From Efficiency to Excellence: AI's Strategic Role in Scaling SaaS Startup Operations

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Dissertation submitted in partial fulfilment of requirements for the MSc in Management (Specialization Strategic Marketing), at the Universidade Católica Portuguesa, 31.12.2024.

Abstract

The Software-as-a-Service (SaaS) industry is projected to grow significantly in the coming decade. However, many startups face challenges in maintaining operations and meeting investor expectations. This thesis primarily investigates the role of Artificial Intelligence (AI) in achieving Operational Excellence (OE) within SaaS startups. It additionally considers the startup ecosystem by examining how such AI adoption influences venture capital (VC) investment decisions. Through qualitative interviews with entrepreneurs and investors, the study explores how AI-driven technologies can improve workforce capabilities, strengthen customer relationships, optimize operational processes, and accelerate product innovation. The findings reveal that AI's influence goes beyond mere efficiency. When strategically integrated, AI fosters a more adaptive, data-driven, and customer-centric operational environment, allowing startups to better align their offerings with market demands. This operational maturity resonates with VC investors, who are increasingly recognizing AI-driven improvements in metrics such as customer acquisition cost and customer lifetime value as strong indicators of scalability and long-term potential. By clarifying the pathways through which AI supports OE and influences investor perceptions, this study enriches the theoretical framework surrounding technology-enabled entrepreneurship. Additionally, it provides valuable guidance for SaaS founders and investors aiming to harness AI as a strategic advantage in a fast-changing digital landscape.

Keywords: Software-as-a-Service, Operational Excellence, Artificial Intelligence, Venture Capital, Startup Ecosystem, AI-driven Improvements

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Sumário

Prevê-se que o sector do software como serviço (SaaS) cresça significativamente na próxima década. No entanto, muitas startups lutam para manter as operações e atender às expectativas dos investidores. Esta tese explora o papel da Inteligência Artificial (IA) na obtenção da Excelência Operacional (OE) em startups de SaaS e examina como a adoção da IA influencia as decisões de investimento de capital de risco. Com base em entrevistas qualitativas com empresários e investidores, o estudo investiga a forma como as tecnologias de IA melhoram as capacidades da força de trabalho, reforçam as relações com os clientes, optimizam as operações e impulsionam a inovação de produtos. Os resultados revelam que o impacto da IA vai para além da eficiência. Quando implementada estrategicamente, a IA promove um ambiente mais adaptável, orientado por dados e centrado no cliente, permitindo que as startups alinhem as ofertas com as demandas do mercado. Essa maturidade operacional reflete nos investidores de capital de risco, que cada vez mais veem métricas orientadas por IA, como custo de aquisição de clientes e valor vitalício, como fortes indicadores de expansão e potencial a longo prazo. Ao detalhar a forma como a IA apoia a EO e molda as percepções dos investidores, esta investigação enriquece o quadro teórico do empreendedorismo apoiado na tecnologia. Além disso, fornece informações úteis para os fundadores e investidores de SaaS que procuram aproveitar a IA como uma vantagem estratégica num cenário digital em rápida evolução.

Palavras-chave: Software como serviço, excelência operacional, inteligência artificial, capital de risco, ecossistema de startups, melhorias orientadas por IA

Título: Da Eficiência à Excelência: O Papel Estratégico da IA na Expansão das Operações das Startups de SaaS

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Acknowledgment

I would like to begin by expressing my gratitude to my supervisors, René Bohnsack and Margarita Oja da Silva, for their invaluable guidance and support throughout this dissertation. Margarita, your encouragement and dedication have been a cornerstone of this work. In moments when I felt lost or unsure of my direction, you helped me regain clarity and focus. Your quick responses, willingness to be available at short notice, and constant presence made a significant difference, keeping me motivated and on track. René, your expertise and constructive feedback have been crucial in shaping this research, and I am deeply thankful for your thoughtful input and guidance.

I would also like to extend my sincere thanks to the entrepreneurs and VCs who participated in the interviews. Their willingness to share insights and experiences provided valuable perspectives that greatly enriched this study.

Lastly, I want to express my deepest appreciation to my family and friends for their unwavering support and belief in me throughout this journey. Your encouragement, patience, and sacrifices have been my foundation, giving me the strength to persevere through every challenge. I am endlessly grateful for your love and for always reminding me of my potential, even when the path felt difficult.

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Abbreviations

AI	3	Artificial Intelligence
CAC	3	Customer Acquisition Cost
CC	3	Cloud Computing
CLV	3	Customer Lifetime Value
GenAI	3	Generative AI
GM	3	Gioia Methodology
GPT	3	General Purpose Technologies
IaaS	3	Infrastructure-as-a-Service
IDP	3	Intelligent Document Processing
ML	3	Machine Learning
NIST	3	National Institute of Standards and Technology
NLP	3	Natural Language Processing
PaaS	3	Platform-as-a-Service
RPA	3	Robotic Process Automation
PRD	3	Product Requirement Document
SaaS	3	Software-as-a-Service
TQM	3	Total Quality Management
UX	3	User Experience
VC	3	Venture Capital
VCs	3	Venture Capitalists
XaaS	3	Everything-/ Anything-as-a-Service

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1 Introduction

1.1 Problem Statement and Research Objective

The Software-as-a-Service (SaaS) industry is experiencing rapid growth, with market value projected to rise from $273.55 billion in 2023 to $1.23 trillion by 2032 (Fortune Business Insights, 2024). This expansion is driven by SaaS startups, the backbone of innovation within the industry. However, only 31% of startups survive beyond five years due to challenges in aligning products with market demands and adapting to evolving customer expectations (Park and Lee, 2017; KCA, 2018). Addressing these challenges is essential for improving startup success rates and ensuring the sector's long-term sustainability. Operational Excellence (OE) is a key driver of organizational success, emphasizing efficient processes, superior service delivery, and customer satisfaction. By contributing to resilience and competitiveness, OE helps companies reduce costs, enhance productivity, and consistently deliver value (Lasi et al., 2014). For resource-constrained SaaS startups, achieving OE is vital for scaling operations and meeting investor expectations. Integrating Artificial Intelligence (AI) with OE practices offers technology companies a unique opportunity, such as greater scalability or prioritized innovation (Chikezie et al., 2024). AI enables process automation, advanced data analytics, and predictive capabilities, helping organizations streamline operations, optimize resources, and gain insights previously unattainable. McKinsey & Company (2023) notes that AI solutions can boost operational efficiency by 20-30% and cut costs by 10-15%.

Research on AI and entrepreneurship is still in its infancy (Obschonka et al., 2024), with the integration of AI technologies into business practices outpacing academic understanding of their impact (Nambisan et al., 2019; Shepherd & Majchrzak, 2022). While AI adoption is expected to grow rapidly, with 83% of SaaS providers planning to adopt AI within the next year (Superside, 2024). Its role in driving OE in SaaS startups remains understudied. Most research has focused on established organizations, overlooking the unique challenges faced by startups. Additionally, the impact on venture capital funding decisions remains understudied. This gap is increasingly important as investors prioritize technological adaptability and operational efficiency in their funding decisions (Janeway et al., 2021).

This study seeks to address these gaps by exploring the role of AI in achieving OE within SaaS startups. It investigates how AI enhances operational dimensions such as process efficiency, customer satisfaction, and product development while examining its broader implications for investor perceptions and the startup ecosystem. By bridging these gaps, this research aims to contribute to a deeper understanding of the intersection between technology and operational strategy in the SaaS industry.

1.2 Research Questions

The following two research questions have been formulated to address the core objectives of this study and guide the investigation into AI's role in enhancing OE within SaaS startups and the effects on the broader ecosystem.

1. How can AI-driven technologies support SaaS startups in achieving Operational Excellence?
2. What role does the adoption of AI in SaaS startup operations play in venture capital investment decisions?

This thesis will address these questions, with the first question being the primary focus of the analysis.

1.3 Thesis Outline

This thesis follows a structured, sequential approach, beginning with an introduction that outlines the research objectives and highlights the study's relevance to AI applications and SaaS startups. The literature review that follows examines existing research on the startup ecosystem, with an emphasis on venture capital, the SaaS model, and AI's role in OE. This theoretical background provides the foundational knowledge necessary for a deeper analysis of the research questions. The methodology section then explains the qualitative approach adopted in this study. Subsequently, the findings from the expert interviews are presented and analyzed. Afterward, the main findings are discussed in relation to existing literature, offering answers to the research questions. This chapter also considers the practical implications of the study, as well as its limitations, and suggests potential directions for future research. The concluding chapter then summarizes the main findings of this study.

2 Literature Review

This entire chapter offers an overview of existing literature on startups and their investment landscape, Software-as-a-Service (SaaS), and Operational Excellence (OE) driven by Artificial Intelligence (AI). It establishes a foundation for examining how these elements interact to improve operational efficiency and influence funding opportunities of SaaS startups.

2.1 Entrepreneurship and the Startup Ecosystem

In the following, startups and scaleups will be introduced, along with an exploration of a startup ecosystem's key characteristics and components. Additionally, a focus is on investors and funding to provide background for the second research question.

2.1.1 Differentiation between Startups and Scaleups

Blank & Dorf (2012, p. xvii) define a startup as "a temporary organization searching for a scalable, repeatable, and profitable business model." Additionally, Ries (2011, p. 27) states that a startup is "a human institution created to develop a new product or service in conditions of extreme uncertainty." Finally, to extend the definition further, it is crucial to highlight that a startup is an organization with limited experience, operating with insufficient resources, and shaped by various factors, including investors, competitors, customers, and the use of dynamic technologies (Crowne, 2002).

More specifically, startups rely on lean structures, consisting of small but highly skilled teams with strong technical and managerial expertise, which facilitates a rapid flow of information and enables them to adapt quickly to changes (Ojaghi et al., 2019). These companies are known for their dynamic and innovative nature and often approach problems with an adaptive 8learning-by-doing' mindset (Müller et al., 2019). Startups face high levels of uncertainty and volatility, which requires them to manage significant risks and respond quickly to emerging demands (Villa Todeschini et al., 2017). Technology plays an important role in their business models, as startups often adopt modern technological solutions and Industry 4.0 approaches to enhance their decision-making, identify and solve problems, and support scalable growth (Gerhardt et al., 2021; Hofmann & Rüsch, 2017).

The journey of startup involves different stages: pre-seed/seed, startup, and growth. As they evolve, many startups transition into scaleups, characterized by their rapid revenue growth and employees over time. Different from startups, scaleups have established services or products and typically have been operating for at least three years. Scaleups aim for fast growth, often with the flexibility to adapt to changes in market conditions and have access to many resources fueling their expansion (Crnogaj & Rus, 2023). Monteiro (2019) highlights that the growth of scaleups mostly depends on the scalability of their business models (Williamson, 1991).

The shift from startup to scaleup requires significant operational restructuring, a phase that 80% of new companies struggle to manage (McKinsey & Company, 2021). This transition requires strategic investments in marketing, technology, and personnel, which are critical for developing an efficient operational framework, building a strong organizational culture, and establishing clear strategic direction and leadership (Crnogaj & Rus, 2023; Monteiro, 2019). Success in scaling also relies on the effectiveness of the business model, which depends on coordinated organizational activities that generate value (McDonald & Eisenhardt, 2020; Tippmann et al., 2023; Zott et al., 2011). AI can support this process by automating routine tasks, facilitating consumer data analysis, enhancing advertising, and enabling AI-driven sales solutions (Chalmers et al., 2021). This expansion of AI's role within organizational operations provides entrepreneurs with various advantages in their activities (Chalmers et al., 2021). Beyond operational efficiency, AI helps entrepreneurs optimize resources, overcome limitations, and meet organizational needs (Obschonka & Audretsch, 2020). Often referred to as the new best friend of entrepreneurs, AI's accessibility makes it an appealing tool for startups, enabling scalable solutions that support cost-saving and operational improvements (Fast Company, 2021; Morantz, 2021). While internal factors are crucial for early growth, startups also rely on the surrounding ecosystem for sustained success. These influences on the ecosystem that came along will be examined in the following section.

2.1.2 Definition and Components of Startup Ecosystems

An ecosystem is a community of living beings interacting with their environment (Ives & Carpenter, 2007). This concept extends to business ecosystems, which are networks of companies that collaborate to create customer value (Moore, 1997). In the 1980s and 1990s, entrepreneurship studies shifted from individual-focused research to community-oriented approaches, emphasizing social, cultural, and economic influences (Aldrich, 1990; Nijkamp, 2003; Steyaert & Katz, 2004). Van de Ven (1993) highlighted that entrepreneurial ecosystems emerge as entrepreneurs lack the resources and functions required for venture development.

A startup ecosystem represents a more concentrated subset of the entrepreneurial ecosystem. Although there is a significant degree of interrelatedness between startups and broader entrepreneurship, they rely on different components. To illustrate, startups frequently necessitate particular product development assistance that may not be essential in general entrepreneurship (Cukier et al. 2016). Startup ecosystems can be defined as a structure composed of entrepreneurs, institutions, and processes that are connected through formal and informal ties, supporting the creation and development of startups. Additionally, the success and growth of startups are influenced by the ecosystem in which they are established and operate (Grilo et al. 2017; Tripathi et al. 2019). According to the research by Tripathi et al. (2019), eight key elements shape a startup ecosystem, particularly in the context of software-intensive products, as presented in Figure 1.

Startup Ecosystem Elements	Role in the Startup Ecosystem
Entrepreneur	Entrepreneurs are central to the startup ecosystem, driving new business ventures. They can be need-based or opportunity-driven and are often supported by incubators and accelerators to develop business models. A balanced mindset is crucial, as overly optimistic approaches may hinder long-term success, while realistic strategies promote steady growth and investor confidence (Tripathi et al., 2019).
Finance	Diverse funding sources, from angel investors and venture capitalists to banks, governments, and crowdfunding, are essential to the startup ecosystem. Startups require varying types of funding throughout their development, typically progressing through seed funding, Series A–B, and Series C–D stages, each critical for growth and scalability (Tripathi et al., 2019).
Incubators and Accelerators	Incubators and accelerators play a crucial role for early-stage founders by providing mentorship, co-working spaces, and networking opportunities to refine ideas into viable businesses (Tripathi et al., 2019). Often based in university tech hubs, accelerators offer resources until startups mature, fostering idea exchange and entrepreneurial activity (David-West et al., 2018; Salamzadeh & Kawamorita, 2017).
Governments	Governments support ecosystems through funding programs, while demographics like culture, language, and immigrant populations shape entrepreneurship (Tripathi et al., 2019).
Market	Startup growth relies on active users and paying customers, which are influenced by the target market. Key market factors include local market reach (access to the local economy and cultural markets) and global market reach (expanding beyond national borders) (Tripathi et al., 2019).
Culture	Culture impacts a startup ecosystem through different factors: Diverse cultures foster creativity, GDP influences funding access, geography provides strategic advantages, historical successes shape ecosystem growth, and immigrants bring innovation and global skills, all of which drive startup development (Tripathi et al., 2019).
Technology	Technology plays an important role in shaping startups through factors such as geography, support from established companies, founders' expertise, industry focus, and innovation. Startups often leverage existing technologies and standardized practices to develop scalable products and align with technology-driven industries (Tripathi et al., 2019).
Human Capital	Human capital development is closely linked to these factors, shaped by education, experience, and government policies, which collectively nurture entrepreneurial talent. Technology and entrepreneurs themselves are also vital, driving innovation and the creation of new businesses (Tripathi et al., 2019).

Figure 1: Key Elements of a Startup Ecosystem (own illustration)

As this thesis explores possible AI integrations that lead to OE, the focus is on SaaS startups with already established operational structures. According to Belluci et al. (2021), Sulillari (2023c), and Tripathi et al. (2019), for high-tech startups in their growth and expansion phase, venture capital (VC) is one of the most important funding sources, which will be examined in the subsequent section.

2.1.3 Venture Capital Investment Decisions

In contrast to alternative sources of finance, venture capitalists (VCs) provide not only financial backing but industry expertise and access to extensive networks. Such connections enable startups to enhance their credibility, attract further investors, partners, or clients, and thereby improve their long-term prospects for success (Sulillari, 2024). Despite the attractiveness of VC as a funding route, Minaev (2022) highlights the difficulties associated with obtaining VC funding, as only approximately 1% of startups can successfully secure such funding. This limited access has resulted in intense competition to obtain VC support, which has further been intensified by the growing number of startups (Sulillari, 2024).

Several factors influence a startup's ability to secure VC funding, including the diversity of the VC's network, which can affect the funding amount (Alexy et al., 2011). Startup characteristics, such as prestigious grants or other recognitions, signal credibility and potential success, ensure that they appear more attractive to VCs (Islam et al., 2018). External factors like the macroeconomic environment, regulatory changes, technological advancements, and liquidity shocks also contribute to VCs investment decisions (Conti et al., 2016; Janeway et al., 2021). In addition, the skills and experience of the startup's founders, the size and growth rate of the target market, product scalability, and the quality of the management team are significant factors that can influence VCs interest (Prohorovs et al., 2018; Miloud et al., 2012). Concerning valuation and performance metrics, Zhao (2023) states that the internal rate of return (IRR) and price-to-earnings ratio are common metrics, while discounted cash flow and net present value are only used limited. Additionally, 10% of VCs rely on no formal metrics at all to assess a startup's value (Zhao, 2023).

VC is particularly suited for startups with high growth potential and scalability (Ganguly, 2022). For SaaS companies, VC support throughout various funding stages can significantly facilitate scaling (Cavallo et al., 2019; Ganguly, 2022). The subsequent section, therefore, presents the characteristics of SaaS business models.

2.2 Cloud Computing and the Software-as-a-Service Model

To better understand the research topic, SaaS startups, this section provides an understanding of cloud service models, including Platform-as-a-Service (PaaS), Infrastructure-as-a-Service (IaaS), and finally SaaS.

2.2.1 The Rise of Cloud Computing and its Service Models

The Internet has been an impetus for the development of numerous technological innovations. Arguably, one of the most discussed among all of these is Cloud Computing (CC). Many researchers (Ghosh et al., 2012; Mitchell & Meggison, 2014; Sarea & Taufiq-Hail, 2021; Simamora & Sarmedy, 2015) follow the definition of the National Institute of Standards and Technology, stating that "Cloud Computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or cloud provider interaction" (Mell & Grance, 2011, p. 2). It combines technology, a hosting platform, and a service on the Internet (Lamba & Singh, 2011), enabling the need for users to own the infrastructure for many different computing services.

A common classification in CC is service models, summarized as Everything- or Anything-as-a-Service (XaaS), as noted by Chen et al. (2022) and Duan et al. (2016). Following the definition of Paasivaar et al. (2014), XaaS describes the range of applications and services that are becoming available to users on demand via the Internet. Three of the most common service models in terms of CC (Duan et al., 2016) are displayed in Figure 2, sorted according to their level of abstraction, while each higher level comprises the levels below it (Ruparelia, 2016).

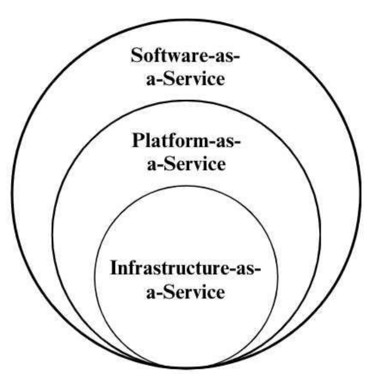

Figure 2: Abstraction Levels of Service Models (modified from Ruparelia, 2016)

The bottom layer, IaaS, provides hardware resources like networks, servers, or storage for running software, but users do not manage the underlying infrastructure. PaaS abstracts this, enabling application deployment and management without handling the infrastructure (Mell & Grance, 2011). SaaS, the topmost layer, generates the largest proportion of revenue within the global CC market (Statista, 2024). It is characterized by consumers using cloud applications via the web or interfaces, with limited control over the underlying infrastructure (Mell & Grance, 2011). In contrast to the other two service models, SaaS is less customizable, easier to use, and requires less technical background to be run by the client (Schneider & Sunyaev, 2016). As this research focuses on SaaS startups, the following section will undertake a detailed examination of this service model.

2.2.2 Particularities of Software-as-a-Service Companies

The advent of the SaaS model has significantly shifted the software industry. According to Ju et al. (2010), one of the biggest changes is the transition from a product-centric approach to a service-based mentality. Unlike traditional software providers, SaaS vendors are responsible for developing applications and delivering the entire customer experience, including training, implementation, maintenance, security services and hosting. For example, Microsoft's transition to a SaaS provider with its first product, the Business Productivity Online Suite (Lai, 2009), allowed the company to maintain its market dominance and achieve a $2.3 trillion market capitalization by 2023 (Statista, 2024).

Within the SaaS environment, recurring revenue models are popular (Khare & Arora, 2024). More specifically, a subscription-based model is most adopted by SaaS companies, whereby customers pay monthly fees that cover the application license, software maintenance, and support costs (Ju et al., 2010). In their study, Li & Kumar (2022) identify a range of other pricing options, including low-cost plans and free trials, as potential strategies for attracting new customers. This pricing flexibility is a fundamental aspect of SaaS business models, enabling customers to evaluate basic services before committing to premium offerings (Li & Kumar, 2022). Additionally, it is possible to adopt other revenue models, such as a success-based revenue model, which is based on the vendor's success and directly correlates with the customer's satisfaction (Ju et al., 2010).

Moreover, a significant number of customers first utilize basic SaaS applications before transitioning to more sophisticated ones. This implies that SaaS providers initially offer these basic services at competitive prices to help customers succeed and then expand their service portfolio.

To ensure recurring transactions, SaaS companies offer supplementary components to the fundamental service, like a premium SaaS platform, to enhance the overall value proposition (Dempsey & Kelliher, 2018). To identify the most suitable additional service packages, SaaS companies must have detailed knowledge of customer needs and preferences. Nevertheless, customization of SaaS solutions can be challenging for startups, as they must cater to a broad user base with disparate requirements. Even though there are various customization options, tailoring these solutions to the specific needs of each customer is a challenging task for the providers (Li & Kumar, 2022).

Khare and Arora (2024) highlight that, due to the recurring revenue model, customer retention is essential for the long-term success of SaaS providers, especially considering the relatively high customer acquisition costs (CAC) related to sales, marketing, and customer training. As a result, SaaS companies must focus on maximizing customer lifetime value (CLV) to ensure long-term profitability (Khare & Arora, 2024). Furthermore, the churn rate, the rate at which customers cancel their subscriptions, is a vital metric for SaaS companies (Xiao et al., 2020). Because there are no upfront investments such as hardware or software for the customer (Ju et al., 2010), switching costs remain low (Khare & Arora, 2024). Consequently, dissatisfied customers can easily switch to competitors, which is why SaaS companies must prioritize customer satisfaction and loyalty to build commitment to their own solutions (Dempsey & Kelliher, 2018; Khare & Arora, 2024; Xiao et al., 2020). To bolster such commitments, it is crucial to offer cost reimbursement and efficient customer service (Xiao et al., 2020). The quality and capacity of services can be enhanced through ongoing improvements (Li et al., 2018).

Furthermore, scalability is a defining feature of SaaS. As mentioned, SaaS applications are cloud-based, enabling them to scale rapidly in response to user demands. This elasticity provides cost efficiency, as SaaS companies can adjust their resources following customer needs (Li & Kumar, 2022). Additionally, economies of scale can be exploited through server load balancing and cost-sharing (Ge & Huang, 2014). While the multitenant architecture, where multiple clients utilize the same software simultaneously, facilitates economies of scale, it simultaneously gives rise to consumer mismatch costs as well as security and data privacy challenges (Chou & Chou, 2007). However, access to large amounts of data is also an advantage for SaaS companies, as they employ user-generated data for continuous improvement. This data enables SaaS providers to analyze customer behavior and make data-driven decisions to enhance both the product and the user experience (UX). The capacity to continuously update and improve the service without user intervention represents a key advantage of the SaaS model (Li & Kumar, 2022).

After establishing a profound understanding of the SaaS model and its potential challenges, it is important to understand which operational areas could be enhanced by applying AI and to what extent this has already been researched in other business areas.

2.3 Impact of Artificial Intelligence on Operational Excellence

This section will present the existing literature on AI technologies and their contribution to achieving operational efficiency. To enable a thorough analysis of their impact in the later stages of this thesis, key concepts will first be defined, followed by an overview of the foundational technologies and other critical factors.

2.3.1 Definition and Key Technologies of Artificial Intelligence

In the context of rapid technological progress, certain innovations impact societies, drive economic growth, and lead to new eras of advancement (Bresnahan & Trajtenberg, 1995; Klinger et al., 2021; Sharma, 2023). Known as General Purpose Technologies (GPTs), these innovations act as engines of growth (Brynjolfsson, 2021) with broad applicability across sectors and high technological strength (Bresnahan & Trajtenberg, 1995). The latest and highly impactful GPT is AI, which fulfills key GPT criteria such as pervasiveness, continuous improvement, and the potential to spur complementary innovations (Brynjolfsson, 2021; Klinger et al., 2021; Sharma, 2023).

Kaplan and Haenlein (2019, p. 17) describe AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". This highlights AI's capacity for learning and adaptation, setting it apart from traditional systems that depend on fixed instructions. Similarly, Baek et al. (2023, p. 918), building on Byun (2017) and Russell (2015), emphasize AI's potential to "automate intelligent human behavior, replace human tasks with advantage from machines, build automated platforms and systems that detect and execute complex and diverse environments," enabling machines to address complex problems with human-like reasoning and understanding.

The implementation of AI in business is driven by several key technologies that can enable companies to improve their operations. However, it must be noted that the specific tools or combinations of tools employed may vary considerably, depending on the requirements of the given context and the availability of relevant data (Taddy, 2018).

Benbya et al. (2020) outline several key AI techniques: Machine learning (ML), a subsection of computer science, involves creating algorithms that learn from data and make predictions. Often regarded as the "engine" of AI, ML detects patterns in unstructured data to produce predictions, supporting applications like predictive analytics, customer retention, user experience optimization, and marketing analysis. Deep learning (DL), a subset of ML, leverages multi-layered neural networks to process large datasets and manage complex tasks. Within DL, generative AI (GenAI), like ChatGPT, stands out for creating content, such as text, images, and music (Stryker & Scapicchio, 2024). In this context, Large Language Models (LLMs), specific DL algorithms trained on massive amounts of textual data, also drive innovation by using extensive datasets to generate human-like text, facilitating Natural Language Processing (NLP) tasks. NLP enables machines to comprehend and interact with human language, which is crucial for chatbots, virtual assistants, and automated customer service. This Conversational AI technology enhances the efficiency and scalability of customer interactions and is applied across various fields, including finance, retail, and healthcare (Benbya et al., 2020).

Another AI technology is robotic process automation (RPA), where repetitive tasks are automated, making certain human skills obsolete (Faraj et al., 2018). For example, tasks like data entry, billing, and customer support ticketing (Benbya et al. 2020) no longer require human support as these applications are capable of undertaking human judgment (Faraj et al., 2018). Kibria et al. (2018) stress that RPA allows businesses to adopt innovative technologies, reconfigure resources, help organizations identify new revenue streams, and improve their strategic planning, productivity, and decision-making.

The last technology is predictive analytics, a key aspect of modern data science. This AI-driven tool employs historical data to project future trends and behaviors. Companies can use predictive analytics to anticipate customer churn, optimize infrastructure, and manage customer lifecycles more effectively, thereby maintaining profitability while scaling (Chalmers et al., 2021).

The overarching objective of AI across all these technologies is to facilitate learning, prediction, and automation to enable businesses to operate more efficiently and responsive to market demands while directing resources toward innovation and growth (Taddy, 2018). To understand where AI can enhance SaaS startups' operations, the subsequent section focuses on the concept of OE and its key areas.

2.3.2 The Concept of Operational Excellence

According to Dawei (2011), alongside other elements like strategic fit, unique voice, and capability to adapt, OE is one component of business excellence. It represents an ideal state for organizations, focusing on continuous improvement in the areas critical for achieving business and mission success. Wiersema & Treacy (1993) characterize OE as a strategy that enables companies to maintain superior quality, competitive pricing, and unique service offerings within their industry. The interpretation of OE can vary across companies and industries, with each organization defining OE based on its unique priorities and perspective (Mitchell, 2015). According to Russell & Koch (2009), OE is the pursuit of operational efficiency through enhanced processes, faster outcomes, and cost reductions. Traditionally associated with optimizing processes, production, and manufacturing, OE has evolved into a key factor in driving profitability and competitive advantage across all industries (Russell & Koch, 2009; Yew & Ahmad, 2014). For instance, technology companies can significantly benefit from OE by optimizing processes, minimizing waste, and efficiently delivering high-quality products (Chikezie et al., 2024). In this context, different frameworks can be applied to help improve processes, deliver products and services, and increase efficiency. The most common method is Lean, which focuses on reducing waste while optimizing processes for better customer value through feedback loops and iteration. Total Quality Management (TQM) framework contributes to OE through continuous improvements, involving employees in quality processes and customer satisfaction, while Six Sigma improves quality through data-driven decision-making (Chikezie et al., 2024). Consequently, achieving OE requires a strategic vision and an alignment of processes, people, and technology with the organizational strategy to achieve lasting improvements (Barua et al., 2014).

To illustrate how to achieve OE by involving different parties and business operations, Dahlgaard & Dahlgaard (1999) created the 4Ps model (Figure 3).

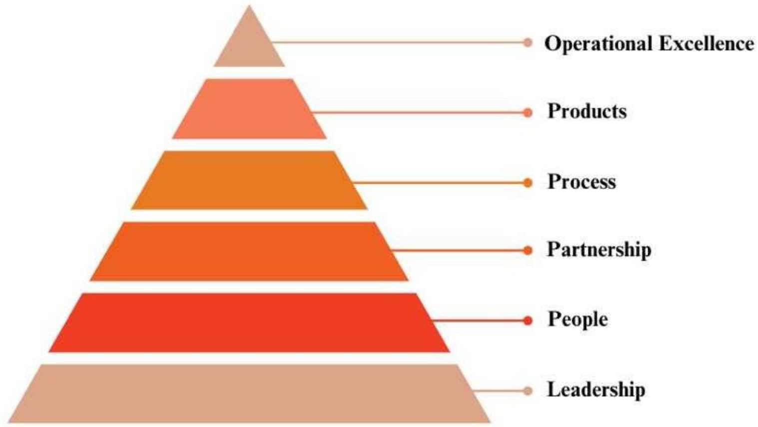

Figure 3: 4Ps of Operational Excellence (modified from Dahlgaard & Dahlgaard, 1999)

For this thesis, the model helps identify the key areas of operations to be further researched. The model consists of excellent “People” who form strong “Partnerships” with suppliers, customers, and society. These partnerships foster excellent “Processes”, which relate to key business and management operations and ultimately lead to excellent “Products” that satisfy and delight customers (Dahlgaard & Dahlgaard, 1999). The model additionally highlights how leadership can drive organizational excellence by using these four components to achieve overall success. However, as this study focuses on the operational perspective, “Leadership” will not further be covered further.

2.3.3 Artificial Intelligence as a Driver for Operational Excellence

For this section, entrepreneurial literature, as well as general management literature, was examined to get a comprehensive overview of where AI already supports companies in achieving OE. It is important to note that in this context no studies focusing explicitly on SaaS startups were found. Therefore, the following will give a general overview of the current situation, while this study explores specifics on SaaS startups in the exploratory research later on.

Research shows that achieving OE with the help of AI primarily happens through advanced algorithms, automation, and self-healing protocols which enable companies to forecast customer needs and gain insights into market behavior, which are key advantages in competitive sectors like software (Rusev & Salonitis, 2016; Shehadeh et al., 2016). For example, AI-driven algorithms assist in predicting customer churn and refining retention strategies (Shehadeh et al., 2016). Moreover, automation and self-healing systems proactively identify and resolve issues, minimizing downtime and improving reliability (Rusev & Salonitis, 2016). McKinsey & Company (2021) highlights that AI initiatives can reduce costs and increase revenue, particularly in areas like supply chain management, service operations, and product development. IBM’s self-healing AI systems, for instance, lower operational costs by addressing IT problems before they escalate, increasing both efficiency and reliability (Lee et al., 2018).

As mentioned, customer engagement and relationship management play a pivotal role in SaaS models and can be enhanced through several AI use cases. By analyzing extensive customer data, AI enables personalized experiences and marketing, which are increasingly important for customer satisfaction and retention (Makar, 2023; Usman et al., 2024). Virtual assistants and chatbots powered by NLP contribute to seamless customer interactions, automating routine inquiries and guiding users through processes like product selection and checkout (Liang et al., 2019; Singh et al., 2019). This dual effect of cost efficiency and personalized service highlights AI’s operational impact (Makar, 2023).

AI also transforms market analysis by facilitating real-time data processing and predictive modeling, uncovering insights that traditional methods might miss (Rathore, 2020; Bharadiya, 2023). Through advanced data analytics, businesses can better understand customer preferences and market trends, enabling faster, data-informed decisions (Giuggioli & Pellegrini, 2023).

Understanding the customer is essential to effective product development. Additionally, AI contributes to OE by expediting ideation, prototyping, and customization. It utilizes customer and market data to create tailored products that increase satisfaction and foster loyalty (Nassar & Kamal, 2021; Zhao et al., 2020). Moreover, automation and self-healing systems proactively identify and resolve issues, minimizing downtime and improving reliability (Rusev & Salonitis, 2016).

In terms of optimizing operational processes towards OE, AI significantly enhances efficiency by automating repetitive tasks, generating insights, and supporting predictive analytics. For instance, AI can streamline HR functions like employee screening and training through people analytics (Pereira et al., 2021).

While AI offers these benefits, limitations are also present. AI systems, especially those based on complex algorithms such as deep learning, often lack transparency, creating a “black box” effect

(Wachter et al., 2021). Additionally, inherent biases in training data can lead to skewed outcomes (Akter et al., 2021; Varona & Suárez, 2022). Privacy and security concerns are significant, as AI systems' data processing capabilities raise questions about data protection, re-identification risks, and cybersecurity vulnerabilities (Bogoviz, 2020; Carmody et al., 2021; Wright & Xie, 2019)

These literature findings indicate that AI has the potential to improve all four key areas of the 4Ps of OE. Besides this main research area, the study aims to offer an additional perspective on the topic by examining the investment perception of VCs towards operational AI in SaaS startups as part of the broader startup ecosystem. The following part will introduce the research methodology of this study.

3 Research Methods

To guarantee the transparency and reliability of the findings, this chapter provides an overview of the research design, the data collection as well as the data analysis. Thereby, qualitative research was selected as the methodology of choice to gain a deep and practical understanding of the application of AI technologies in SaaS startups and their impact on VCs' funding decisions.

3.1 Research Design

Qualitative research in the form of in-depth interviews was conducted as it allows for a more detailed exploration of themes (Berger-Gabner, 2016) and a more accurate representation of practice through the subjective and individual perspectives of the interview participants (Döring & Bortz, 2016). As mentioned by Harrison & Corley (2011, p. 410), qualitative research aims to provide "local (i.e. realistic and precise) interpretations of a phenomenon" and offers interpretation, description, and explanation (Chiva et al., 2014). Silverman (2000) supports this, pointing out that a qualitative research approach is an optimal method for addressing "how" and "why" questions.

Given the broad range of AI applications and the rapid pace of their development, this research design effectively collects, explains, compares, and presents AI applications, challenges, and learnings in SaaS startups. To ensure proper execution, two semi-structured interview guides were developed based on the theoretical analysis. This interview type aligns well with the study's inductive research design, offering flexibility to uncover new knowledge as conversations evolve (Saunders et al., 2015). Gioia et al. (2013, p. 19) highlight the advantage of "obtain[ing] both retrospective and real-time accounts by those people experiencing the phenomenon of theoretical interest." In line with the Gioia methodology (GM), the guides were not standardized but adapted to the flow of conversation and emerging findings. Additional questions were asked to explore insights based on initial responses. The SaaS interview guide comprised three sections, with the second addressing the first research question through seven main questions and sub-questions. The VC guide included five parts and eleven questions, focusing on AI in SaaS startups, success metrics, and AI risk assessment in parts two to four.

3.2 Sampling and Data Collection

To answer the first research question, SaaS startups were selected through a purposive sampling procedure according to the criteria mentioned in Figure 4 (Emory & Cooper, 1991).

Factor	Criteria
Company Stage	1-7 years in operation
Nr. of Emoployes	2-50 employees
Industry	Diverse selection within SaaS startups
Geographic Location	Mix of locations

Figure 4: Selection Criteria for SaaS Startups (own illustration)

For the second research question, VCs focusing on SaaS startups were purposely selected and contacted. In addition, other sampling techniques, such as the snowball method, were employed to identify exemplary instances of the phenomenon of interest (Patton, 2014) while simultaneously reducing sampling error through word-of-mouth recommendations (Creswell, 1998). For this research, 18 interviews, 13 SaaS startups, and five VCs, were conducted (Figure 5).

Nr.	Position	Company Area	Referred to as
1	Head of Operations	SaaS	RK
2	CTO	SaaS	GK
3	Co-Founder & Head of Marketing	SaaS	TA
4	Co-Founder & CEO	SaaS	OD
5	Head of GTM & Growth	SaaS	NP
6	Co-Founder & CEO	SaaS	BW
7	Founder & CMO	SaaS	AH
8	Product Analyst	SaaS	AM
9	Founder	SaaS	AN
10	Product Manager	SaaS	ML
11	Founder	SaaS	DW
12	Head of Sales	SaaS	HK
13	Founder & Board Member	SaaS	RM
14	Founding Partner	VC	FF
15	Senior Investment Manager	VC	MM
16	Investment Manager	VC	PR
17	Investment Manager	VC	JS
18	Platform Analyst	VC	CB

Figure 5: Overview of Interview Partners (own illustration)

The SaaS interviews concluded after 13 sessions, as no new themes emerged, indicating data saturation. Although 27 VCs and two VC associations were contacted, only five participated. While this limited response may not achieve full data saturation, recurring topics and themes suggest a degree of consistency. As the VC perspective primarily supplements the focus on AI in SaaS startups, it successfully provides additional context to the broader startup ecosystem. The interviewees were contacted via email, LinkedIn, or third-party connections. Data was collected from 12.11.2024 to 06.12.2024, with interviews lasting on average 30 minutes. Conducted online via Microsoft Teams and Google Meet, interviews were recorded with consent and transcribed using Microsoft Word's transcription feature and Wisper.ai. Since the focus was on analyzing the content of the conversation, simplified transcription rules were used to provide quicker access to what was said. During the transcription, the semantic rule deduced the content, suitable for developing content, topics, and knowledge (Dresig & Pehl, 2018).

3.3 Data Analysis

To respond to the research questions and analyze the qualitative data collected, this study employed the GM for qualitative data analysis, which is based on interpretive research. The aim was to capture respondents' understandings, aligning with this study's goal of exploring ways SaaS startups use AI to nurture OE and VC funding perceptions (Gioia et al., 2013; Langley & Abdallah, 2011). Although the method is rooted in grounded theory (Glaser et al., 1968; Strauss & Corbin, 1990), Gioia et al. (2013) developed a specific approach for inductive research to generate new concepts (Figure 6). The methodology involves coding interview transcripts to identify First-Order Concepts, which progress to Second-Order Themes and then Aggregate Dimensions. Using the software MAXQDA, excerpts were extracted, grouped into First-Order Concepts in Excel, and refined. Second-Order Themes were then developed by iteratively combining concepts to create a conceptual framework. These themes were categorized for abstraction, leading to Aggregate Dimensions as the foundation for the data structure. Finally, a data structure (Appendix A) was created to visualize the emerging concepts and their development process (Gioia et al., 2013).

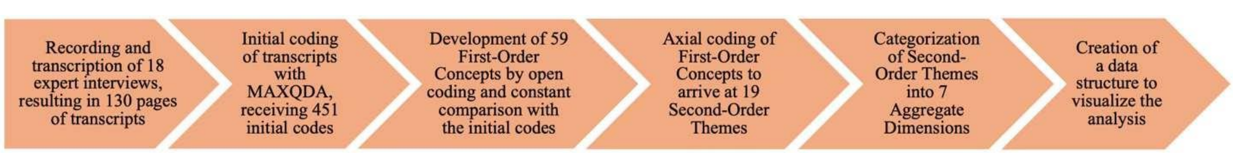

Figure 6: Overview of the Data Analysis Steps, based on Gioia et al. (2013)

4 Results

This chapter presents the results of the interviews, supported by secondary data. Following the GM, the subsequent sections display the broken-down data structure at an Aggregate Dimension level. The first part of this chapter focuses on the primary research regarding the use of AI in SaaS startups. The second part provides insights into investment decisions and VC funding perceptions related to the use of operational AI in SaaS startups.

4.1 AI Contributions to OE in SaaS Startups

The first research question concerns the application of AI for OE, the results are presented in four subsections aligning with the 4Ps of OE: people, partnerships, process, and product.

4.1.1 People

As shown in Figure 7, AI influences the people dimension within the 4Ps framework by improving communication and content creation, supporting employee training, and changing work dynamics.

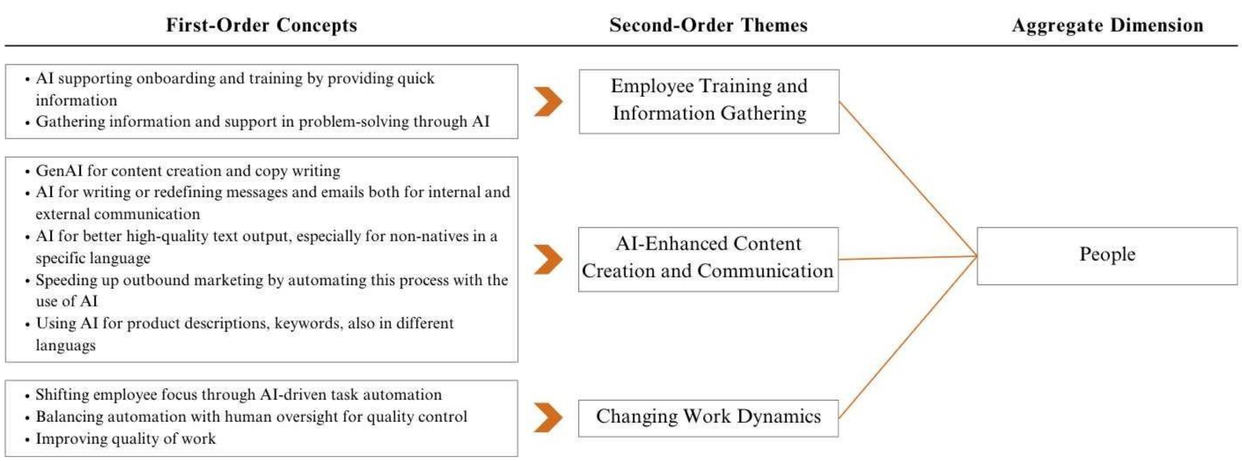

Figure 7: Data Structure first SaaS Aggregate Dimension

AI's ability to serve as an instant source of knowledge enables employees to overcome skill gaps and adapt to their roles more quickly. Giving employees access to LLM *"where they can ask questions, [&] helps them to speed up their working process"* (RK). Additionally, LLMs function as onboarding and training support for new employees, as *"AI can give the same if not even a better answer than colleagues"* (GK). Consequently, using AI reduces learning curves and allows employees to operate with greater confidence early in their roles. AI's problem-solving capabilities further contribute to employee autonomy. AI fosters a self-directed learning and problem-solving culture by offering resources tailored to specific needs:

> *"For technical decisions, I use AI quite a lot. I9m still at the beginning of my career [&] and still don't know everything. So if we have some problems that we need to solve with like a technical approach, I use AI."* (GK)

Furthermore, GenAI facilitates the creation of high-quality content in a time-efficient manner. One founder noted, *"I am not a copywriter. Let's say I know what I want to write [&], but without AI, it would definitely take like 3-4 hours to create a decent article"* (AN). Additionally, advances in email communication are evident. Not only do non-native speakers benefit from AI by improving their writing, leading to better external communication, but AI also speeds up outbound marketing activities. *"We are sending between 2000 to 5000 emails a week. Before AI every member of the team had to block two to three hours to go through every email"* (NP). Furthermore, AI is used for different translation purposes, such as product descriptions or keyword creation:

> "*One of the features of OpenAI is that it can translate from different languages. [...][even though] all of the explanation is in Japanese, AI can still understand it and transfer it to English and general English keywords. Without it, I need to find another team of translators. I don't know what the cost of this task would be without AI."* (AM)

Integrating AI into workflows leads to adjustments in employee roles, responsibilities and work dynamics. AI automates repetitive and time-consuming tasks, freeing employees to focus on more strategic or creative activities. *"It means specialists will have more time to do other tasks or focus on more complex projects"* (AH). This was complemented by AM saying, *"AI can be some kind of assistant, maybe on a junior/middle level, that can solve your small urgent problems."* At the same time, human intervention remains important *"for quality control and for handling nuanced customer interactions that require empathy and understanding"* (OD). Lastly, respondents emphasized how AI improves the overall quality of work by enabling more consistent and efficient processes. One interviewee shared, *"If people think differently and use AI, they can make their work not just faster and efficient but also improve it"* (RK).

4.1.2 Partnerships

The findings indicate improvements in the relationship with customers by driving customer engagement, personalization, and customer service operations (Figure 8).

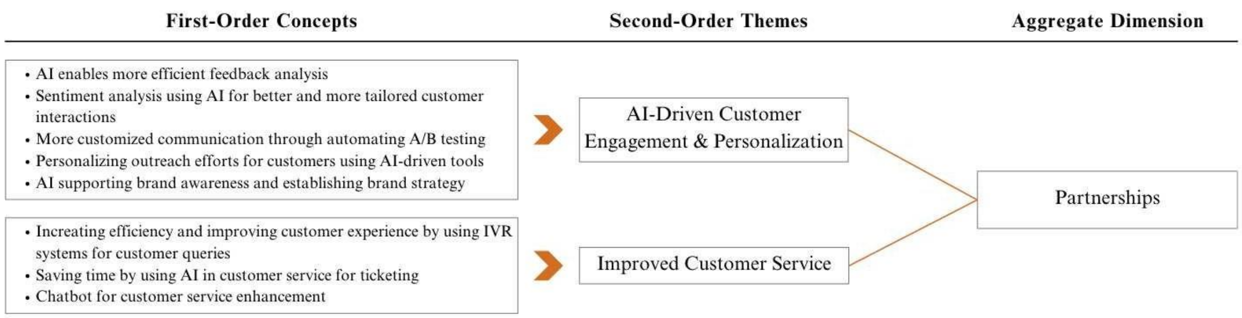

Figure 8: Data Structure second SaaS Aggregate Dimension

Firstly, AI improves customer engagement. Through analyzing feedback with the help of AI, customer needs and pain points can be understood and addressed more effectively. A Product Manager stated,

> *"If I don't understand what the actual problem is I go to ChatGPT and try to kind of get more sense out of it [and ask] which kind of problem is underlying there? And then give me next steps to validate how which solution would solve this problem best."* (ML)

Additionally, the amount of analyzed feedback can be increased through AI. *"Only 5-10% of feedbacks are currently analyzed while 100% can be analyzed thanks to AI, which brings more customer knowledge and then more capacity to prevent churn"* (OD). In this context, sentiment analysis was highlighted to deliver more tailored and personal relations, as *"[it] is a powerful tool for understanding the emotional tone of customer interactions"* (DW). OD additionally explained: *"Patterns have shown that personalized interactions, that were made possible by AI-driven sentiment analysis and language recognition, correlate strongly with customer loyalty."* Furthermore, startups benefit from AI in developing branding strategies and raising awareness. As one participant noted, *"If you want to establish a brand you need brand awareness basically and before AI it was so much work but now I talk a lot [...] with our AI in order to do that"* (TA) and added, *"AI benchmarks our thoughts and provides options to visualize ideas [or] refine brand names"* (TA). Additionally, AI is beneficial in automating A/B testing, enabling *"customize[ed] communication for millions of consumers across devices, platforms, and channels"* (HK). Several respondents shared that AI is being used for crawling LinkedIn profiles and websites to identify specific information like contact details. One specific use case is email outreach: *"We noticed reply rates go down [so] we can use AI to crawl LinkedIn profiles, look for specific signals, and create personalized outreach emails"* (AN).

The second theme is concerned with AI improving customer service. AI tools like IVR systems and chatbots streamline interactions with faster, more accurate responses: *"AI helps us route customer queries more efficiently in IVR systems using speech recognition, which reduced the wait times and improved the overall experience"* (OD). At the same time, three other startups noted the value of AI for ticketing. Especially the benefit of suggesting and answering customer tickets automatically but also smartly categorizing them, resulting in time savings. In the context of answering customer inquiries, chatbots were frequently named, as they provide information in real-time, leading to greater customer satisfaction.

4.1.3 Process

Figure 9 illustrates that process excellence can be achieved through three themes but reveals challenges and potential solutions to them.

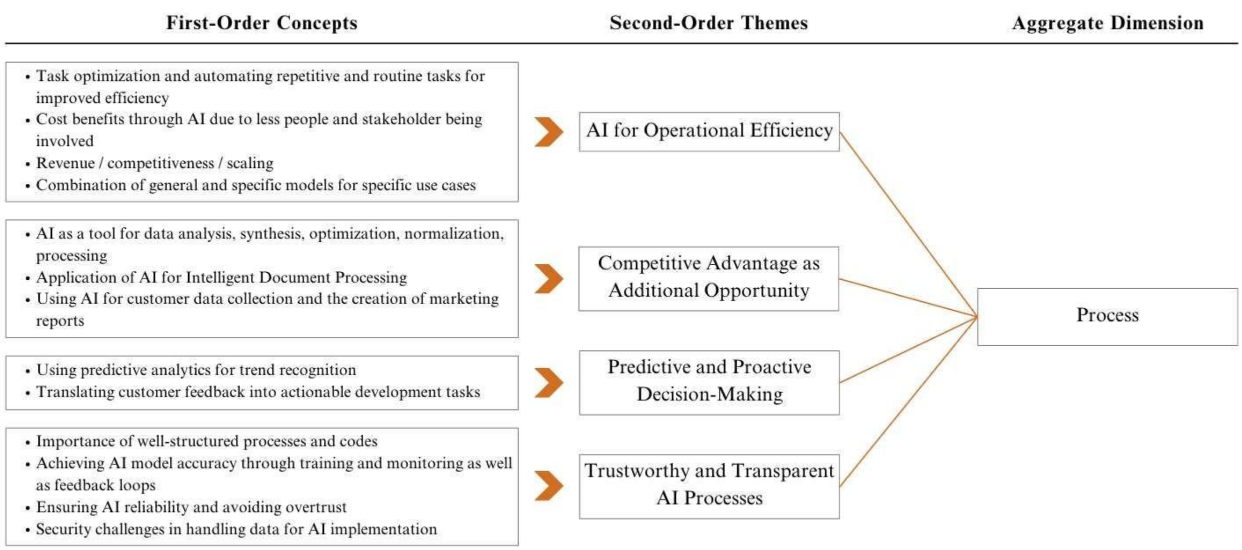

Figure 9: Data Structure third SaaS Aggregate Dimension

The first theme highlights that AI enhances the operational efficiency of SaaS startups by optimizing tasks, enabling teams to work more efficiently. *"The biggest importance for us is saving time, and that's why we have task optimization"* (HK). The automation of repetitive tasks is another benefit. Examples include contract management, data pre-processing, and model validation. OD shared, *"Our internal processes are also enhanced through AI-driven optimizations, such as automating repetitive tasks [...] and continually adjusting for efficiency".* Another noted, *"AI can manage contract renewals by automating alerts, drafting contracts, notifying clients, and handling signatures"* (RM). Cost savings through AI were highlighted, as using AI applications reduces reliance on other human resources such as experts, designers, or agencies: *"With the use of AI, you don't need to talk to a lot of agencies, and this obviously also ends up being a lot cheaper for us at the end"* (AM). Additionally, AI drives scalability by allowing operations to handle greater capacities like customers or products. *"If you want to do this for 1000 or 5000 people a week, you need huge processes that use AI, specific tools, automation, APIs"* (DW). HK highlighted,

> *"Usually, we would start off with one product, and then the whole challenge is to scale that from 1 to 50, from 50 to 500, and 500 to 1000. But at day one, we don't start off with one. The beauty of AI is, that this IT provides us that leverage, that room, to scale up the whole operations."* (HK)

This further results in competitiveness and can be used as a catalyst for future growth. As stated, *"Embracing AI ensures competitiveness and success, we will undoubtedly continue to invest in AI capabilities"* (OD). Another referred to growth, saying, *"The most benefit is using AI as a growth feature for the company"* (RM). Of importance is the possibility of customized AI models to improve solutions for specific use cases. The combination of general and specific models solves additional hurdles: *"We solved this by implementing a Compound AI approach, which combines LLMs with smaller, more efficient models for specific use cases"* (OD).

When looking closer at SaaS, it became evident that data management and analytics benefit heavily from AI. Analyzing, normalizing, and processing data, such as clustering or mapping it, can be taken over by various AI models: *"For is data normalization [...] you upload a CSV and say, 'Check it' or 'Make it all in this format,' 'Remove duplicates, ' etc. as it is super logical, AI can handle it very well"* (RK). Furthermore, AI simplifies working with large amounts of data: *"If you have to do some manual data work, like work with a large data set and getting insights out of it [&] this is where you can benefit a lot from AI"* (GK). Several respondents pointed out AI's ability to work with documents. BW explained, *"Customers just upload those documents and then we have an AI processing algorithm, that is basically organizing the documents and then extracting different attributes out of those documents."* In the context of data processing, marketing activities are being enhanced by AI, as *“It collects data for us, customer data, and gives us specific reports for some KPIs that we can define, like bounce rate, average session duration time”* (TA).

Furthermore, AI supports predictive and proactive decision-making in SaaS startups, helping organizations detect future trends and translate customer feedback into actionable insights for continuous improvement. TA emphasized, *“AI helps us match our understanding and predictions with market trends by providing historical data and predictive analytics”*. This capability improves informed decision-making by offering foresight into emerging patterns and shifts in the market. AN highlighted, *“We must understand the journey of the market we’re entering [&] with AI, we predict how trends will develop.”* In addition, AI facilitates the product decision-making process, as it helps translate customer feedback into actionable development tasks by processing data, which enables continuous product improvement. ML described this workflow: *“With AI, product development translates customer feedback into specific instructions for developers.”* Another explained,

> *“We funnel KPIs, discuss them with the sales team, and leverage this data to improve customer service management. Then we give it back to development, gain insights, and improve the builder.”* (TA)

Within the interviews, it became clear that AI systems must be trustworthy and transparent to support processes effectively: *“AI excels when the process is well-structured. It’s not a silver bullet but rather a powerful tool that amplifies well-designed workflows”* (HK). High-quality data is equally critical: *What is really important is that you have good data and in our case, data is our code, our code base*” (GK). AI accuracy also relies on continuous training, monitoring, and feedback loops. *“For training the AI, we try to collect as much data as possible. And then we also have to make sure that we narrow down that data”* (RK). Data reliability can be enhanced through post-processing checks and manual evaluations: *“We would check manually, take products where we know the exact text code and compare the result based on human decisions”* (BW). Furthermore, ensuring AI reliability and avoiding overtrust remains a challenge. Participants stressed the issue that AI is *“not deterministic. You can run the same input ten times and get ten different results”* (HK). To mitigate these risks of inconsistent or unpredictable results, human oversight is critical. Finally, security challenges in handling data for AI implementation emerged as a significant concern, particularly regarding the secure handling of sensitive data for bigger clients, stating that *"enterprises will definitely be concerned about where this data goes"* (HK). Nevertheless, one effective solution to privacy concerns is data anonymization, which involves removing identifiable details or limiting data granularity. One participant shared, *"We are trying to use no personal information at all till we have [&] more specific laws here"* (AM). Another explained, *"We use geographical data and take it up until the city so it's not really a privacy concern"* (PK). While anonymization ensures compliance and mitigates risks, restricting data usability can be a solution: *"Data that is private, we store it in the database that we do not want to share, meaning you are limited with what you can do with this data"* (GK).

4.1.4 Product

Figure 10 shows how AI improves the 4P product dimension by driving innovation in product management and simplifying coding and UX.

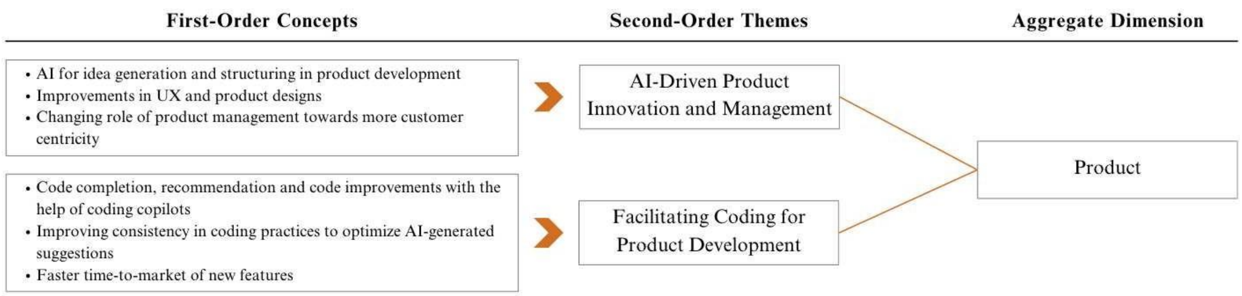

Figure 10: Data Structure fourth SaaS Aggregate Dimension

The first theme shows how AI affects product innovation and management. It first contributes to idea generation and structuring in product development. It was mentioned that AI tools support brainstorming, competitor analysis, product research, and "*to get ideas of something that we don't have on our agenda or which we have not thought about"* (TA). A Product Manager highlighted the process of creating Product Requirement Documents (PRDs): *[AI] helps me write a PRD by asking me questions so that I have a more guided process of drafting this document or improving the existing PRDs"* (ML). AI also supports evaluating ideas more effectively by assessing whether *"it's a good idea, something customers ask for, or something that would improve our workflow"* (RK). In addition, AI helps to *"transform ideas into something tangible by processing user input more efficiently"* (HK). In this context, predictive analytics have been highlighted: *"AI will also enhance predictive capabilities within our product, allowing us to anticipate customer needs more effectively"* (OD). Besides developing new product ideas, AI enhances existing products and features. As TA stated, automated heat map creations are being used to improve UX and optimize product design. As such AI tools detect *"where the eyes go first, where they are staying, what has been clicked, scrolled, and so on."* These abilities lead to AI reshaping roles in product development and management: *"The product role is changing to the sense that you need fewer engineers to do your work, and you can focus on other parts of the software"* (GK). ML added that *"the role as a product manager will definitely change more to being really focused on the customers and the problems."*

The engineering aspect of product development is a cornerstone for SaaS startups; the findings highlight how AI is transforming these coding processes. As stated by many interviewees, one of the most important advancements in coding is copilots like GitHub or Cursor. They enable developers to automate repetitive coding tasks, simplify development, and reduce errors. As shared by the CTO: "*In the development process itself, AI has a huge impact [...] IDEs like VS Code have integrations of tools like Copilot where you can get code completion, recommendations, and code improvements"* (GK). Efficiency gains are frequently mentioned:

> *"For coding copilots [...] you just give your intention, some endpoints, or describe a feature, and they execute. Coders gained much efficiency through large language models."* (AM)

This functionality smoothens workflows, with another participant emphasizing, *"AI can help a lot in order to fuel the velocity of development teams through automation and through automatic code reviews"* (NP). AN additionally added: *"Writing code gets much, much faster, things that would take one hour now take 10 minutes."* To maximize the benefits of AI in coding, participants emphasized the importance of maintaining consistency and adhering to standardized practices across codebases, as this enhances the effectiveness of AI-generated suggestions. RK highlights the importance *"to do one thing that you consider the best solution over and over again and not have variations of it because this also helps AI make better suggestions."* To ensure consistency in coding processes, the engineering team should establish guidelines. Similarly, consistent naming conventions were highlighted as essential, with one participant noting, *"If you name it differently across the code base, AI would just take a guess and name it in some kind of way"* (GK). Lastly, as AI streamlines development and deployment processes, startups can release features more quickly. A CTO stated, *"Everyone can see the difference [of using AI] because you release features much faster and catch more bugs"* (GK). Another shared, *"AI also enables us to automate and* *streamline our deployment processes, reducing time-to-market for new language integrations"* (OD). Finally, HK stressed the importance of AI in SaaS product development: *"The most impactful area is the faster time to market."*

4.2 The Role of Operational AI in SaaS Startups for VCs Investment Decision

The findings to answer the second research question are presented in the following. Through three gated dimensions, an understanding of the perception of VCs towards AI in SaaS startup operations, their investment evaluation criteria and metrics, and a risk and opportunity assessment of operational AI in SaaS startups will be established.

4.2.1 VC Investor Perception of AI in SaaS Startups

The first dimension (Figure 11) illustrates what role operational efficiency has for VCs and how from an investor point of view, AI can be utilized most effectively.

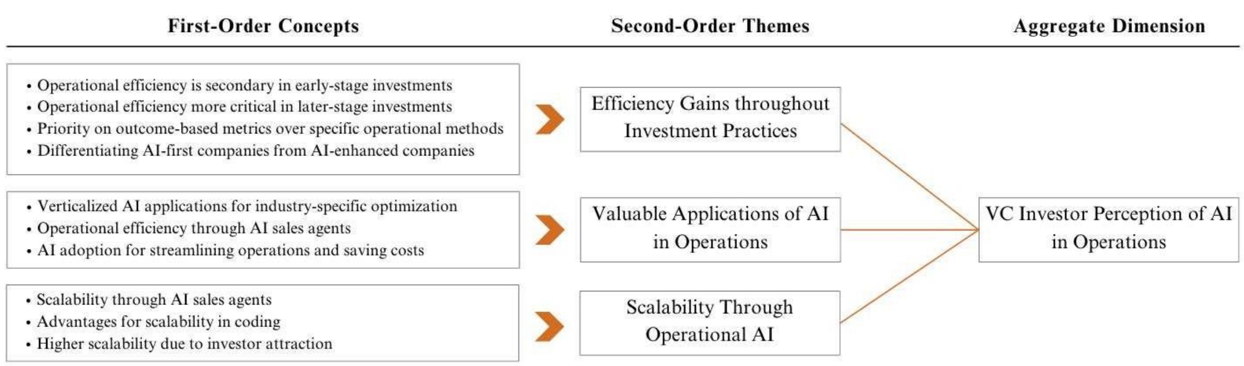

Figure 11: Data Structure first VC Aggregate Dimension

To evaluate the importance of operational AI for VCs, it is necessary to understand the role of operational efficiency in VC investment decisions, which varies depending on the startup's stage and the specific focus of the investor. Multiple VCs emphasized that operational efficiency is not a key factor at the pre-seed or seed stage. Two investors pointed out that at this early stage, only a certain degree of operational level is in place: *"The companies are pre-revenues or have only a few pilot customers so at that stage they don't really have operations. So at the beginning, it is not an important investment decision"* (FF). Similarly, others noted that growth potential is prioritized over operational efficiency in the early stages. However, as startups mature, operational efficiency takes on a greater role. One participant shared, *"If we look at Series A, for example, there's been a* *lot of cases that we had to kill in the end because their operational efficiency was not good enough for us"* (PR). Another mentioned, *"PE firms or very big VC firms [&] investing in growth-stage companies have higher operational requirements compared to early-stage funds"* (CB). Investors consistently highlighted that while they value operational efficiency at a certain stage, their focus lies on measurable results rather than the specific methods or tools, such as AI, used to achieve them. PR explained that they prioritize outcome-based metrics rather than asking startups detailed questions about their operations or tools. CB noted that the proper use of AI tools should naturally reflect in the metrics, which are ultimately what investors evaluate most closely. Furthermore, Many VCs highlighted the importance of distinguishing between startups using AI within their business model and those using AI as a tool to enhance operations.

> *"You have to differentiate between AI-first companies, which wouldn't exist without AI, and then companies being improved by that. And if we talk about the latter category, I don't see it yet as make or break."* (FF)

The second theme summarizes AI applications that VCs value most in SaaS startups. Besides operational AI not being deeply rooted in the decision-making, it was still acknowledged as an impetus for operational efficiency:

> *"Of course, it is in our key interest that the startups we back operate as efficiently as possible. AI could be the biggest lever for creating efficiency in operations."* (JS)

Additionally, VCs highlighted how operational efficiencies in sales, achieved through AI integration, translate to improved outcomes.

> *"If you break those down, [customer acquisition costs] include salaries of sales personnel, which then directly relates to efficiency in operations because you'll probably have fewer salaries in sales teams when you deploy AI agents efficiently."* (JS)

Another shared, that automating sales processes *"helps startups to just with fewer resources get to your goal quicker and that's something we as VCs really like to see and highly value"* (PR). Investors also said startups leveraging AI to improve operations and save costs align well with their expectations. As one explained, *"Startups need to implement something with AI, whether it's to really speed up their own processes internally or on the actual product itself"* (CB). In addition, MM emphasized the importance of motivating startups to integrate AI internally "*to be more* *proficient and focused on their core models"* (MM). In this context, investors expressed a preference for vertical AI solutions: *"We are not fans of these big holistic AI approaches [&] we are rather focusing on vertical models, so really industry specific question specific things"* (MM). Others highlighted the value of these solutions, stating, *"We believe in these especially verticalized AI tools a lot, and I think it can boost productivity by quite much"* (PR). VCs further emphasized the abilities of verticalized AI with examples such as AI-driven chatbots for customer satisfaction and lead generation or sales agents for automated sales processes (RP, JS). *"I think [vertical AI] helps startups a lot to just with less resources get to your goal quicker, and that's something we as VCs really like to see and highly value."* (PR)

The last theme shows how operational AI contributes to the scalability of SaaS startups by optimizing sales processes, accelerating product development, and contributing to investor attraction. It became evident that AI tools in sales processes enable startups to scale more efficiently by shortening sales cycles and reducing costs:

> *"I believe specifically in sales; it can create efficiencies in terms of money you save and the length of sales cycles. If you sell quicker, you scale faster, so it does create scalability."* (JS)

In addition, AI's impact on coding and product development was noted as a key driver of scalability. As FF shared,

> *"So we are seeing some kind of hyperscalers in that field, which [&] within a few months, half a year, get to 10, 20 million revenue. But that's super few examples. What AI does help, I think, on a wider scale is tech product development. Obviously, developer productivity increases a lot. You can bring out products much faster at less cost."* (FF)

Lastly, operational efficiencies created by AI can make startups more attractive to investors, which in turn enhances their scalability. PR remarked:

> *"So I think, especially in your growth potential in the early days, it would help you a lot. And then because of that also your scalability will be higher because you can attract investors more easily."* (PR)

4.2.2 Decision-Making Metrics and Investment Criteria

This aggregate dimension (Figure 12) elaborates on criteria and metrics that influence VC investment decisions within SaaS startups, which are of both tangible and intangible nature.

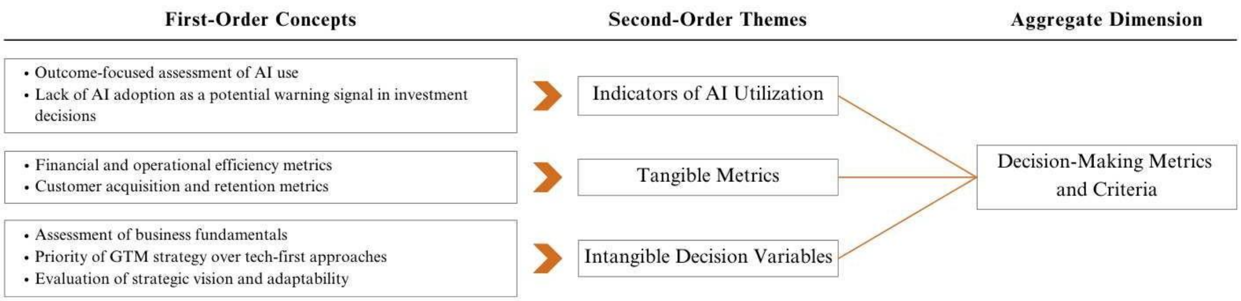

Figure 12: Data Structure second VC Aggregate Dimension

As mentioned in 4.2.1, it became evident that founders are not specifically questioned about which AI tools they use, as VCs rather *"just want to see is it working or is it not"* (PR). Additionally, one investor takes *"it for granted, more or less, that in some way AI is deployed"* (JS), but adds that the focus is on *"the results of what they [operations in connection with AI] translate to"*. While AI adoption is not a strict requirement, investors noted that its absence could negatively affect perceptions of a startup. CB explained that being overly traditional or avoiding AI entirely might raise concerns, describing it as an unspoken but noticeable red flag. They further emphasized that startups failing to use AI effectively or appearing naive in their approach could leave a poor impression. A similar sentiment regarding the application of AI was echoed by JS, *"If not, it could be a red flag."*

As there are no explicit tangible metrics of AI's impact on business operations, investors noted costs associated with the efficiency gains AI can bring, with JS sharing, *"In sales, with specific sales agents, there can be a lot of efficiencies created in speed and conversion, and also in terms of HR costs on the startup side, which makes the model for us more attractive"*. In addition, others pointed out, *"The two most important measurements [are] burn multiple, so how much cash they burn divided by their new ARR that they get in a month and [this number] should be around 1.5"* (PR). Furthermore, key metrics such as cost of goods sold (MM), the *"rule of 40 [&] with which you can see the relation on how much cash they burn, how operationally efficient they are in relation to their growth"* (PR) or the *"magic number [&] a very, very much used KPI in evaluating SaaS businesses"* (JS) were mentioned. Metrics related to acquiring and retaining customers were highlighted as critical for SaaS evaluation. CAC and CLV, as well as their ratio, were mentioned several times, while one respondent further explained, *“You obviously want to see a very high multiple on lifetime value compared to acquisition costs because, in the end, you spend money on customer acquisition”* (JS). PR stated that the efficiency of SaaS startup operations can also be examined through their churn and net retention rates. Early-stage startups must demonstrate strong customer centricity, with one investor noting, *“Customer centricity, retention, all of that is super important, especially early stage, because you don’t have a lot of customers”* (CB).

Besides hard metrics, soft ones are being applied to evaluate SaaS startups: *“You’re trying to figure out what are the basic mechanics of a business model [such as] qualifying a lead, closing deals”* (MM). Additionally, investors value insights into how founders think and approach key areas like financial planning (PR). Early-stage evaluations further often rely on a combination of narrative and hypotheses, as another respondent shared, *“In the seed case, it’s very simple [&] you’re just selling a storyline, but you have to underlay this with certain ideas, metrics, hypotheses”* (MM). Additionally, VCs often place more weight on the strength of a startup’s go-to-market strategy than its underlying technology. One investor said,

> *“But in the end of the day, for me, it’s a go-to-market play. It makes sense what they’re offering, but they need to win B2B customers and that’s kind of the main challenge.”* (FF)

Investors assess the strategic vision and adaptability of the founding team as evaluation criteria. Strategic questions such as *“Why is this a good time now? Why are we doing this? Why is this the market? Why is this our target group?”* (MM) play a critical role. Another highlighted the importance of a visionary mindset:

> *“We look at the people a lot, because in early-stage investment, you really look at the founding team. And so we look at people that are visionaries, that see the future and not only the present. Usually, these people are also the first users of the new tools.”* (CB)

4.2.3 Ethical Concerns and Staying Competitive within AI Adoption

VCs acknowledged both, risks associated with the use of operational AI and additional opportunities, which are being presented in the data structure below (Figure 13).

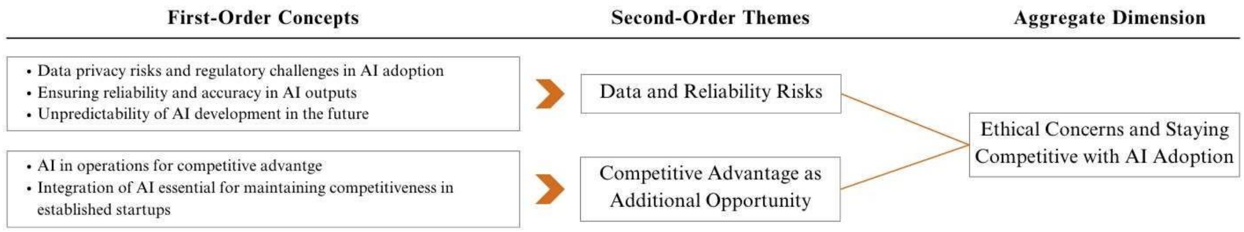

Figure 13: Data Structure third VC Aggregate Dimension

VCs saw data privacy and compliance as significant concerns for startups adopting AI. As one explained, *"For some business models, data privacy can be quite an issue and could be detrimental to some startups' business models in the future"* (PR). In this context, SaaS startups *"with big patent filings in deep tech, where data is very proprietary, have to look out for [risks] a little more"* (PR). Another VC added the risk of leaking internal data as *"employee data and corporate data [are] being processed somehow into the unknown space of these algorithms that learn on your data"* (JS). In Europe, the increasing number of strict regulations further complicates AI adoption (PR). Next, investors emphasized the importance of quality assurance to *"make sure that same input delivers same output, which needs different safeguards"* (FF). Another added, that as *"the machine still hallucinates and you can't always trust the results I would always advise double-checking it yourself"* (JS). With the fast evolution of AI one VC pointed out *"The biggest risk with AI right now is that not a lot of AI companies will survive"* (CB). Another expressed concerns about volatility, sharing:

> *"The emphasis [in our future investment philosophy] is on software rather than AI specifically. AI is seen as too volatile and unpredictable to fully integrate into the philosophy."* (CB)

The speed of technological advancements creates uncertainty among VCs, questioning how long AI-driven advantages will last (MM).

Despite the risks, investors emphasized that effectively leveraging AI tools allows SaaS startups to stand out in the market. As one investor explained, *"If you use these AI tools correctly, you can for sure get ahead of the curve and differentiate from your competition"* (PR). The findings also highlight the importance of AI adoption for more mature startups. One respondent stated, *"We have a set of companies, five years old, they have to go basically in transition process and change otherwise, they will change to a competitor which is kind of built on one AI"* (FF). Another noted, *"We already see that founders are reacting to [AI's appeal]. Startups that aren't primarily AI-based still adopt AI tools a lot"* (PR). The relevance of AI was further emphasized:

> *"Companies will have to learn and understand AI regardless of their industry or focus. It's a critical area with undeniable benefits."* (CB)

5 Discussion

This study examined how AI-driven technologies support SaaS startups in achieving OE through the lens of the 4Ps model as well as the influence of AI adoption on VC perceptions.

The findings answer the first research question by illustrating that AI, especially GenAI and LLMs, supports SaaS startups across all four OE dimensions. From LLM-based content creation tools to predictive analytics and coding copilots, operational AI nurtures efficiency and continuous improvements for excellent outcomes. Employees benefit from fast skill acquisition and reduced onboarding times, while customer relationships deepen through more personalized and efficient communication channels. In addition, customer satisfaction and loyalty can be strengthened through chatbots and AI-powered ticketing. Internally, repetitive tasks are automated, data handling is improved, and predictive insights guide decision-making. In product development, AI accelerates coding, shortens time-to-market, and enables more continuous product improvement. These results show that AI's influence extends beyond conventional beliefs of operational efficiency, fostering SaaS startups to become more agile, customer-centric, and innovative.

Additionally, the second research question could be addressed by interviewing VCs, indicating that while investors may not explicitly demand operational AI tools, they highly value outcome-based metrics that AI adoption influences (FF; PR; CB). Although they may not explicitly ask about which AI technologies a startup uses, their expectation for including efficiency-increasing solutions is rising, making the absence of AI-driven operations a potential "red flag" (CB; JS). VCs differentiate between AI-first companies, which rely on AI to exist, and those integrating AI as an operational improvement. Both models can be attractive if they gain positive metrics. For SaaS startups, improved operational metrics, like reduced CAC, enhanced CLV, higher net retention, and improved burn multiples, signal strong potential for sustainable scaling. Investors recognize verticalized AI solutions as particularly valuable, as these industry- and domain-specific tools can improve operational flows more precisely (MM; PR). At the same time, VCs remain cautious about risks. Regulatory challenges, data privacy, and the volatility of AI markets cast uncertainty on long-term outcomes (PR; FF; JS; CB; MM). Nevertheless, VCs see AI as a powerful lever for growth and differentiation, potentially leading to better investment propositions and chances of securing funding.

The findings of this study both align with and extend the existing literature on AI's role in achieving OE. Prior studies have established that AI-driven solutions contribute to improved efficiency, data-driven decision-making, and enhanced customer engagement (Benbya et al., 2020; Chikezie et al., 2024; Nambisan et al., 2019; Shepherd & Majchrzak, 2022). Yet, the literature has largely concentrated on established or AI-first firms rather than on resource-constrained SaaS startups, leaving several gaps that this research helps to fill. However, the topic around AI adoption in SaaS for enhanced operations appears to be very relevant in the business context as practitioners like McKinsey & Company have already conducted studies in this field, which will be referred to in the subsequent sections.

For the people dimension, existing research acknowledges AI's potential to automate repetitive tasks and streamline processes, noting efficiency gains of 20330% in operational areas (McKinsey & Company, 2023). However, it seldom discusses AI's capacity to speed up employee onboarding, close skill gaps, or enhance workplace learning, which frequently emerged in the interviews (RK, GK). While Lean and TQM frameworks stress continuous improvement and skill development (Chikezie et al., 2024; Dahlgaard & Dahlgaard, 1999), the literature has not yet integrated AI's potential to reduce the time new hires need to become fully productive. For SaaS startups, which often rely on small, multi-skilled teams (Ojaghi et al., 2019), having AI tools that can provide technical or contextual knowledge means employees can contribute more quickly, improving internal agility and resilience. This finding goes beyond previous research, suggesting that AI boosts both efficiency and the people dimension of OE.

Literature on AI and customer engagement already emphasized personalization and improved service quality (Makar, 2023). McKinsey & Company (2023) further notes that AI-driven enhancements in sales and service can boost productivity by 30-45% and potentially increase revenue by 3-5%. Studies have also shown AI's ability to strengthen customer relationships through service chatbots and personalized marketing campaigns (Liang et al., 2019; Makar, 2023; Singh et al., 2019; Usman et al., 2024). Yet, the specific context of SaaS startups, where recurring revenue models and low switching costs make retention critical (Khare & Arora, 2024), was largely unaddressed. In SaaS, metrics like CAC, CLV, and churn are central performance indicators (Khare & Arora, 2024; Xiao et al., 2020). The current research confirms that AI's detailed feedback analysis and automated outreach can improve customer satisfaction and reduce churn by identifying pain points more effectively (AN, ML, OD, TA). Moreover, the discovery that AI can crawl websites and professional profiles to inform more tailored outreach introduces a tangible, SaaS-specific application that was not previously discussed in the literature. By aligning marketing activities with customer insights, which can now be processed at full scale rather than a small fraction, SaaS startups can better personalize their service, increase CLV, and maintain a competitive advantage.

Regarding the processes**,** prior studies highlight AI's operational benefits in speeding up processes, which was further backed by McKinsey & Company (2023) discovering that up to 70% of repetitive work could be automated through GenAI. However, the literature generally focuses on large organizations, supply chains, or manufacturing (Rusev & Salonitis, 2016; Shehadeh et al., 2016) rather than data-intensive, scaling SaaS environments. This thesis confirms these known efficiencies but also illustrates how SaaS startups use AI to handle large and growing volumes of data. During the interviews, Intelligent Document Processing (IDP) was mentioned for the first time. It emerges as a powerful AI technology that automates document handling by using ML and NLP to extract, classify, and understand data from complex documents across various formats. Thus, by integrating IDP, RPA, and predictive analytics, SaaS firms can normalize, cluster, and map data or documents more effectively, supporting both operations and predictive decision-making (BW, GK, HK, OD, RK). These findings align with the literature's emphasis on OE as a strategy for maintaining competitiveness (Chikezie et al., 2024; Lasi et al., 2014) but extend it to show how SaaS-specific data challenges are met through compound AI approaches. This refined view addresses a gap in the literature concerning data workflows and scaling issues SaaS companies face as they evolve from startups to scaleups.

Existing research acknowledges AI's role in faster product development and delivery. However, detailed discussions of coding copilots and their impact on developer productivity are lacking. The McKinsey & Company (2023) report states that GenAI tools can boost developer productivity by 20-45%, and an example from Forrester (2023), citing a 50% productivity increase after implementing Microsoft Copilot, indicates that these improvements are not merely theoretical. This current study adds depth to this understanding by showing how SaaS startups use AI-driven coding assistants to speed up feature releases, reduce errors, and better align products with changing customer demands (AM, AN, GK, NP, RK). Past literature has underlined the importance of time-to-market and customer-centric product iterations in SaaS (Ju et al., 2010; Li & Kumar, 2022). The present findings confirm these principles while incorporating the direct impact of AI tools, which streamline development workflows and enhance product-market fit, an area previously not fully explored in detail.

Another topic that occurred during the interviews was data privacy and transparency**.** While literature on AI often references data privacy, compliance, and trustworthiness as general concerns (Bogoviz, 2020; Carmody et al., 2021; Wright & Xie, 2019), no studies known to the author contextualize these issues specifically for SaaS startups. Earlier research has not examined how smaller digital firms handle the tension between large datasets and user confidentiality. The current findings introduce concrete strategies, like data anonymization and restricted usage, adopted by SaaS firms to mitigate these risks (AM, PK). This contribution extends the literature by suggesting that challenges in privacy and trust-building are present even for younger companies.

The literature on VC investment decision-making often points to the importance of operational efficiency, team capabilities, and growth potential, noting how technology adoption can influence investor perceptions (Conti et al., 2016; Janeway et al., 2021). Yet, the role of AI in shaping these VC perceptions for SaaS startups is less discussed. This study shows that while VCs are interested in improvements of hard metrics (e.g., lower CAC, higher CLV, and better burn multiples), they also consider softer metrics, such as founder adaptability and the intelligent application of AI to solve operational problems (CB, FF, JS, PR). By closing the gap between established literature on VC decision-making and the operational realities of AI integration in SaaS, the current research demonstrates how startups that thoughtfully implement AI can be perceived as more scalable, resilient, and investment-worthy.

5.1 Theoretical Contributions

This study adopts the 4P framework into the managerial context of SaaS startups and provides a novel perspective on achieving OE by leveraging AI as the most recent GPT. First, AI enriches the people dimension by showing how it accelerates onboarding, skill development, and problem-solving, enhancing workforce capabilities by closing knowledge gaps and improving creativity. Second, it refines the partnerships dimension, demonstrating how AI tools like feedback analysis and automated lead targeting help SaaS startups turn customer data into actionable insights, improving engagement in subscription-based contexts. Third, in the process dimension, the study shows how integrating tools like IDP and data normalization addresses operational complexity, with OE arising from combined AI tools rather than isolated ones. Finally, in the product dimension, AI accelerates development cycles and improves product quality using coding copilots and generative AI, enabling faster time-to-market and better product-market alignment. These findings emphasize AI's role in driving innovation and meeting evolving customer demands.

The study's findings contribute to OE's underlying TQM framework, which emphasizes continuous improvement, efficiency, and customer-centric quality management. In the SaaS context, AI becomes a key enabler of TQM by eliminating operational inefficiencies, supporting data-driven decision-making, and contributing to continuous learning. Additionally, AI aligns with Lean principles by streamlining processes, reducing waste, and maximizing value delivery through automation and predictive insights.

Lastly, this study enriches theory by showing that AI-driven operational improvements can shape how VCs assess startups. Instead of focusing solely on product-market fit or technological novelty, investors value the internal capabilities that AI fosters, such as lower CAC, improved scalability, and faster product development. Thus, AI-enabled OE emerges as a strategic signal of maturity and growth potential, extending theoretical models of entrepreneurial finance and strategic entrepreneurship to include AI's influence on investment decision-making.

5.2 Managerial Implications

From a managerial perspective, the findings suggest that founders should integrate AI throughout the entire 4Ps framework rather than limiting its use to obvious efficiency gains. Adopting more creative and strategic approaches, such as compound AI solutions that combine general LLMs with specialized models, can increase adaptability and scalability. Similarly, the preference for vertical AI from a VC perspective highlights the importance of focusing on industry-specific use cases for stronger investor appeal.

SaaS startups can draw on the insights provided by VCs, who encourage broad AI adoption not only to improve metrics like CAC and CLV, but also to demonstrate forward-thinking leadership and a clear vision of AI's future role. In this sense, founders should continuously check emerging AI technologies to stay competitive and refine their strategies accordingly. By developing a roadmap that includes how AI will shape operations and product innovation over time, startups can meet both the hard metrics VCs value and the soft metrics, like visionary leadership and strategic intent, that signal long-term resilience and growth potential.

As a summary, figure 14 comprises the main contributions of this study for both theory and practice.

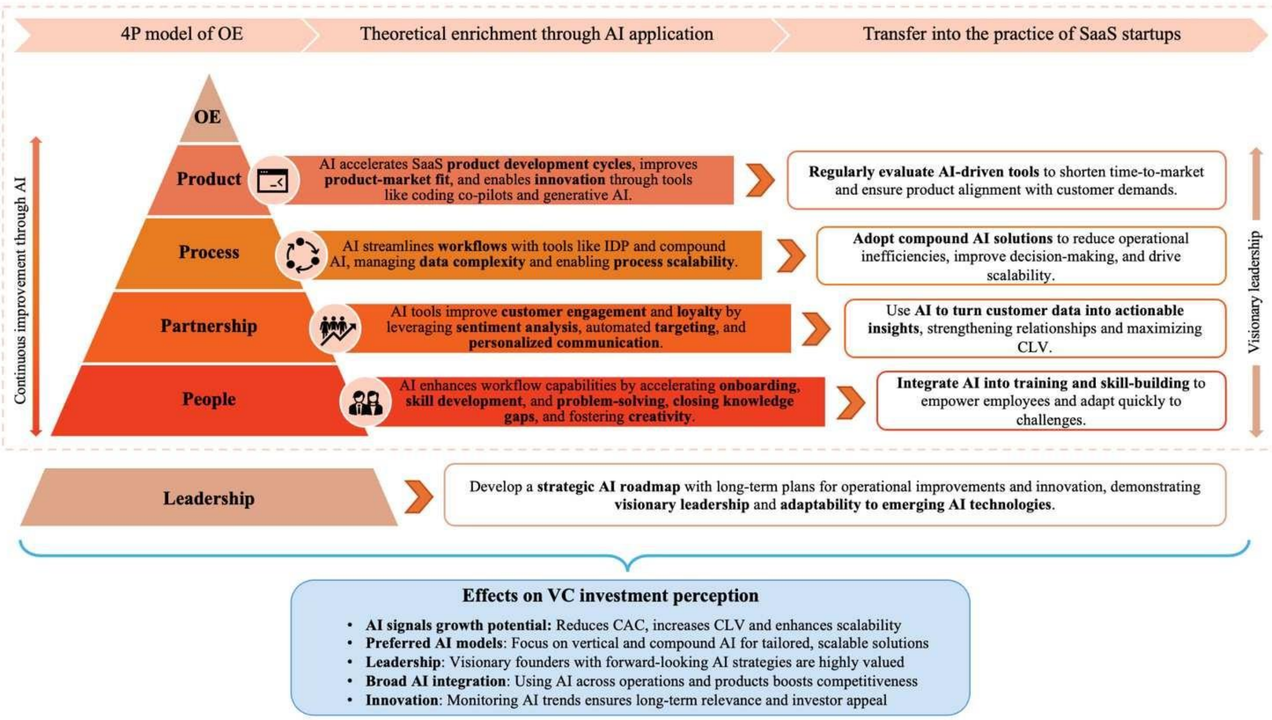

Figure 14: AI for Operational Excellence in SaaS Startups 3 Theoretical and Managerial Contribution (own illustration)

5.3 Research Limitations and Future Directions

Besides the future research opportunities mentioned in 5.1, this study has several limitations that offer additional potential for future research. First, the focus on customers within the 4P partnerships dimension excludes other key stakeholders such as partners or suppliers. Second, while this research highlights the perception of VCs towards AI adoption, other entities within the ecosystem, like accelerators and incubators, could be investigated for their potential contributions to OE. Additionally, the limited data saturation concerning VC perspectives necessitates further exploration. As the study mostly reflects insights from pre-seed to seed stage investors, it potentially misses larger funds' different dynamics and investment criteria (Series A and B). Furthermore, adopting operational AI in these contexts could present unique challenges or opportunities that were not captured fully. Lastly, the small sample size, particularly of interviewees, may limit the diversity of perspectives.

Future research could focus on sector-specific applications of AI in SaaS startups, exploring how industry-specific challenges influence adoption and impact. Longitudinal studies could track the long-term effects of AI implementation on scalability and customer retention. Finally, examining the effectiveness of innovative approaches discovered in this thesis, like compound AI models or vertical AI, in optimizing operations offers another promising avenue.

6 Conclusion

This study explored how AI-driven technologies can enhance OE in SaaS startups and further influence VC investment decisions. With the SaaS industry projected to grow exponentially and startups facing high attrition rates, improving operational metrics and aligning operations with market demands are pressing concerns.

The research shows that AI, when integrated seamlessly, has the potential to support SaaS startups in becoming operationally excellent by more than just streamlining workflows or providing faster analytics. It overhauls organizational capabilities, provides teams with the confidence and agility to adapt quickly, improves how startups interpret and respond to their customers, and enables product design and go-to-market at a pace aligned with the market's continuous evolution. Therefore, the function of AI evolves from a simple motivator of productivity to a strategic partner with a focus on the customers and innovation. Investors do not overlook such operational restructuring. While VCs do not focus on specific AI solutions, they preferably consider outcome-based metrics. However, these metrics can be improved through AI adoption, resulting in reduced CAC, increased CLV, and reduced customer churn. Furthermore, the adoption of a forward-thinking AI strategy contributes positively to VCs' soft metrics, indicating that the founding team has the foresight to refine its business model in tandem with technological shifts continually.

While this research offers insights into how SaaS startups benefit from AI's potential for reaching OE, it also recognizes certain constraints. The qualitative approach and early-stage focus may limit broader generalizations. Nevertheless, these findings establish a valuable foundation for scholars and practitioners alike, encouraging a redefinition of AI as a multifaceted catalyst rather than a standalone enhancement.

In a world where digital ventures either rise rapidly or fade quietly, the ability to embrace AI as a fundamental strategic force will set apart those SaaS startups that not only endure but redefine what it means to move from efficiency to excellence.

7 Bibliography

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y.K., D'Ambra, J., & Shen, K.N. (2021). Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management, 60(1)*, 102387.

Baek, C. H., Kim, S.-Y., Lim, S. U., & Xiong, J. (2023). Quality evaluation model of artificial intelligence service for startups. *International Journal of Entrepreneurial Behavior & Research*, *29*(4), 913-940.

Barua A., Konana P., Whinston A., Yin F (2014). Managing e-business transformation: opportunities and value assessment. *Sloan Management Review*, 1-26.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial Intelligence in Organizations: Current State and Future Opportunities. *MIS Quarterly Executive, 19*, 9-21.

Berger-Gabner, D. (2016). *Wissenschaftliches Arbeiten in den Wirtschafts- und Sozialwissenschaften* (Ed. 3). Wiesbaden: Springer Gabler.

Blank S., & Dorf B. (2012). The startup owner's manual: The step-by-step guide for building a great company. BookBaby, Pennsauken.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics*, *13*(1), 333-372.

Bogoviz, A.V. (2020). Perspective directions of state regulation of competition between human and artificial intellectual capital in Industry 4.0. *Journal of Intellectual Capital, 21*(4), 583-600.

Byun, D.H. (2017). An exploratory study on Kano quality attributes of artificial intelligence secretary. *E-Business Research*, *18*(4), 167-178.

Carmody, J., Shringarpure, S., & Van de Venter, G. (2021). AI and privacy concerns: a smart meter case study. *Journal of Information, Communication and Ethics in Society, 19*(4), 492-505.

Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. *Entrepreneurship Theory and Practice*, *45*(5), 1028-1053.

Chen, Q., Wu, L., & Jiang, C. (2022). ES-PPDA: An efficient and secure privacy-protected data aggregation scheme in the IoT with an edge-based XaaS architecture. *Journal of Cloud Computing*, *11*(1), 20.

Chikezie, P., Godwin, O., Adams, G., Okeke, I., & Chukwunweike, M. (2024). Strategic Planning and Operational Excellence: A Conceptual Model for Growth in Tech Businesses. *International Journal of Engineering Research*, *20*, 342-351.

Chiva, R., P. Ghauri, & Algere J. (2014). Organizational learning, innovation and internationalization: a complex system model. *British Journal of Management*, *25*, 687-705.

Chou, D., & Chou, A. (2008). Software as a Service (SaaS) as an outsourcing model: An economic analysis. *Proceedings of the 7th International Conference on E-Business Engineering (ICEBE 2008)*, 1-8.

Creswell, J. W. (1998). *Qualitative Inquiry and Research Design: Choosing among Five Approaches.* Carlifornia: Thousand Oaks.

Crnogaj, K., & Rus, M. (2023). From Start to Scale: Navigating Innovation, Entrepreneurial Ecosystem, and Strategic Evolution. *Administrative Sciences, 13*(12), 254.

Crowne, M. (2002). Why software product startups fail and what to do about it. *Proceedings of the IEEE International Engineering Management Conference, 2002. IEMC902*, 1, 338-343. IEEE.

Cukier D., Kon F., & Thomas L. (2016). Software startup ecosystems evolution: The new york city case study. *Proceedings Second International Workshop on Software Startups.*

Dahlgaard, J. J., & Dahlgaard, S. M. P. (1999). Integrating business excellence and innovation management: Developing a culture for innovation, creativity and learning. *Total Quality Management*, *10*(4-5), 465-472.

Dawei, L., & Betts, A. (2011). Re-investigating business excellence: Values, measures and a framework. *Total Quality Management, 22*(11), 1263-1276.

Dempsey, D., & Kelliher, F. (2018). *Industry Trends in Cloud Computing*. Springer International Publishing.

Döring, N., & Bortz, J. (2016). *Forschungsmethoden und Evaluation in den Sozial- und Humanwissenschaften.* Heidelberg: Springer-Verlag.

Dresig, T., & Pehl, T. (2018). *Praxisbuch Interview, Transkription & Analyse: Anleitung und Regelsysteme für qualitativ Forschende* (Vol. 8). Marburg: dr. dresig & pehl GmbH.

Duan, Y., Sun, X., Longo, A., Lin, Z., & Wan, S. (2016). Sorting Terms of "aaS" of Everything as a Service: *International Journal of Networked and Distributed Computing*, *4*(1), 32.

Emory, C. W., & Cooper, D. R. (1991). *Business Research Methods* (4th ed.). Homewood, IL: Irwin.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and Organizing in the Age of the Learning Algorithm. *Information and Organization*, *28*(1), 62-70.

Forrester (2023). *Generative AI Trends for Business: Why, When, and Where to Begin.* Retrieved from https://www.forrester.com/technology/generative-ai/ (Accessed on December 16, 2024).

Fortune Business Insights (2024). *Software as a Service (SaaS) Market Size, Share & Industry Analysis, By Deployment Type (Public, Private, and Hybrid), By Application (Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), Content, Collaboration & Communication, BI & Analytics, Human Capital Management, and Others), By Enterprise Type (Large Enterprises and SMEs), By Industry (IT & Telecom, BFSI, Retail & Consumer Goods, Healthcare, Education, Manufacturing, and Others), and Regional Forecast, 2024-2032*. Retrieved from https://www.fortunebusinessinsights.com/ software-as-a-service-saas-market-102222 (Accessed on October 20, 2024).

Ge, C. & Huang, K.-W. (2014). Analyzing the Economies of Scale of Software as a Service Software Firms: A Stochastic Frontier Approach. *IEEE Transactions on Engineering Management, 61*(4), 610-622.

Gerhardt, V., Santos, J. D., Rubin, E., Neuenfeldt, A., & Mairesse Siluk, J. C. (2021). Stakeholders´ Perception to Characterize the Start-ups Success. *Journal of Technology Management & Innovation*, *16*(1), 38-50.

Ghosh, A., Chakraborty, A., Saha, S., & Mahanti, A. (2012). Cloud computing in Indian higher education. *IIM Kozhikode Society & Management Review*, *1*(2), 85-95.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15-31.

Glaser, B. G., & Strauss, A. L. (1968). The Discovery of Grounded Theory: Strategies for Qualitative Research. *Nursing Research, 17*, 364.

Grilo, A., Agueda, A., Zutshi, A., & Nodehi, T. (2017). Relationship between investors and European startup ecosystems builders. 2017 *International Conference on Engineering, Technology and Innovation (ICE/ITMC).*

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5-14.

Harrison, S. H., & Corley, K. G. (2011). Clean climbing, cara- biners, and cultural cultivation: developing an open-systems perspective of culture. *Organization Science*, *22*, 391-412.

Hofmann E., & Rüsch M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry, 89*, 23-34.

Ju, J., Wang, Y., Fu, J., Wu, J., & Lin, Z. (2010). Research on Key Technology in SaaS. *International Conference on Intelligent Computing and Cognitive Informatics*, 384-387.

Kibria, M. G., Nguyen, K., Villardi, G. P., Zhao, O., Ishizu, K., & Kojima, F. (2018). Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. *IEEE Network, 6,* 32328-32338.

Klinger, J., Mateos-Garcia, J., & Stathoulopoulos, K. (2021). Deep learning, deep change? Mapping the evolution and geography of a general purpose technology. *Scientometrics*, *126*(7), 5589-5621.

Lai, E. (2009). Services Firms Boost Microsoft's SaaS Plans. *Computerworld*, *43*(23), 10.

Lamba, H. S. & Singh, G. (2011), Cloud Computing-Future Framework for e-management of NGO's. *International Journal of Advancements in Technology*, *2*(3).

Langley, A., & Abdallah, C. (2011). Templates and Turns in Qualitative Studies of Strategy and Management. *Research Methodology in Strategy and Management, 6*, 201-235.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering, 6*(4), 239-242.

Li, B., & Kumar, S. (2022). Managing Software0as0a0Service: Pricing and operations. *Production and Operations Management*, *31*(6), 2588-2608.

Li, S., Cheng, H. K., & Jin, Y. (2018). Optimal distribution strategy for enterprise software: Retail, SaaS, or dual channel? *Production and Operations Management, 27*(11), 1928-1939.

Liang, C. C., Liang, W. Y., and Tseng, T. L. (2019). Evaluation of intelligent agents in consumer-to-business e-commerce. *Computer Standards & Interfaces*, *65*, 122-131.

Makar, K. Š. (2023). Driven by artificial intelligence (AI) 3 Improving operational efficiency and competitiveness in business. *2023 46th MIPRO ICT and Electronics Convention (MIPRO)*, 1142-1147.

McDonald, R., & Eisenhardt, E. (2020). Parallel play: Startups, nascent markets, and effective business-model design. *Administrative Science Quarterly, 65*, 483-523.

McKinsey & Company. (2021). *Winning formula: How Europe's top tech start-ups get it right*. Retrieved from https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/winning-formula-how-europestop-tech-start-ups-get-it-right (Accessed on October 23, 2024).

McKinsey & Company. (2023). *Beyond the hype: Capturing the potential of AI and Gen AI in TMT*. Retrieved from https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/beyond-the-hype-capturing-the-potential-of-ai-and-gen-ai-in-tmt#/ (Accessed on December 16, 2024).

Mell, P., & Grance, T. (2011). *The NIST Definition of Cloud Computing*.

Mitchell, J. S. (2015). *Operational Excellence: Journey to Creating Sustainable Value*. New York, NY: Wiley.

Mitchell, R. B., & Meggison, P. F. (2014). Strategies for integrating cloud computing concepts. *Journal of Applied Research for Business Instruction*, *12*(2), 1-6.

Monteiro, G. F. A. (2019). High-growth firms and scale-ups: A review and research agenda. *RAUSP Management Journal, 54,* 96-111.

Müller, S. D., Påske, N., & Rodil, L. (2019). Managing Ambidexterity in Startups Pursuing Digital Innovation. *Communications of the Association for Information Systems, 44*(1), 273-298.

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy, 48*(8), 103773.

Nassar, A., & Kamal, M. (2021). Ethical dilemmas in AI-powered decision-making: a deep dive into big data-driven ethical considerations. *International Journal of Responsible Artificial Intelligence*, *11*(8), 1-11.

Obschonka, M., & Audretsch, D. (2020). Artificial Intelligence and Big Data in Entrepreneurship: A New Era Has Begun. *Small Business Economics, 55*(10).

Obschonka, M., Gregoire, D., Nikolaev, B., Ooms, F., Lévesque, M., Pollack, J., & Behrend, T. (2024). Artificial intelligence and entrepreneurship: A call for research to prospect and establish the scholarly AI frontiers. *Entrepreneurship Theory and Practice*.

Ojaghi, H., Mohammadi, M., & Yazdani, H. R. (2019). A synthesized framework for the formation of startups' innovation ecosystem: A systematic literature review. *Journal of Science and Technology Policy Management, 10*(5), 1063-1097.

Park, J. G., & Lee, H. J. (2017). Startup teamwork and achievements. *The Journal of Venture Startup Research, 11*(2), 101-111.

Patton, M. Q. (2014). *Qualitative research and evaluation methods* (4th ed.). Thousand Oaks, CA: SAGE Publications.

Pereira V., Hadjielias E., Christofi M., & Vrontis D. (2021). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review, 33*(10).

Rathore, B. (2020). Predictive metamorphosis: unveiling the fusion of AI powered analytics in digital marketing revolution. *International Journal of Transcontinental Discoveries*, *7*(1), 15-24.

Ries, E. (2011). The Lean Startup: How Today's Entrepreneurs use Continuous Innovation to Create Radically Successful businesses. Crown Books, New York.

Ruparelia, N. (2016). *Cloud Computing*. The MIT Press.

Rusev, S., & Salonitis, K. (2016). Operational excellence assessment framework for manufacturing companies. *Procedia CIRP, 55*, 272-277.

Russell, S. (2015). *Artificial Intelligence: A Modern Approach*. Pearson, New York.

Russell, R. H., & Koch, J. I. (2009). Operational Excellence: The New Lever for Profitability and Competitive Advantage. Palladium Group, 1-24.

Sarea, A., & Taufiq-Hail, G. A. M. (2021). Evaluation of compatibility of cloud-based applications, credibility, and trust perceptions on the adoption of cloud technology: A review. In A. E. Hassanien, K. C. Chang, & M. T. Mincong (Eds.), *Advanced Machine Learning Technologies and Applications: AMLTA 2021. Advances in Intelligent Systems and Computing* (Vol. 1339, pp. 37-50). Springer, Cham.

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2015). *Research methods for business students* (7th edition). Pearson Education.

Schneider, S., & Sunyaev, A. (2016). Determinant factors of cloud-sourcing decisions: Reflecting on the IT outsourcing literature in the era of cloud computing. *Journal of Information Technology*, *31*(1), 1-31.

Sharma, R. (2023). The Transformative Power of AI as Future GPTs in Propelling Society Into a New Era of Advancement. *IEEE Engineering Management Review*, *51*(4), 215-224.

Shehadeh, R. M., Zu'bi, M. F., Abdallah, A. B., & Maqableh, M. (2016). Investigating Critical Factors Affecting the Operational Excellence of Service Firms in Jordan. *Journal of Management Research*, *8*(1), 157-190.

Shepherd, D., & Majchrzak, A. (2022). Machines augmenting entrepreneurs: Opportunities (and threats) at the nexus of artificial intelligence and entrepreneurship. *Journal of Business Venturing, 37*(5), 106227.

Silverman, D. (2000). *Doing qualitative research: a practical handbook.* London: Sage.

Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., & Le Meunier-Fitz Hugh, K., et al. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: concepts, priorities, and questions. *Journal of Personal Selling and Sales Management, 39*, 2-22.

Simamora, B. H., & Sarmedy, J. (2015). Improving services through adoption of cloud computing at Pt Xyz in Indonesia. *Journal of Theoretical & Applied Information Technology*, *73*(3), 395-404.

KCA (Korea Consumer Agency) (2018). Problems and Improvements of Artificial Intelligence Appliances. *Survey report*, 1-33.

Statista (2024). Largest SaaS providers worldwide as of 2023, by market capitalization. Retrieved from https://www.statista.com/statistics/802887/worldwide-top-saas-providers-public-companies/ (Accessed on October 23, 2024).

Strauss, A. L., & Corbin, J. (1990). Basics of Qualitative Research: Grounded Theory Procedures and Techniques. Thousand Oaks, CA: Sage.

Stryker, C., & Scapicchio, M. (2024, March 22). What is generative AI? IBM. Retrieved from https://www.ibm.com/topics/generative-ai (Accessed on October 16, 2024).

Superside (2024). *The role of AI in SaaS: Transforming the future of software*. Retrieved from https://www.superside.com/blog/role-of-ai-in-saas (Accessed on December 16, 2024).

Taddy, M. (2018). The technological elements of artificial intelligence. In *The Economics of Artificial Intelligence: An Agenda* (pp. 61-87). National Bureau of Economic Research, Inc.

Tippmann, E., Ambos T. C., Del Giudice M., Monaghan S., & Ringov D. (2023). Scale-ups and scaling in an international business context. *Journal of World Business*, *58*, 101397.

Tripathi N., Seppänen P., Boominathan G., Oivo M., & Liukkunen K. (2019). Insights into startup ecosystems through exploration of multi-vocal literature. *Information and Software Technology, 105*, 56-77.

Usman F. O., Eyo-Udo N. L., Etukudoh E. A., Odonkor B., Ibeh C. V., & Adegbola A. (2024). A critical review of AI-driven strategies for entrepreneurial success. *International Journal of Management and Entrepreneurship Research*, *6*(1), 200-215.

Varona, D., & Suárez, J. L. (2022). Discrimination, bias, fairness, and trustworthy AI. *Applied Sciences, 12*(12), 5826.

Villa Todeschini, B., Sosa Boelter, A., & Siqueira, J. et al. (2017). Risk Management from the Perspective of Startups System. *European Journal of Applied Business Management*, *3*(3), 40-54.

Wachter, S., Mittelstadt, B. & Russel, C. (2021). Bias Preservation in Machine Learning: The Legality of Fairness Metrics Under EU Non-Discrimination Law. *West Virginia Law Review,* 123(3), 1-49.

Wiersema, F. D., & Treacy, M. E. (1993). Customer intimacy and other value disciplines. *Harvard Business Review, 71*, 84-93.

Williamson, O. E. (1991). Strategizing, economizing, and economic organization. *Strategic Management Journal, 12*, 75-94.

Wright, S.A., & Xie, G.X. (2019). Perceived privacy violation: Exploring the malleability of privacy expectations. *Journal of Business Ethics, 156,* 123-140.

Xiao, X., Sarker, S., Wright, R. T., Sarker, S., & Mariadoss, B. J. (2020). Commitment and replacement of existing SaaS-delivered applications: A mixed-methods investigation. *MIS Quarterly, 44(*4), 1811-1857.

Zhao, W., Yao, T., Xu, L., Chen, X., & Song, X. (2020). Multi-objective optimization design of a modular linear permanent-magnet vernier machine by combined approximation models and differential evolution. *IEEE Transactions on Industrial Electronics, 68*(6), 4634-4645.

Zhao, Y. (2023). A study on the factors affecting investment decision of venture capitalists. *Proceedings of the 2nd International Conference on Business and Policy Studies*.

Zott, C., Amit R., & Massa L. (2011). The business model: Recent developments and future research. *Journal of Management, 37*(4).

8 Appendix

Appendix A: Data Structure based on Gioia et al. (2013)

First-Order Concepts	Second-Order Themes	Aggregate Dimension
• AI supporting onboarding and training by providing quick information • Gathering information and support in problem-solving through AI	Employee Training and Information Gathering	People
• GenAI for content creation and copy writing • AI for writing or redefining messages and emails both for internal and external communication • AI for better high-quality text output, especially for non-natives in a specific language • Speeding up outbound marketing by automating this process with the use of AI • Using AI for product descriptions, keywords, also in different languags	AI-Enhanced Content Creation and Communication	People
• Shifting employee focus through AI-driven task automation • Balancing automation with human oversight for quality control • Improving quality of work	Changing Work Dynamics	People
• AI enables more efficient feedback analysis • Sentiment analysis using AI for better and more tailored customer interactions • More customized communication through automating A/B testing • Personalizing outreach efforts for customers using AI-driven tools • AI supporting brand awareness and establishing brand strategy	AI-Driven Customer Engagement & Personalization	Partnerships
• Increating efficiency and improving customer experience by using IVR systems for customer queries • Saving time by using AI in customer service for ticketing • Chatbot for customer service enhancement	Improved Customer Service	Partnerships
• Task optimization and automating repetitive and routine tasks for improved efficiency • Cost benefits through AI due to less people and stakeholder being involved • Revenue / competitiveness / scaling • Combination of general and specific models for specific use cases	AI for Operational Efficiency	Process
• AI as a tool for data analysis, synthesis, optimization, normalization, processing • Application of AI for Intelligent Document Processing • Using AI for customer data collection and the creation of marketing reports	Competitive Advantage as Additional Opportunity	Process
• Using predictive analytics for trend recognition • Translating customer feedback into actionable development tasks	Predictive and Proactive Decision-Making	Process
• Importance of well-structured processes and codes • Achieving AI model accuracy through training and monitoring as well as feedback loops • Ensuring AI reliability and avoiding overtrust • Security challenges in handling data for AI implementation	Trustworthy and Transparent AI Processes	Process
• AI for idea generation and structuring in product development • Improvements in UX and product designs • Changing role of product management towards more customer centricity	AI-Driven Product Innovation and Management	Product
• Code completion, recommendation and code improvements with the help of coding copilots • Improving consistency in coding practices to optimize AI-generated suggestions • Faster time-to-market of new features	Facilitating Coding for Product Development	Product
• Operational efficiency is secondary in early-stage investments • Operational efficiency more critical in later-stage investments • Priority on outcome-based metrics over specific operational methods • Differentiating AI-first companies from AI-enhanced companies	Efficiency Gains throughout Investment Practices	VC Investor Perception of AI in Operations
• Verticalized AI applications for industry-specific optimization • Operational efficiency through AI sales agents • AI adoption for streamlining operations and saving costs	Valuable Applications of AI in Operations	VC Investor Perception of AI in Operations
• Scalability through AI sales agents • Advantages for scalability in coding • Higher scalability due to investor attraction	Scalability Through Operational AI	VC Investor Perception of AI in Operations
• Outcome-focused assessment of AI use • Lack of AI adoption as a potential warning signal in investment decisions	Indicators of AI Utilization	Decision-Making Metrics and Criteria
• Financial and operational efficiency metrics • Customer acquisition and retention metrics	Tangible Metrics	Decision-Making Metrics and Criteria
• Assessment of business fundamentals • Priority of GTM strategy over tech-first approaches • Evaluation of strategic vision and adaptability	Intangible Decision Variables	Decision-Making Metrics and Criteria
• Data privacy risks and regulatory challenges in AI adoption • Ensuring reliability and accuracy in AI outputs • Unpredictability of AI development in the future	Data and Reliability Risks	Ethical Concerns and Staying Competitive with AI Adoption
• AI in operations for competitive advantge • Integration of AI essential for maintaining competitiveness in established startups	Competitive Advantage as Additional Opportunity	Ethical Concerns and Staying Competitive with AI Adoption