roles

The aspect of building trust was further elaborated on by all the candidates in the form of intermediary roles between humans and machines. Above all stands the apparent demand of founders and startup executives to be involved in the various decision-making processes due to the high stakes involved. Mrs. Scherzinger stated: “Es darf sich nicht ausschließlich auf das System verlassen werden, es muss diese Selbstbestimmtheit, die ich noch beibehalten möchte, auch geben, aber es soll sich miteinander ergänzen. Also das ist so meine Vision.“ [There must not be an exclusive reliance on the system, there must also be this self-determination, which I would still like to maintain, but it should complement each other. So that's my vision.] (R. Scherzinger, personal interview, Vienna, May 4, 2022). Other candidates further elaborated on this desired symbiosis between humans and machines in order to automate processes as well as to make faster and more consistent decisions, amongst other factors.

These highlighted forms of collaboration are particularly relevant during the dawn of AI applications in business operations as highlighted by Mr. Mitrovic. He argued: “Das ist das, was ich glaube, was wirklich nützlich ist oder wo der Mehrwert wirklich massiv entstehen kann. ... zumindest für alles, wo es ein bisschen komplexer wird, ist das der Way to Go, wenn man mich fragt.“ [That's what I think is really useful or where the added value can really come from on a massive scale. ... at least for anything where it gets a bit more complex, that's the way to go if you ask me.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). In addition to interpretive and explaining roles, tasks concerned with the technical implementation are just as crucial seeing as such form the foundation for later results. Mr. Schwärzler described this element of humand and machine collaboration during the setup by stating: ”Ja die kann es schon zumindest für eine Übergangsfrist geben, denke ich. Also es beginnt ja damit, dass diese AI ja irgendwie trainiert oder konfiguriert werden muss und dass die da ein stückweit nachher draufschauen, was da rauskommt und ob das mit dem zusammenpasst, was wir uns vorstellen oder wo wir hinwollen. Also ja, ich denke, die kann es schon geben oder die wird es geben oder eher die muss es geben.“ [Yes, such could exist at least for a transitional period, I think. So it starts with the fact that this AI has to be trained or configured in some way and that they look at it afterwards to see what comes out of it and whether it matches what we imagine or where we want to go. So yes, I think there can be, or there will be, or rather there must be.] (B. Schwärzler, personal interview, Vienna, May 6, 2022).

The candidates did not describe in detail any envisioned intermediary roles which have been highlighted in the literature review of this paper for future scenarios or setups. A potential reason for this are the non-technical backgrounds of four of the candidates as well as a strong focus by all of the interviewees on the short-term impact of AI. Nevertheless, they all agreed that the two elements of human and machine should not be viewed as separate entities and that it will require various forms of collaboration to fully unlock the true potential of AI.

4.2.4.3 Challenges

Similarly to the technical aspects concerning the implementation and adoption of AI technologies in startup business processes, the candidates raised certain challenges associated with the human element in relation to this innovative technology. As previously highlighted, most of the following challenges are related to the overarching issue of overall trustability. All of the candidates described this to be a fundamental part of any innovation’s adoption curve and arguably the most important critical success factor with regards to this technological evolution, as previously outlined.

4.2.4.3.1 Familiarity with other Systems & Routines

The factor of familiarity with other systems and routines affects decision-makers and employees alike, albeit on two different levels. When it comes to decision-makers, such particular closeness to certain procedures or tools might result in an unintentional ignorance towards new technologies such as AI as a everything is seemingly functioning perfectly. Despite the fact that such innovations might in fact propel the business even more forward. Mrs. Hallmann noted: “Es läuft irrsinnig gut. So gut, dass ich ein zweites Geschäft aufmachen konnte. Deswegen hatte ich nie das Gefühl, dass ich mir jetzt jemanden holen muss, der mich berät, der mir zeigt, was kann man optimieren, weil ich das Gefühl habe, es läuft sehr gut. Aber ich nehme mal an, es gäbe wahnsinnig viel Potenzial noch mehr rauszuholen und noch mehr zu erleichtern.“ [It's going insanely well. So well that I was able to open a second business. That's why I've never had the feeling that I need to get someone to advise me, to show me what can be optimized, because I have the feeling that it's going very well. But I suppose there is a lot of potential to get even more out of it and to make it even easier.] (L. Hallmann, personal interview, Vienna, April 20, 2022). On the other hand, this familiarity with established processes and tools on the side of a startup’s employees might decelerate or even halter the adoption of new technologies such as AI. The handling of this challenge highly depends on factors such as business-internal decision-making, an established failure culture as well as working interdisciplinarily. All of these elements are discussed later on in this paper.

4.2.4.3.2 Loss of Human Interaction

The challenge of losing human interaction touchpoints has been thoroughly highlighted by Mrs. Hallmann and Mrs. Scherzinger. It concerns employee and customer touchpoints alike. Both raised the concern that task and process automation solutions powered by AI in this context could be more counterproductive. This is due to the fact that in the case of certain processes and touchpoints human interaction is arguably indispensable. Both interviewees highlighted the importance of the human element in the context of customer interaction such as via chatbots - an AI-powered CRM tool which arguably falls in the category of internal processes due to the amount of data it can collect and processes it can facilitate. On offering various machine-automated services to custmers, Mrs. Hallmann stated: “Aber ich muss ehrlich gestehen, ich hoffe, dass es nicht sehr in die Richtung Voll-Automatisierung geht, weil das ist natürlich das, was ich kann und was ich auch anbiete. Das ist auch das, wo ich auch davon überzeugt bin, dass das mit künstlicher Intelligenz in diesem Bereich nicht alleine funktioniert.“ [But I have to be honest, I hope that it does not go very much in the direction of full automation, because of course that's what I can do and what I also offer. That is also where I am convinced that artificial intelligence alone will not work in this area.] (L. Hallmann, personal interview, Vienna, April 20, 2022).

Adding to this notion of CRM automation and the importance of the human element in this context, Mrs. Scherzinger added: “Irgendwie möchte man dann doch das Gefühl haben, dass man mit einem Menschen kommunizieren und, dass man auch ernst genommen wird, dass man jetzt nicht von einer Art Maschine einfach so abgefertigt wird. ... Man muss wirklich gemeinsam schauen, dass der Kunde das Gefühl zumindest bekommt, dass da ein physischer Mensch sitzt, der ein wirkliches Interesse hat, einem zu helfen und der wirklich auch das Problem versucht zu verstehen und versucht wirklich mit einem Lösungsvorschlag zu kommen, der jetzt nicht irgendwo aus einer FAQ Section kommt. Es darf keine Abarbeitung von irgendeinem intelligenten System sein, sondern so, dass man wirklich diesen Austausch fördert. Ich glaube, das ist gerade für Unternehmen, die am Anfang stehen, sehr wichtig.“ [Somehow you want to have the feeling that you are communicating with a human being and that you are being taken seriously, that you are not being processed by some kind of machine. ... You really have to look together that the customer at least gets the feeling that there is a physical person sitting there who has a real interest in helping you and who really tries to understand the problem and really tries to come up with a solution suggestion that does not come from a FAQ section somewhere. It should not be a processing of some intel-ligent system, but in such a way that one really promotes this exchange. I think that is very important, especially for companies that are just starting out.] (R. Scherzinger, personal interview, Vienna, May 4, 2022).

As highlighted in the literature review of this paper as well as by Mr. Mitrovic however, NLU solutions are becoming increasingly sophisticated. Furthermore, the aspect of partially automating such processes with some level of human interaction could also represent a formidable solution approach for the short-term. Nevertheless, this important element of maintaining some level of human interaction is an important consideration with regards to large-scale AI solutions.

4.2.4.3.3 Ethical Factors

Similarly to the issue of data privacy and security, a comparably large group of four interviewees highlighted the significant challenge of ethical considerations and implications in the interplay between humans and machines. To begin with, an important aspect in this regard are various intentional or unintentional biases that might be introduced during the setup of different algorithms. Mr. Ardaiz noted: “And then the intention, right, the intention of the programmer writing the algorithm. I think this is the other massive factor. Right? So if you have got a lot of white males writing a lot of algorithms for AI, then you might have an issue, right, because not everybody is a white male on this planet. So you have got to have and think about the implications around diversity and the implications associated with the biases of white male programmers in relationship to writing algorithmic functions of artificial intelligence is a massive, massive problem to that I already foresee and that it is already happening and will continue to happen until we get a lot more diverse thoughts and opinions in the room around how and why to write those algorithmic programs.” (S. Ardaiz, personal interview, Vienna, April 19, 2022). Mr. Mitrovic added to this extremely serious concern while also pointing out, that various AI communities in Austria as well as internationally are aware of these monumental issues and that they have become significantly more prominent over the past few years. The more applicable AI becomes, the more businesses have a high degree of social responsibility to introduce checking and controlling mechanisms as well as escalation points. This holds particularly true for startups given their ability to scale up fast and impact a vast number of people very rapidly.

4.2.4.3.4 Fear

One challenge closely related to the overarching aspect of trust is the reactionary rejecting emotion of fear. Similarly to the familiarity with established systems and tools, fear also concers the two levels of decision-makers as well as operational staff. When it comes to the decision-making level, people in such positions tend to operate more visionary as highlighted by Mrs. Hallmann and Mr. Schwärzler. Nevertheless, the uncertainty of attaining a good ROI with a new investment and change of process can also be quite daunting. With regards to implementing arguably even more innovative tools such as AI-powered technologies, Mr. Stangl stated: "Aber ich glaube die größte Hürde ist die, dass man sich hier darüber traut und auch nicht versucht, spezialisierte Machine Learning oder AI Technik zu finden, sondern auch einfach verschiedene Sachen ausprobiert und sich Schritt für Schritt vorhantelt." [But I think the biggest hurdle is that you dare to go over it and also that you do not try to find specialized machine learning or AI technologies, but you just try different things and you dare to go step by step.] (S. Stangl, personal interview, Vienna, April 27, 2022). This consideration certainly also feeds into the aspect of an encouraged failure culture as described later on in this section.

The second considerable hurdle concerns the staffing level. The reactionary emotion of fear is a common observation when it comes to change processes. Mr. Mitrovic argued that the fear in relation to AI probably stems from its potential to automate and thus eradicate jobs. He noted: "Das ist quasi standardmäßig bei Veränderung. Jede Einführung einer Technologie und Change ist ein Prozess und man hat hier das gesamte Spektrum an menschlichen Reaktionen. Im AI Bereich, das was ich gesehen habe, ist tatsächlich die Angst vor dem Arbeitsplatz-Verlust - ganz klar. Das unterscheidet sich eigentlich nicht von allen anderen Automatiesierungs-Prozessen. Die Schichten werden immer breiter." [That's pretty much standard for change. Any introduction of technology and change is a process and you have the full spectrum of human reactions here. In the AI space, what I've seen is actually the fear of job loss - clearly. That is really no different from any other auto-matization process. The layers are getting wider and wider.] (D. Mitrovic, personal interview, Vienna, April 14, 2022). As discussed previously and as outlined again by Mr. Mitrovic on this note, the transition to AI-powered businesses will concern more educated people. Nevertheless, as pointed out in the literature review of this paper, the aspect of new jobs as well as various forms of interdisciplinary collaboration might represent different alternatives for potentially affected parties. When it comes to the initial adoption of partially or even fully AI-powered tools and systems, Mrs. Hallmann described the key practice of providing trainings or courses in order for her employees to gain awareness and consequently trust with such novelties. She said: "Ich nehme an, in erster Linie die Schulungen oder den Mitarbeiter überhaupt soweit zu bringen, dass man ihm das näherbringt, dass das was Positives, was Gutes ist. ... Und da die Schulung so umzusetzen, dass sich erstens alle auskennen und zweitens, dass sich Gruppen finden und es dann weiter so machen wollen." [I suppose, first and foremost, the training or getting the employee to that point in the first place, that they are made to understand that that is something positive, that it is something good. ... And to implement the training in such a way that, first of all, everyone is familiar with it and, secondly, that groups find each other and want to continue to do it in this way.] (L. Hallmann, personal interview, Vienna, April 20, 2022). Awareness is a crucial factor with regards to implementing and adopting AI technologies in business processes. The point raised by Mrs. Hallmann could prove to be a great measure in this context.

4.3 Startups

4.3.1 Coding & Evaluation Approach

The second overarching topic concerned the collection of all the observations and statements on startup dynamics, dependencies and particularities. Within this section, some of the subgroups included general challenges, specifics on internal processes and dynamics as well as observations on the Austrian startup scene. Due to the overlapping and dependencies of some statements and observations, the subgroup of Austrian startup scene was split up and merged with the respective subgroups in this paper. Quantitively, the most observations and statements were made with regards to the internal dynamics. As thoroughly described later on in this section. These aspects are key driving forces when it comes to a large-scale business transformation.

FIGURE 10 - OBSERVATION CODES & LABELS ON STARTUPS

4.3.2 Challenges

In order to guarantee a successful transition to becoming an AI-powered business, several factors were highlighted, which did not fall into any of the three dimensions, namely, staff, technological or financial. The findings highlighted in the previous section can clearly be associated to one of the three. However, seeing as there are a number of additional challenges that startups face, such must also be considered when discussing the implementation of such radical innovations. Furthermore, some of these challenges are either increasingly evident in the Austrian startup scene or accommodated and facilitated through various systems and mechanisms.

4.3.2.1 Vision & Focus

One key element when it comes to startups is the overall vision and ever-changing strategy or approach. Seeing as young startups start with a basic vision and approach, such are often changed in order to accommodate new obstacles, as highlighted by Mr. Resch. Furthermore, a startup's development is also defined by continuously evolving products or services as well as new ones. This feeling of never reaching a definite goal has also been highlighted on a personal level by Mr. Resch. He described both sensations: "... du startest mit einem Grundgedanken und mit einer Grund-Vision. Aber diese wird so oft verhindert, dass du immer bereit sein musst, diese Vision zu verändern. Das habe ich auch stark bei mir gespürt. Zum Beispiel das Gefühl, dass wir niemals fertig werden. Du bist niemals fertig. Du kommst immer rein in dieses Verbessern, Verändern, Erweitern. Und dieser lange Atem und diese Neuinterpretation und diese neue Definierung einer Vision stetig und ständig, das ist schon eine große Hürde und ja, einfach ein Druck." [You start with a basic thought and a basic vision. But this is so often hindered that you always have to be ready to change this vision. I have also felt this strongly in myself. For example, the feeling that we are never finished. You are never finished. You are always getting into this improving, changing, expanding. And this staying power and this reinterpretation and this new definition of a vision constantly and constantly, that is already a big hurdle and yes, simply a pressure.] (B. Resch, personal interview, Vienna, April 27, 2022). In addition, this vision and current focus points must always resonate with potential investors or other external partners. Mrs. Scherzinger pointed out: "Wenn man nicht an sich selbst glaubt, an sein eigenes Projekt, wie soll der mögliche Partner dann an dich glauben?" [If you do not believe in yourself, in your own project, how can a potential partner believe in you?] (R. Scherzinger, personal interview, Vienna, May 4, 2022). Such intangible factors of a changing intrinsic purpose and different focus areas can highly influence the growth and network of a startup as highlighted by the candidates.

4.3.2.2 Pressure from Stakeholders

Adding to the element of external collaborating bodies, startups are connected with a number of different stakeholders. Such can also exert high amounts of pressure in a number of different ways. A couple of points stand out in the eyes of the candidates. First, the considerable amount of perceived pressure from investors and business partners. Second, the aspect of societal pressure and social responsibility forms the other component in this regard.

To begin with, investors and business partners can be involved in a startup in various forms ranging from financial support to network opportunities as well as access to different expertises and knowledge. In return, such external stakeholders have high expectations from the respective startup and more specifically, the people within such startups. The aspect of time was the most prominent factor highlighted by Mr. Resch, Mrs. Scherzinger and Mr. Stangl, particularly on the side of financial investors. Such expect a rapid ROI given the amount of uncertainty surrounding startups. Mr. Stangl further elaborated on this point by highlighting their involvement in order to reach this point faster. He stated: "… da braucht man wieder Unterstützung von Investoren, ob die dann auch dabei sind, bei jeglicher Entscheidung." [... again, you need the support of investors, whether they are then also on the same page, with any decision.] (S. Stangl, personal interview, Vienna, April 27, 2022). Mr. Mitrovic outlined the aspect of losing a considerable amount of say in the business in case external partners are heavily involved. Such strong involvement and a consequent introduction of different interests may deter a startup from its vision and ambition. The subsequent challenge of finding the right partners is further explored in the context of financial constraints, particularly in the Austrian startup scene.

The second element in this regard represents societal pressure. This can be due to unattainable success stories lived by industry peers as highlighted by Mr. Resch. In addition, Mr. Resch described a previously existing trend of promoting oneself unrealistically in front of other founders and that such untrue success stories truly harmed their own feeling of self-worth, despite their considerable progress. This goes hand in hand with the fact that in the Austrian startup scene, failures were deemed horrendous up until recently. This has changed but Mr. Resch highlighted the earlier advances in this regard in other markets such as in the USA. Lastly, the aspect of social responsibility is also a key element for founders. Mr. Resch described a number of project they did not set out to do despite their potentially tremendous impact due to the involvement of sensitive data.

4.3.2.3 Resource Limitations

4.3.2.3.1 Human Capital

The challenge of attracting and attaining the right talent represents a considerable hurdle as mentioned in the previous section. This holds particularly true for startups and even more so for the Austrian labor market as thoroughly described by all candidates. According to Mr. Mitrovic, Mr. Stangl, Mrs. Scherzinger and Mr. Resch, startups fall behind larger corporations or startups in terms of overall competitiveness. This competitiveness is based on two important factors, namely financial possibilities and working condiditons. Seeing as these two variables are often unstable in the context of startups, finding specialists in certain areas often represents a considerable challenge. This is even more emphasized in the area of AI as previously highlighted by Mr. Mitrovic. Mr. Stangl added to this point by stating: "Bei technischen Berufen muss man diesen Mitarbeitern sehr viel bieten können. Es wird sehr viel nach diesen Spezialisten gesucht und da muss man sich abheben von der Masse. Das muss nicht unbedingt mit Gehalt oder so sein, sondern einfach die ganzen Benefits rundherum. Das kann auch ein Mitspracherecht im Startup sein. Ein weiterer Faktor ist, ob man auf die Ideen dieser Leute hört und ob ihre Ideen ausprobiert werden, oder man praktisch den Menschen als Arbeitsmaschine sieht. Der Status im Unternehmen ist sehr wichtig. Da gibt es sehr viele Punkte, welche man bedenken muss." [In technical professions, you have to be able to offer these employees a great deal. There is a lot of demand for these specialists and you have to stand out from the crowd. It does not necessarily have to be related to the offered salary or anything like that, but all the surrounding benefits. That can also be a say in the startup. Another factor is whether you listen to the ideas of these people and whether their ideas are tried out, or whether you practically see people as working machines. Status in the company is very important. There are a lot of points that you have to consider.] (S. Stangl, personal interview, Vienna, April 27, 2022).

Mr. Stangl also highlighted the aspect of making certain compromises which in turn affect the business positively in other ways such as culture and individual motivation. Such intangible factors are crucially important. However, such compromises and respective decisions must be made in the beginning. He noted: "Und als Startup mit wenig Budget ist es unrealistisch, dass man da komplett ausgebildete Fachkräfte hat. Man muss den Kompromiss eingehen und sagen ja wir nehmen einen HTL Absolventen, zum Beispiel und baut den dann auf über Monate, aber wir wissen, dass dieser mit Herzblut dabei ist. Das ist viel besser als eine Fachkraft, die das nur als Job sieht. Da muss man eine wichtige Entscheidung gleich am Anfang treffen." [And as a startup with a small budget, it is unrealistic to have fully trained specialists. You have to make a compromise and say yes, we'll take an HTL graduate, for example, and then build him up over a period of months, but we know that he will put his heart and soul into it. That is much better than a specialist who only sees it as a job. You have to make an important decision right at the beginning.] (S. Stangl, personal interview, Vienna, April 27, 2022). Mrs. Scherzinger further outlined the indispensable factor of cultural fit in the context of startup employees as a shared vision and ideally passion are key driving forces of the company's success.

4.3.2.3.2 Financial Constraints

The challenge of financial constraints has been mentioned by six out of the seven interviewees. It certainly represents a significant hurdle for startups in general but Mr. Mitrovic, Mr. Schwärzler and Mr. Stangl further outlined the additional difficulty in the Austrian economic area. According to Mr. Mitrovic, this is due to large players pushing into the European market with Austrian startups not being able to compete on such levels both on the labor market as well as with regards to the development and distribution of products or services. Nevertheless, Mr. Mitrovic as well as Mr. Resch and Mrs. Scherzinger also described the emergence of various forms of support mechanisms and systems offered in Austria over the past few years from which startups can truly benefit in relation to such financial issues. Nevertheless, as highlighted by Mr. Schwärzler, such supporting systems are considerably better established in other markets. According to him, this is partially due to higher business valuations in countries such as Germany or the USA.

As a result, for an Austrian startup, not only is the aspect of finding investors and partners a challenge, but also the factor of limited financial ressources. Mr. Schwärzler highlighted the fact that most money goes straight into marketing and distribution nowadays as hardly any product or service sells on its own. On that note he also described the expectation of many investors in Austria who expect high sales numbers without dedicating large amounts of money towards marketing. According to him, many Austrian investors consider such money wasted. Nevertheless, it is needed and this expensive lifeline for startups can threaten the growth of a business as less resources are available for product or service development as well as team expansion. Mr. Ardaiz further added: “As a founder, you are always trying to figure out cash flow, obviously cash flow and funding and financing.” (S. Ardaiz, personal interview, Vienna, April 19, 2022).

4.3.3 Internal Processes & Dynamics

Another key part in the context of understanding Austrian startups concerned the different internal dynamics, mindsets and approaches. As highlighted in the discussed literature, such intangible cultural aspects are crucial when it comes to large scale business transformations. The aim of the corresponding question was to examine whether such established cultural beliefs and processes could be a differentiating factor as well as a critical success factor in the context of the implementation and adoption of AI technologies.

4.3.3.1 Failure Culture

One of the three key elements of a successful implementation of AI technologies in a business context is the concept of encouraging errors and failures in order to learn, as discussed in the literature review of this paper. Overall, this factor was thoroughly described and highlighted by all seven interviewees as an integral element of their respective businesses. Mr. Schwärzler outlined the aspect of hindering future contributions in case errors are disparangingly disregarded or even punished. Mr. Resch stated, that everyone including decision-makers make mistakes, whose are arguably even more impactful. Despite the fact that such errors occur, he also noted the incredibly important aspect of learning from them, particularly in the beginning. In order to learn from such errors, Mrs. Hallmann described her team's practice of processing past experiences together. She stated: "... dieses Zusammensetzen und gemeinsames Überlegen ... Wir setzen uns manchmal zusammen und sagen, so einen Fall habe ich noch nie gesehen. Was würdest du tun?" [… this sitting down and thinking together ... We sometimes sit down together and say, I've never seen a case like this. What would you do?] (L. Hallmann, personal interview, Vienna, April 20, 2022). Mrs. Scherzinger outlined the aspect of leading stakeholders embracing errors of their own as this sets the tone for the entire business. She added that egos and stubborn opinions can be very harmful with regards to the development of a startup.

It has to be noted however, that despite the fact an error culture is encouraged by all interview partners, a certain notion of trying to avoid impactful errors has also been mentioned. This factor is closely tied to the elements of resource limitations and pressure from external stakeholders. As a result, Mr. Stangl and Mr. Resch highlighted the aspect of testing and iterating new elements in smaller environments. Based on a product-focused perspective, the pair described different A/B and sometimes even A/B/C testing practices of new features in order to avoid large scale setbacks. From an internal perspective, Mr. Schwärzler described a personal testing period including some feedback rounds later on. He stated: "Und gemacht habe ich das immer, indem ich das für mich selber aufgesetzt habe und ausprobiert habe. Und wenn ich das gut fand, dann habe ich das vielleicht noch jemanden gezeigt bei uns im Management Team und habe so auch Feedback eingeholt. Und wenn die das auch gut fanden, dann haben wir das aufgesetzt und dann zu einem passenden Zeitpunkt dann an alle Mitarbeiter weitergegeben." [And I always did that by setting it up for myself and trying it out. And if I thought it was good, then I might have shown it to someone else in our management team to get feedback. And if they also liked it, then we set it up and passed it on to all employees at an appropriate time.] (B. Schwärzler, personal interview, Vienna, May 6, 2022). Such controlling mechanisms in order to still allow for mistakes to happen but to minimize their potential impact are a valuable insight shared by the interviewees.

4.3.3.2 Decision-Making

The second key variable for successful business transformations according to the literature concerned interdisciplinary decision-making. One of the most important insights shared by the interviewees in this context is the fact that due to the smaller team sizes in the beginning, certain cultural values and beliefs can be established early on which helps such mindsets to be nourished when reaching a larger company size. Mr. Mitrovic highlighted the fact that smaller companies hape personalities to a decidedly large extent in comparison which might be a crucial factor in the long-term. When in comes to the operational execution of such dynamics, Mr. Resch stated: "Nein, es war immer so, es war immer demokratisch und es ist sehr viel diskutiert worden." [No, it has always been like that, it has always been democratic and there has been a lot of discussion.] (B. Resch, personal interview, Vienna, April 27, 2022). Such interdisciplinary discussion between employees as well as leadership teams is crucial in order to be agile and to anticipate potentially beneficial pivots. It also helps with regards to drawing learnings from failures and errors across departments. Mrs. Scherzinger further explored this topic including the considerations of external partners when it comes to decisions. She added: "Also ich finde, bei diesem Thema ist es sehr wichtig, wenn man selber die Expertise nicht hat, dass man sich Experten ins Boot holt und dass die auch ganz klar drauf hinweisen, was es überhaupt für Möglichkeiten gibt. Also ich glaube, das ist für mich auch noch ein Thema, weil ich noch sehr viel Lernbedarf habe und mich noch viel intensiver mit diversen Themen beschäftigen muss, wie wir da vorgehen können." [I think it's very important in this area, if you do not have the expertise yourself, that you bring experts on board and that they also clearly point out what options are available. So I think this is also a topic for me, because I still have a lot to learn and I have to deal much more intensively with various topics, how we can proceed.] (R. Scherzinger, personal interview, Vienna, May 4, 2022). Given the importance of interdisciplinary decision-making, as highlighted in the literature review of this paper, the candidates certainly shared very favourable insights with regards to startups fostering the right mindsets and practices in order to undergo such a fundamental business transformation.

4.3.3.3 Forms of Collaboration

Similarly to interdisciplinary decision-making, cross-departmental collaboration is another important factor when it comes to implementing and adopting AI in a business context. Seeing as deeply embedded AI infrastructures use and provide data from different points, such open collaboration practices are crucial to guarantee the success of such. The interview candidates all highlighted the fact that they not only agree in principle but that they also encourage different practices of such interdisciplinary forms of collaboration. During the interview, Mr. Schwärzler showcased a model of such a practice whereby the teams are organized and intertwined along the customer journey. For instance, teams that are somewhat close such as CRM and marketing, there exists an increased number of collaboration touchpoints. This is less the case for teams which are not so closely tied together such as product development and CRM. Mr. Resch went even further in his example during one of his company's growth phases by stating: "Das Team ist auch gewachsen, wir sind größer geworden, wir haben mehrere Projekte gehabt. Also von dem her, war es total wichtig, dass wir agil zusammenarbeiten. Es war teilweise fast schon zu agil, weil wir auf tägliche News oder Einflüsse oder Strömungen von den Produkten von diesen Usern reagiert haben." [The team has also grown, we have become bigger, we have had several projects. So from that point of view, it was totally important that we work together in an agile way. It was almost too agile in some cases, because we reacted to daily news or influences or trends from the products of these users.] (B. Resch, personal interview, Vienna, April 27, 2022). As highlighted by the interviewees, interdisciplinary collaboration is thoroughly lived and promoted within startups. This could prove to be a vital success factor once these types of companies reach scalability and look towards establishing AI-powered infrastructures.

4.3.3.4 Growth Phases

Different considerations raised by some of the interview candidates are also worth mentioning in the context of outlining critical success factors for the implementation of AI technologies. First, Mr. Schwärzler, Mr. Resch, Mrs. Hallmann and Mr. Stangl all highlighted the fact that they found it extremely difficult to anticipate certain growth phases and that such are often triggered by unexpected events. Such can often represent a considerable change in numerous ways of working as well as with regards to other established processes and tools. Mr. Stangl noted: "Normalerweise sagt man bei einem großen Ansturm, dass das das Beste ist, was einem passieren kann. Die Frage ist dann, ob alles gut funktioniert." [Normally, when you have a big rush, you say that's the best thing that can happen to you. The question is then whether everything works well.] (S. Stangl, personal interview, Vienna, April 27, 2022). This uncertainty over potentially upcoming growth phases and subsequent changing tools and processes may represent an additional nourishing and testing ground for smaller applications and use cases. Due to the highlighted agile nature of startups, iterations can be decided and implemented considerably quicker.

When it comes to the decision-making in general, a few insights were shared by the interviewees in relation to change. As highlighted by Mr. Resch and Mr. Stangl, their businesses always aimed at acting based on data and concrete information. In addition to the previously highlighted discussion, Mr. Resch described this numbers-driven aproach by stating: "Auch wenn eine AI implementiert worden ist und man dachte okay, ich weiß nicht ob das es richtig ist, aber es hat dann zu besseren Ergebnissen geführt. Dann haben sie dafür entschieden und wir waren sehr Zahlen-getrieben. Und wenn die Zahlen um 0,1% besser waren, dann war es die ausgewählte Variante.“ [Even if an AI was implemented and you thought okay, I do not know if this is right, but it then led to better results. Then they decided for it and we were very numbers driven. And if the numbers were 0.1% better, then it was the chosen option.] (B. Resch, personal interview, Vienna, April 27, 2022). As highlighted in the literature review of this paper, data-driven decision-making is key when it comes to working with AI. As described by the interviewees, startups act accordingly even in very uncertain circumstances which is a prime prerequisite with respect to a large-scale business transformation.

5 INTERPRETATION OF FINDINGS

The findings and analysis of both the literature review as well as the semi-structured interviews revealed a range of different affirmative and contrary arguments as to whether AI technologies would generally represent a good investment for startups' internal processes and operations. Furthermore, the research of this paper outlined several critical success factors concerning an impactful implementation and adoption of such technologies in a startup context. As discussed in the literature review of this paper as well as based on the insights mabe by the interview candidates, one can generally say a large-scale AI-powered business infrastructure would arguably not be economically feasible for startups nor would it be possible to define the different applications required due to the ever-changing circumstances startups find themselves in. However, the research has also shown that startups feature a number of favourable traits and particularities which would truly be beneficial with regards to a prospective AI business transformation during a scale-up phase. This is due to internal cultural dynamics such as an encouraged failure culture for continuous iterations and improvements, interdisciplinary decision-making as well as cross-departmental collaboration. All of these aspects are repeatedly highlighted as necessary elements in the existing literature for established companies aiming to undergo a successful AI transformation.

The two most challenging success factors come in the form of overall trust by all of the acting stakeholders as well as in the form of financial considerations with regards to the development and implementation. As thoroughly outlined by the interviews, the cultural aspect of trust in the technology is a key factor leading stakeholders must ensure when commiting to such a foundational transition. This trust spans across numerous levels and highlighted observations. This is due to the outlined fact that this new era of digital transformation foresees several roles, positions and tasks between humans and the machines and such must be occupied and successfully fulfilled by understanding and mitigating people. One potential measure to facilitate such a transition would be adequate trainigs and education. As highlighted by the interviewees, general awareness revolving around the topic of AI exists but foundational knowledge is more rare. This can ultimately lead to non-founded suspicion and consequently rejection. However, seeing as the human element in this fundamental business transformation is arguably the most important critical success factor, such facilitation must be provided by leading stakeholders. Furthermore, the technology is still in its beginnings in this context. As a result, employees have to deal with currently existing bottlenecks and technological limitations. If a base layer of trust is not a non-existent variable, the long-term success of a startup transitioning towards being an AI-powered business during a scale-up phase is highly unlikely.

Secondly, the challenge of dedicating and allocating enough budget towards the required sectors is another key success factor for startups. Resources are generally scarce in the context of startups and even more so in the Austrian startup scene due to the highlighted smaller market size and comparably less supporting mechanisms. With regards to the latter, there have been positive developments over the past few years according to the interview candidates. Nevertheless, the Austrian startup scene is still behind in many aspects in comparison to cities such as Berlin or London, to name a few. It has to be noted at this point, that several interviewed founders also highlighted the possibility of raising funds in other markets where the circumstances are more favourable while remaining a business operating out of Austria. When it comes to a business transformation of this size however, leading stakeholders have to continuously allocate such funds towards the chosen tools and applications and even more so towards other options in case the initially chosen ones fail. This persistence and long-term thinking is clearly outlined in the existing literature. The interview candidates on the other hand described the established notion within startups of continuous iteration and rapid pivots towards more ideal solutions and methods. This aspect represents a great prerequisite in the context of an AI business transformation as through ongoing testing and tweaking, ideally suited tools and solutions can be explored and scaled up as soon as the business experiences larger growth phases.

Ultimately, a viable possibility for startups to commence such a transitioning period including all its learning aspects and cultural implications would be an initial sampling of third-party solutions. Currently, the tools and systems offered by large global corporations with extensive amounts of research and development budgets are more suited for startups. Despite the fact, that it is arguably difficult to find some particularly suitable for a specific business need, more general business applications such as CRM tools or communication solutions are already quite established. Such can be used to raise the awareness of AI in the eyes of the employees while also establishing different best practices for a given startup. Once the business experiences more stable economic periods with clearer focus points, a transition to internally built applications would be more suitable. Then, higher investments in larger systems could be made with a generally reduced risk of unimpactful use cases and wasted resources. One aspect that was mentioned several times by the interview candidates is the outlined great use of third-party solutions for trial and testing periods. This holds particularly true for more complex technologies such as AI as the products offered by large companies are already very capable as well as more than sufficient for startups in an early stage. At such a point, dedicating a lot of resources towards internally built solutions would not be reasonable given this option for more uncertain periods. Nevertheless, the learnings, cultural observations and best practices obtained during such a testing period might prove very valuable in light of future large scale technological developments and adoptions.

6 CONCLUSION

The main objective of this thesis aimed at highlighting critical success factors concerning the implementation of AI technologies in the context of startup business operations as well as the overall necessity and purpose filling of such an investment. The research consists of two parts, namely, a secondary data analysis in the form of a literature review as well as a primary data examination based on insights gathered during seven semi-structured in-depth interviews. The interviews were conducted with startup founders in Austria in order to ascertain the outlined findings highlighted in the literature review. The research questions based upon which the interview guideline for the respective sessions was formed reads as follows: *What are the critical success factors concerning an impactful implementation of AI technologies in startup business operations and processes?* Furthermore, these critical success factors were categorized into business-, technological- as well as staff-related considerations and observations. This breakdown aimed at facilitating the insights from both data analyses seeing as the research resulted in a number of different factors and challenges.

The literature review described the arguably fundamental potential of AI in a business infrastructure context. The highlighted data processing capabilities and interdisciplinary data-driven insights already contextualize various competitive advantages in the business world. Given the rapid technological advances, such will only further develop in the future. As a result, numerous businesses are developing internal AI-powered infrastructures or utilize existing third-party solutions provided by large corporations with a strong expertise in the field. Transitions of this magnitude are however always accompanied by a number of different challenges ranging from intangible factors affecting people as trust, fear and uncertainty to tangible business-related ones as technological considerations and limitations as well as financial implications. These variables and challenges vary depending on the size of the respective business as well as factors such as industry and corporate culture.

As outlined in the results discussion of this paper, such large-scale and internally-built AI infrastructures are arguably not economically viable as well as purpose filling for startups which are close to or during a scale up phase. This is due to the highlighted resource limitations as well as the given circumstantial uncertainty startups face. Nevertheless, these businesses feature a number of advantageous traits and cultural particularities which would tremendously support an AI business transformation. Seeing as startups can reach a critical size very quickly, it might prove to be very valuable for these businesses to foster these favorable elements and test different tools and best practices before acting reactionarily rather than proactively. As thoroughly described in this paper, a potential intermediary step might be to trial and test different third-party solutions including attentive reflection and feedback rounds between team members. That way, people would get used to the technology and learn about its different facets while also collecting insights as to what works and what does not for the respective business.

Such insights can then be used as soon as more resources are available and the company experiences more stable economic periods to develop and implement internally-built systems. The reason for this is that such custom-made infrastructures have the ability to cater much more precisely to the specific needs and particularities of a given business.

In light of the overall research question, the insights resulting from the literature review as well as from the knowledge and experiences shared by the interview candidates, there are a few outstanding critical success factors relevant for startups in this context. In addition to the overarching factors described below, the research revealed a number of smaller ones which can be categorized into the following main ones.

When it comes to the technological dimension, one factor concerns data privacy and security. As soon as the data concerns people, different control mechanisms and security systems must be ensured. The previously highlighted ethical considerations and legal implications contribute significantly towards this aspect. Secondly, the used system or tools must fulfil the highest usability and simplicity standards. As noted by Mr. Schwärzler, no one will use a given tool just because it features an AI component. The overall goal would be to facilitate processes and to make them more efficient.

With regards to the financial dimension, one of the most important critical success factors would be the aspect of defining areas and use cases with the largest potential ROI. This is due to the scarcity of resources. As Mr. Mitrovic noted, AI is only economically viable in a number of niches. Seeing as such a technological transition is a continuous learning process and startups face pressure from the likes of investors, learnings should be drawn from applications with the smallest chance of capital loss.

Lastly, the staff dimension is arguably the most critical one as a whole. The aspect of establishing trust is indispensable. As highlighted in the paper, trust spans across several elements affecting the development, implementation and adoption of AI. As a result, leading stakeholders as well as employees must both be educated and encouraged with regards to decision-making and commiting to this transition as well as working with it and providing feedback, respectively. Secondly, startups must anticipate intermediary roles which will be crucial for these systems to work in a larger business context. Such can bridge the challenge of establishing trust in the form of interpreting and explaining roles as well as anticipate and outline required system changes and new business opportunities.

7 LIMITATIONS & FUTURE RESEARCH

7.1 Limitations

Seeing as any piece of research features certain imperfections the chosen methodology of this research represents no exception. Considering that the qualitative approach aimed at validating different findings from the literature review as well as highlighting new insights, some factors must be mentioned with regards to this methodology. First, the convenience sampling approach was chosen due to its effectiveness, it is a method which has a high likelihood of including various forms of biases as highlighted previously in this paper. Consequently, the results presented in the section above might not be generalizable for a larger population. Nevertheless, all of the candidates were chosen with the utmost awareness with regards to the issue of potential biases. As a result, the selection included startup founders with roughly the same number of years of experience with their respective businesses while also containing a wide scope of different industries.

Secondly, the the majority of interviews were held virtually via the communication platform Microsoft Teams. This was mainly due to many people continuing to prefer working remotely. Furthermore, some of the candidates faced pressing business challenges due to the aftereffects of COVID-19-related economic restrictions as well as the war unfolding in Ukraine. As a result, these interview candidates requested online sessions. However, virtual interviews may affect factors such as interpersonal connection or virtual tiredness, to name a few. Nevertheless, these challenges were tackled to the best of the researcher's abilities including provisional briefings and introductions as well as additional interactive elements during the interview.

Lastly, the aspect of geography has to be noted. This research focused entirely on the Austrian market and, more specifically, on founders and businesses located in Vienna. The outlined findings provided a number of interesting insights with regards to these specific locations. Nevertheless, various factors unique to other markets or geographic locations are subsequently not included in this research. In order to draw more generalizable and broadly confirming conclusions additional markets and cities may be worth exploring.

7.2 Recommendation & Future Research

As highlighted above, further research in other geographic areas would be very insightful as to how the various concepts are overlapping and to what extent they are isolated in the examinded region. More generalizable insights from a variety of different markets could be used to define a concrete guideline for startups and businesses alike undergoing such a monumental technological business transformation. Such an approach could also foster various forms of collaboration between participating and endevouring startups.

Secondly, it would be interesting to include the perspectives and opinions of various external stakeholders including the likes of angel investors and venture capitalists, incubator and accelerator program directors as well as technology-providing business partners. Seeing as people with such vested interests collaborate with a number of different startups, such insights and experiences could be useful to grasp an understanding of potential financial cost breakdowns and overall feasibility studies.

In conclusion, given the comparably small study size, any future research should aim at exploring more far- and deep-reaching topics and concepts across a variety of different stakeholders and geographic regions.

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9 APENDICES

Appendix 1: Consent Form

Thank you for reading the information sheet about the interview. If you are happy to participate then please complete and sign the form below.

Research project title: Critical Success Factors for Implementing AI Technologies in the Context of Startup Business Operations

Research investigator: Paul Kippes

Research Participants name:

The interview will take 40-60 minutes. The researcher does not anticipate that there are any risks associated with your participation, but you have the right to stop the interview or withdraw from the research at any time. Thank you for agreeing to be interviewed as part of the above research project. This consent form is necessary for the researcher to ensure that you understand the purpose of your involvement and that you agree to the conditions of your participation. Would you therefore read the accompanying information sheet and then sign this form to certify that you approve the following:

- the interview will be recorded, and a transcript will be produced
- you will be sent the transcript and given the opportunity to correct any factual errors
- the transcript of the interview will be analyzed by Paul Kippes
- access to the interview transcript will be limited to Paul Kippes and academic colleagues/researchers with whom he might collaborate as part of the research process
- the actual recording will be kept for future research purposes such as publications related to this study after the completion of the study
- any variation of the conditions above will only occur with your further explicit approval

Quotation Agreement

I also understand that my words may be quoted directly. With regards to being quoted, <u>please initial next to any of the statements that you agree with:</u>

	I wish to review the notes, transcripts, or other data collected during the research pertaining to my participation.
	I agree to be quoted directly.
	I agree to be quoted directly if my name is not published and a made-up name (pseudonym) is used.
	I agree that my name may be used for citation purposes only.

	I agree that the researchers may publish documents that contain my quotations.

All or part of the content of your interview may be used;

- In academic papers, policy papers or news articles
- On our website and in other media that we may produce such as spoken presentations
- On other feedback events
- In an archive of the project as noted above

By signing this form, I agree that;

1. I am voluntarily taking part in this project. I understand that I do not have to take part, and I can stop the interview at any time;
2. The transcribed interview or extracts from it may be used as described above;
3. I have read the Information sheet;
4. I do not expect to receive any benefit or payment for my participation;
5. I can request a copy of the transcript of my interview and may make edits I feel necessary to ensure the effectiveness of any agreement made about confidentiality;
6. I have been able to ask any questions I might have, and I understand that I am free to contact the researcher with any questions I may have in the future.

____

Printed Name

______________________________________ __________________

Participants Signature **Date**

______________________________________ __________________

Researchers Signature **Date**

Contact Information

This research has been reviewed and approved by the Institutional Review Board (IRB), an independent ethics committee for research involving human subjects. If you have any further questions or concerns about this study, please contact:

Mr. Paul Kippes, BSc
Tel: +43 650/9432523
E-mail: paul.kippes@gmail.com

You can also contact the researcher’s supervisor:

Dr. Mag. Mag. rer. soc. oec Stefan Bauer Bakk.
E-mail: stefan.bauer@modul.ac.at

Appendix 2: Interview schedule

Entrepreneur	Sex	Industry	Interviewing Mode	Interview Date	Duration
Mrs. Scherzinger	F	Retail & E-Commerce	Microsoft Teams	04/05/22	00:38:58
Mrs. Hallmann	F	Medical Products	Microsoft Teams	20/04/22	00:32:21
Mr. Schwärzler	M	Industrial Software	Microsoft Teams	06/05/22	00:28:43
Mr. Resch	M	Online Dating & Medical Products	In Person	27/04/22	00:42:37
Mr. Mitrovic	M	Insurance & NLU Software	Microsoft Teams	14/04/22	00:52:07
Mr. Stangl	M	Online Dating & Medical Products	Microsoft Teams	27/04/22	00:33:33
Mr. Ardaiz	M	HR Data & Consumer Products	Microsoft Teams	19/04/22	00:23:31

TABLE 2 - FURTHER INFORMATION ON INTERVIEWS & CANDIDATES