Western Norway University of Applied Sciences

Leveraging the Potential: How Founders are Adopting Generative AI for Entrepreneurial Tasks

Master's Thesis for Responsible Innovation and Sustainable Value Creation
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Written by Thomas Solberg Irgens
Main supervisor: Tore Frimanslund
Supervisor: Emil Tomson Lindfors
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Abstract

Generative AI applications (GenAI) has the potential to benefit early-phase ventures by lowering costs and time spent solving tasks. Despite its growing prominence, there's a gap in understanding how founders adopt and perceive this new technology. This research investigates whether founders perceive that GenAI truly is beneficial to their work.

This is investigated through an abductive multiple-case study, leveraging thematic analysis of six semi-structured interviews and two collaborative workshops with founders of startups in Norway and South Africa. The study leverages Technological Adoption Model 3 (TAM3) as a theoretical lens. The aim is to answer whether founders perceive GenAI as useful, and to learn how and why they adopt the technology.

I identify four key factors influencing the adoption and perceived usefulness of GenAI: Playfulness, Capability Awareness, Skill Level, and Subjective Norm. These findings largely align with the traditional TAM3 framework, with some exceptions. My findings indicate a specific form of computer anxiety directed towards AI, and social media seems to function as a subjective norm. Applying TAM3 reveals an adoption pattern where founders who enjoy using technology are more likely to adopt GenAI and find it useful for entrepreneurial tasks, mostly after gaining some experience with it and learning how to improve the output. When they become experienced, they find the technology to be very helpful.

This research enhances our understanding of how GenAI can be effectively utilized by startups and may inspire founders to invest time in mastering this technology in situations where it suits their needs. However, further research is necessary to quantify the impact of GenAI adoption on entrepreneurial tasks, assess the significance of each influencing factor, distinguish between traditional computer anxiety and AI-specific computer anxiety, and further explore why some founders choose not to adopt these tools. This additional research will provide a more comprehensive view of the potential benefits and challenges associated with GenAI in entrepreneurial settings.

Foreword

This work represents the master's thesis for my degree in Responsible Innovation and Sustainable Value Creation. With a background in Cognitive Sciences, and hoping to build a venture myself, I find the topic researched very intriguing and I believe that it provides fruitful insight for me and others in future endeavours.

I extend my gratitude to all the participants of the interviews and workshops for dedicating their valuable time to contribute to my research. Special thanks go to my main supervisor, Tore Frimanslund, for his availability, insightful advice, and motivational support. I also appreciate the feedback from supervisor Emil Tomson Lindfors.

A heartfelt thank you to my friend and co-founder, Philip Hodne, for his encouragement and invaluable expertise on the current state of AI and user experience. Our discussions have been very productive in defining the scope, purpose and background for this research.

I am truly grateful for the support from my network of wise and helpful individuals who have made this journey possible.

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1 Introduction

“There’s this betting pool for the first year that there’s a one-person billion-dollar company, which would’ve been unimaginable without AI, and now it will happen.”

Those are the words of OpenAI CEO Sam Altman at the Annual 2024 J.P. Morgan Investors Conference (Ohanian, 2024). Alluding to the potential of Generative AI (GenAI) as a catalyst to automating and enhancing work efficiency, it underscores his profoundly high expectations of applying AI to entrepreneurial ventures. In this study, I am referring to GenAI as widely available tools and applications based on generative AI technology.

The successful employment of GenAI by founders signifies, then, a decrease in the costs associated with performing entrepreneurial tasks. With humans as the current custodians, this potential directly addresses a fundamental challenge faced by these ventures: the scarcity of accessible capital and knowledge necessary to develop and commercialize products and services while founding a company. But do these claims align with the perception of founders? And are the founders able to leverage the current technology to achieve these results? This study aims to provide insight into this matter from a founder's perspective, exploring and explaining adoption and usefulness of GenAI, informing founders and identifying future research areas.

2 Background and Context

In this section, I will justify the research gap and present the problem statement, beginning with a definition of Generative AI as a technology. Then, I will provide descriptions on the contexts the study is conducted in, namely Norway and South Africa. This will provide a clear outline of the research aim of this work, as well as the context from which results will be interpreted and discussed.

2.1 Defining Generative AI

In the last section, we introduced the term Generative AI, outlining a technology with a broad range of applications, and with it, high expectations. Generative AI itself represents an advancement in statistical learning, enabling the creation of human-like content in various forms such as text and code (OpenAI, 2024; Driess et al., 2023; Touvron et al., 2023; Brown et al., 2020; Devlin et al., 2019), media (Ramesh, 2022; Saharia et al., 2022; Rombach, 2022), and audio (Huang et al., 2023; Ghosal et al., 2022), based on user prompts.

While traditional statistical learning methods often focus on analyzing patterns and making predictions based on observed data, GenAI has the capability to create new content. This transformation was heralded, amongst others, by the introduction of Generative Adversarial Networks (GANs) (Goodfellow et al., 2014), and advanced by the transformer architecture (Vaswani et al., 2017), which improved the understanding of context and semantic relationships in data at scale. With the growing affordability of computational resources and continual advancements in machine learning techniques, applications such as ChatGPT (Oyang, at al., 2022; Brown et al., 2020;), Sora (Brooks et al., 2024), and Sima (SIMA Team, 2024) aim to produce outputs that enrich creativity, streamline efficiency, and enhance problem-solving capabilities. Thus, Generative AI can be defined as is a statistical learning technology able to generate new and human-like content.

2.2 Research Gap and Goal

Generative AI technologies in general has proliferated in diverse domains, like medicine (Clusmann et al., 2023), robotics (Andrews, 2024), banking (Yusof & Roslan, 2023), hospitality, and tourism (University of West Florida, 2024). At the same time, concerns regarding safe and responsible deployment have been raised (Li et al., 2023). Studies have attributed an overall supply chain efficiency increase in the Operations and Supply Chain across various company sizes to GenAI (Wamba et al. 2023), and demonstrated GenAI potential for entrepreneurship (Short & Short 2023). These studies suggest that GenAI can have a significant impact on startups, with Short & Short even going beyond Sam Altman's speculations, contemplating whether GenAI can launch a full entrepreneurial venture on its

own. They indicate that more exploration in the area of entrepreneurial applications is needed and Wamba et.al suggest testing their framework outside the G-7 countries (Wamba et al. 2023). Gupta & Yang (2024) has identified a similar knowledge gap in GenAI for startups, highlighting the importance of ascertaining factors which impact the uptake of ChatGPT in their research protocol stating that they will be the first to do so (Gupta & Yang, 2024). My study has a similar purpose, with a goal of bridging the research gap of GenAI adoption in a startup context, allowing stakeholders to make informed choices regarding whether to invest time in learning to apply GenAI tools for entrepreneurial tasks. The study will contribute to the TAM3 framework, which I will use as a theoretical lens in a GenAI context in addition to proposing future research.

3 Problem Statement

As discussed, for the companies that arguably need knowledge and capital efficient work done, GenAI could have a positive impact. While performance increase has already been researched broadly and quantitatively (Wamba et al., 2023), the question remains whether and how founders are able to make use of these benefits. The need for an in-depth investigation on adoption and usefulness of GenAI technologies for startup founders can be formulated as these questions:

RQ1: How do startup founders perceive the usefulness of GenAI tools?
RQ2: How are startup founders adopting GenAI?

Whether founders perceive that the theoretical potential of GenAI can be harnessed for their tasks is an important question to answer because the theoretical upside of a technology doesn't necessarily mean that they are able to reap the benefits in-practice.

I will explore and discuss these questions, leveraging thematic analysis of qualitative data gathered through semi-structured interviews and collaborative workshops with early-phase ventures in Norway and South Africa. I outline how founders perceive GenAI's usefulness

for ventures, and how and why these tools are adopted. First, I will provide some context on entrepreneurship and GenAI adoption in the countries studied.

3.1 Context

3.1.1 Norwegian and South African Entrepreneurship and Economy

As of 2023, both Norway and South Africa face distinct economic and entrepreneurial challenges that shape their respective startup ecosystems. Norway, amidst an economic downturn with rising inflation and interest rates coupled with a weakened currency, continues to showcase a resilient financial system. The government is maintaining a commitment to supporting entrepreneurship, especially targeting youth and export-oriented sectors (Hill et al., 2024). South Africa grapples with severe economic slowdown, marked by GDP growth slowing and disrupted by electricity shortages and high inflation, significantly straining both consumers and businesses (Hill et al., 2024).

Norway's government expenditure on entrepreneurship, initially increased during the COVID-19 pandemic, has reverted to pre-pandemic levels. This fiscal normalization occurs as Norway's National Entrepreneurial Context Index (NECI) score declines, indicating a less supportive entrepreneurial environment in spite of maintained commitments (Hill et al., 2024). In South Africa, the introduction of the National Small Enterprise Amendment Bill in 2023 aims to mitigate similar hardships by providing small businesses a platform for resolving disputes outside the traditional costly legal system. This legislative effort reflects an adaptive response to the harsh economic conditions impacting the entrepreneurial sector (Hill et al., 2024).

Both countries exhibit fluctuations in their entrepreneurial activities as influenced by their economic states. Norway's NECI score drop is attributed to diminished assessments across multiple Entrepreneurial Framework Conditions (EFCs), notably in Entrepreneurial Education and Government Policy Support, despite slight improvements in Entrepreneurial Finance and Market Dynamics. South Africa's NECI score also fell, with significant

reductions in crucial areas like Social and Cultural Norms and Government Entrepreneurial Programs, reflecting one of the lowest scores among surveyed economies (Hill et al., 2024).

The social landscape for entrepreneurship in Norway suggests an inclusive environment, as evidenced by relatively high scores for social support for women entrepreneurs. South Africa, despite lower scores, shows a relatively better assessment for women entrepreneurs compared to other EFCs, indicating a nuanced but challenging environment for inclusive entrepreneurship (Hill et al., 2024).

In conclusion, Norway and South Africa both have established entrepreneurial ecosystems, and have both experienced economic challenges recently. However, South Africa is arguably in a more challenging economical situation, signified by a much lower GDP per capita and lower NECI score than Norway (Hill et al., 2024).

3.1.2 Generative AI adoption

In the last section, I shed light on the economic environment of entrepreneurship in both Norway and South Africa, showing that they both have an established, and arguably, comparable entrepreneurial ecosystem, despite different economic adversities. Indeed, the Ipsos Social Media Tracker reported that 39% of Norwegian individuals aged 18-29 were using ChatGPT weekly (Ipsos & Chernykh, 2024). In contrast, In On Africa (IOA) conducted a survey in South Africa and found that approximately 64% of the workforce aged 18-34 were using it (IOA, 2023). There is a notable difference in the sampling methods of these reports: Ipsos sample was representative of the general Norwegian population, whereas IOA's sample was restricted to employed individuals who were familiar with ChatGPT (Ipsos & Chernykh, 2024; IOA, 2023). This distinction could be attributed to the high unemployment rate in South Africa, where over 30% of the population is unemployed, particularly among young people (Bowmaker-Falconer et al., 2023). Furthermore, in 2022, 21% of the South African population lacked internet access (SAnews, 2024), potentially excluding a significant portion of the population from adopting online generative AI tools simply for that reason. This difference in sampling, excluding groups in South Africa who are most likely not to adopt GenAI, could explain the higher adoption rate in South Africa reported by IOA

compared to the Ipsos study in Norway. Nevertheless, the results indicate an arguably widespread GenAI usage in both countries.

3.1.3 Implications for Comparing GenAI Adoption between Norway and South Africa

Given the comparable entrepreneurial ecosystems and similarly widespread usage of GenAI ((Hill et al., 2024; IOA, 2023; Ipsos & Chernykh, 2024), I argue that there are common underlying factors contributing to its adoption and usage. Despite the differences in sampling methods, the high usage rates of ChatGPT reported in both studies suggest that GenAI adoption is prevalent across the workforces of both countries. In spite of differences in their separate economies, similarities in adoption indicate that common factors drive the adoption pattern.

4 Theory

In this section, theories and frameworks relevant to the discussion on GenAI adoption among founders are presented. TAM3 will be used as the theoretical lens guiding data collection and discussion.

4.1 Generative AI Capabilities

Being trained on large datasets and understanding the semantic relationships of the data, enables the GenAI models to predict correctly with few or no examples. This is called few or zero-shot learning. This means the same model can effectively recognize and work with objects and concepts it hasn't encountered before, providing a platform for a wide range of downstream tasks. (Rahman et al., 2018). Thus, the models are able to, for instance, not have to train on thousands of pictures of a foreign planet before generating an educated guess on how it would look.

Generalizations across multiple domains and modalities are also emerging (Girdhar, et al., 2023), representing a marked shift. When models demonstrate the capability to interpret

multiple inputs and utilize natural language to, for instance, generate executable code for any action within a operating system or robot (Wang et al., 2024;), it can be contended that the premise of a diverse array of tasks being facilitated by the same autonomous system simultaneously is not implausible (see also Ahn, et al., 2024; Brohan et al., 2023). Still, opponents of this claim (e.g. Manduchi et al., 2024), highlight unresolved issues hindering the versatility and reliability. Challenges include the absence of benchmark datasets and metrics for evaluating counterfactual quality, violations of strong assumptions in real-world applications, and the necessity of integrating causal principles.

Hofman et al. (2021) identified six key functional capabilities of GenAI: creating, transforming, modifying, reconstructing, reducing dimensionality, and predicting data. Table 1 provides examples of these functionalities.

Capability	**Create**	**Transform**	**Modify**	**Reconstruct**	**Reduce dimensionality**	**Prediction**
Example use	Generating images	Text to voice audio	Changing characteristics such as face in pictures	Sharpen unsharp image	Reduce size of big data sets without losing too much information	Future human brain from current human brain, predicting aging process

Table 1, summary and examples of GenAI capabilities, adapted from Hofman et al., 2021

While acknowledging the limitation of solely relying on theoretical sources, suggesting potential oversight, the above synthesis arguably shows a varied application of the same technology. Thus, GenAI demonstrates the potential to be an applicable tool in a broad range of use cases, with challenges in ensuring a consistently high quality of the output.

4.2 Entrepreneurial Tasks and Abilities

Having defined the main capabilities for GenAI, I will identify the main areas of entrepreneurial tasks and abilities associated with successful entrepreneurship. This creates the basis for comparing entrepreneurs across industries.

Chen et al. (1998) have identified five entrepreneurial task factors that are central to the concept of entrepreneurial self-efficacy (ESE). These tasks are:

- Marketing: This involves setting and meeting market share goals, establishing a position in the product market, conducting market analysis, and expanding the business.
- Innovation: This includes generating new ideas, developing new products and services, exploring new markets and geographic territories, and implementing new methods of production and marketing.
- Management: This entails reducing risk and uncertainty, strategic planning, developing information systems, managing time by setting goals, and defining organizational roles and policies.
- Risk-taking: This involves taking calculated risks, making decisions under uncertainty, taking responsibility for ideas and decisions, and working under pressure.
- Financial Control: This includes performing financial analysis, developing financial systems and internal controls, and controlling costs.

These tasks collectively represent the diverse roles that entrepreneurs must undertake, highlighting their need to wear many hats and handle various aspects of their businesses effectively. This need to wear many hats is supported by neuroscientific methods, demonstrating a difference between habitual entrepreneurs and managers. Habitual entrepreneurs, individuals who have started three or more ventures, seem to have a higher cognitive flexibility than other managers (Ooms et al., 2024). Cognitive flexibility is defined as *"the readiness with which one can selectively switch between mental processes to generate appropriate behavioral responses"* (Dajani & Uddin, 2015, p. 571).

Successful entrepreneurs typically perform a range of tasks, and tend to have an increased ability to switch between mental processes. With few employees, a larger portion of these tasks are dependent on the entrepreneurs abilities to complete them alone, and it seems like entrepreneurs need some generalist knowledge. However, being a generalist can be perceived as a negative trait by investors (Souitaris et al., 2022), and having specialized knowledge of

an industry is related to higher performance in acquisitions (Chen et al., 2021). It can be inferred that starting a venture requires both generalist and specialist knowledge, skills which are arguably challenging to acquire.

With GenAI having the ability to aid in a diverse range of tasks, there seems to be a synergy between GenAI capabilities and entrepreneurial tasks. If GenAI can aid in generalist tasks, such as management, it might lower the barrier of cognitive flexibility, freeing up time which the founders can leverage to focus on their area of expertise, thus increasing their credibility among investors and performance in tasks like acquisitions.

4.3 Technological Acceptance Model (TAM)

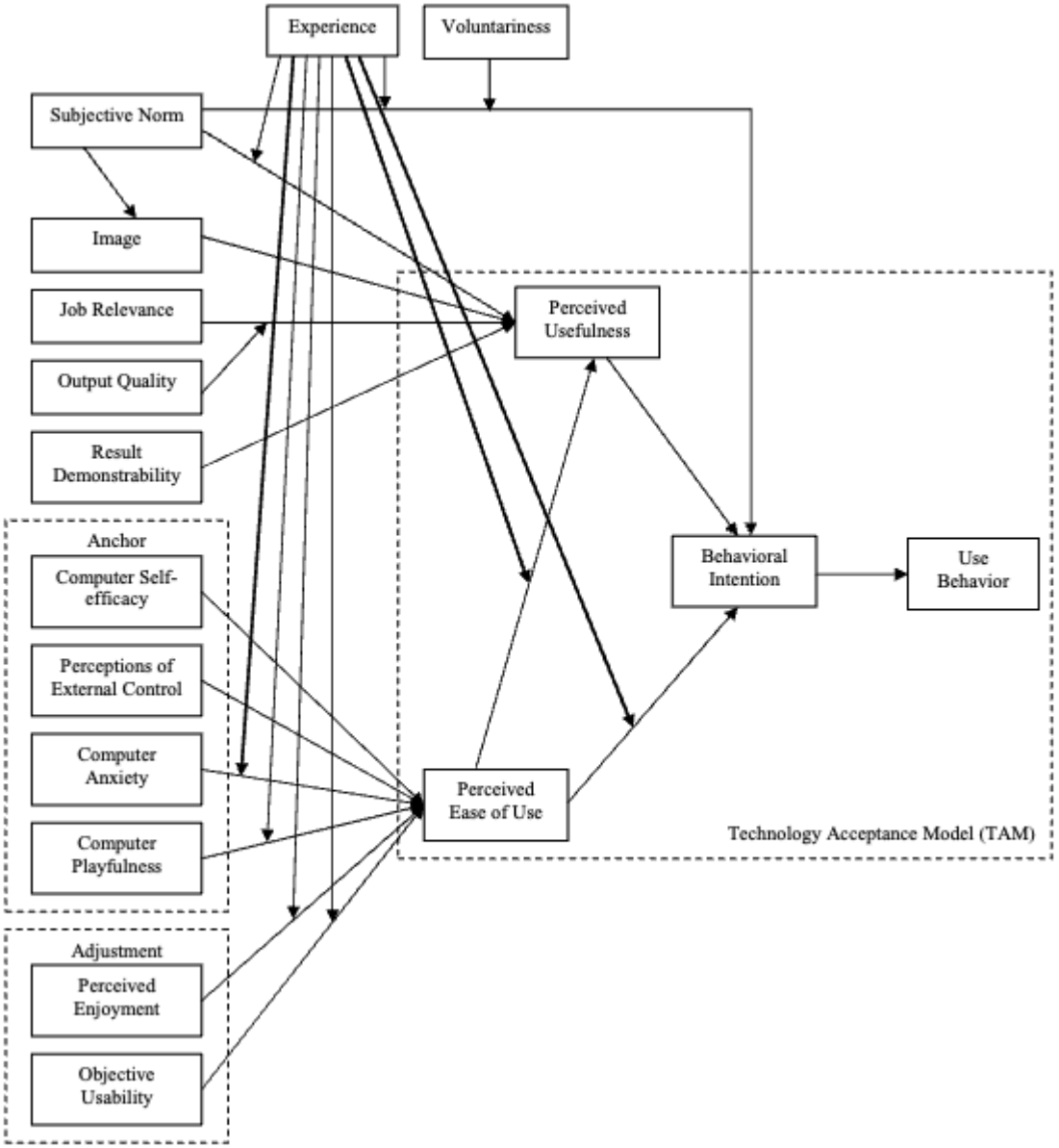

Figure 1: TAM3 Theoretical Framework (Venkatesh & Bala, 2008)

The Technology Acceptance Model 3 (TAM3), proposed by Venkatesh and Bala (2008), constitutes an extension of Davis's seminal Technology Acceptance Model (TAM) introduced in 1989. The foundational TAM posited Perceived Usefulness (PU) and Perceived Ease of

Use (PEOU) as the primary determinants influencing an individual's intention to adopt and utilize new technologies (Davis, 1989). Building upon the original model's framework, TAM3 introduces additional constructs and moderating variables aimed at providing a more comprehensive understanding of the factors affecting technology acceptance and utilization behaviors. The framework is still seen as robust in explaining adoption of recent technological developments (Marikyan & Papagiannidis, 2023), including Cloud Computing (Nikolopoulos & Likothanassis, 2018)**.**

Individual differences, such as computer self-efficacy, perception of external control, computer anxiety, and playfulness, are incorporated as moderators that impact the core TAM constructs, accounting for variance in users' responses to new technology. System characteristics—specific features of the technology itself like objective usability and output quality—also play a crucial role, affecting both PU and PEOU directly (Venkatesh & Bala, 2008).

TAM3 also acknowledges the influence of social elements by including Subjective Norm and Voluntariness, thus recognizing the impact of social processes and the degree of autonomy experienced by the user. The model suggests that as users gain experience over time, their perceptions of the technology's usefulness and ease of use can evolve, indicating a dynamic relationship between user experience and technology acceptance (Venkatesh & Bala, 2008).

Furthermore, Facilitating Conditions are highlighted as critical components influencing both Perceived Ease of Use and actual Use Behavior, encapsulating external control factors such as technical infrastructure and organizational support. Ultimately, these perceptions inform the Behavioral Intention to use the technology, which leads to the actual Use Behavior (Venkatesh & Bala, 2008).

The framework has met some criticism (Marikyan & Papagiannidis, 2023). They argue that extensive use of TAM has led to concerns about its over-replication, which might hinder progress in Information Systems (IS) research by leaving some areas underexplored. TAM's focus on technology use also tends to overlook the impact of technology on performance and the importance of system design and fit with the user's tasks. Finally, limitations in extended

models like TAM2 include being tailored for organizational contexts and methodological issues, such as reliance on self-reported measures, which can introduce bias. Despite these limitations, TAM demonstrates strong predictive power to assess individuals intentions (Marikyan & Papagiannidis, 2023).

Being an arguably robust framework for understanding technology adoption, I choose to leverage TAM3 as a theoretical lens for my study.

5 Methodology

This chapter outlines the ontological, epistemological, and methodological assumptions that underpin my study of GenAI adoption among founders. It also outlines the research design, including data collection and analysis methods, while discussing reflexivity, and the criteria for trustworthiness. I advocate for a qualitative research approach, specifically employing an abductive case study method, arguing that this method is well suited to identify new findings whilst drawing support from and contributing to established theory. The qualitative approach will not only facilitate a deeper understanding of GenAI adoption from a founders perspective, but also aims to bridge empirical gaps where this phenomenon previously has been studied quantitatively (Wamba et al., 2023).

5.1 Philosophical Assumptions

Ontology concerns the nature of reality, while epistemology focuses on how we acquire knowledge (Easterby-Smith et al., 2015). These concepts are interrelated; one must assume what reality is (ontology) before seeking knowledge (epistemology). Easterby-Smith et al. explain how epistemology guides methodology, determining suitable methods for inquiry. They illustrate ontology on a continuum from realism, which assumes an objective world directly observable through data and measurement, to relativism, which posits multiple realities based on perspectives.

Thus, realism suits studies regarding observable phenomenon but is less effective for understanding complex human behaviors (Easterby-Smith et al., 2015). While studying why and how founders adopt GenAI, a relativist approach is thus fitting. The relativist approach acknowledges diverse truths based on individual viewpoints (Easterby-Smith et al., 2015). While studies show a positive link between GenAI and efficiency (Wamba et al., 2023), understanding subjective reasons behind adoption arguably requires a relativist approach.

This ontological viewpoint limits my epistemological assumptions. Similarly to the ontological views Easterby-Smith et al. (2015) illustrate epistemological views on a continuum with Positivism on the left and Social Constructivism on the right (see table 2). Applying our individual-focused approach, human interests should drive our research. Therefore, Social Constructionism is a suitable approach.

	Positivism	Social Constructionism
The observer	must be independent	is part of what is being observed
Human interests	should be irrelevant	are the main drivers of science
Explanations	must demonstrate causality	aim to increase general understanding of the situation
Research progresses through	hypotheses and deductions	gathering rich data from which ideas are induced
Concepts	need to be defined so that they can be measured	should incorporate stakeholder perspectives
Units of analysis	should be reduced to simplest terms	may include the complexity of 'whole' situations
Generalization through	statistical probability	theoretical abstraction
Sampling requires	large numbers selected randomly	small numbers of cases chosen for specific reasons

Table 2: Epistemological positions (Easterby-Smith et al., 2015)

5.1.1 Triangulation and abductive reasoning

Furthermore, Easterby-Smith et al. (2015) summarize the associations between ontology, epistemology and methodology. As the constructionist position assumes that there are many different realities, they argue that mixed methods and many perspectives are needed to gather a comprehensive understanding of a phenomena. This is sometimes described as the method "Triangulation", which is how I will refer to it.

As I both build and use GenAI tools extensively, I want to contribute with my personal insight in a constructive way, leveraging my experience rather than discarding it as bias. Therefore, I will be supplementing Constructivist methods with methods from the Strong Constructivist position, where it is recognized that theories apply to both the subjects and the observer (Easterby-Smith et al., 2015). In the Research Design section I present a workshop as a data collection method, which will allow me to be part of the data collection in a meaningful and controlled manner.

The study also draws from Positivism by including the TAM3 framework. TAM3 assumes determinism as it is derived from quantitative data analysis (Venkatesh & Bala, 2008; Easterby-Smith et al., 2015). The rigidity of this framework might be helpful in shaping the qualitative data collection.

Dubois and Gadde (2002) propose that a systematic combination of induction and deduction can improve qualitative studies. Instead of conducting research in a linear matter, they found that the abductive method expands their understanding of theory and phenomenon by constantly going back and forth between an analytical framework and observations. They argue that theory cannot be understood without empirical observation and vice versa. Applying this type of abduction will allow me to draw support from an analytical framework to keep the data collection and analysis focused, without excluding findings outside the established theories, and might also shed new light on TAM3 through qualitative scrutiny.

5.2 Research Design

This section introduces my research design and data collection methods, which combines the use of case studies and participatory observation.

5.2.1 Case Studies

This study adopts a holistic approach to case studies by conducting one-hour interviews with individual founders from six distinct startups—three located in Norway and three in South Africa. A case study is an in-depth research method designed to explore complex phenomena within their real-life contexts. It is relevant in disciplines such as social sciences, education, business, and health, particularly for investigating contemporary events where variables cannot be directly manipulated (Yin, 2014). In contrast to embedded approaches, holistic case studies investigate phenomena as a whole, instead of breaking it down to parts (DePoy & Gitlin, 2015). As I am investigating founders of small companies, I find the holistic approach to be feasible, as I focus on the individual and tasks associated with the startup, and not the startup itself.

Yin (2014) advocates for the use of multiple case studies to enhance the generalizability of research findings. Unlike single case studies that explore the unique dynamics of a particular case, multiple case studies enable the analysis of patterns across different contexts, facilitating a deeper understanding of complex issues (Yin, 2014). This multiple-case study design aligns with my constructivist assumptions, focusing on individuals and their perceptions, which may reveal persistent patterns or notable differences across various environments.

Dubois and Gadde (2002) highlight the challenges of adopting flexible research strategies, noting that case studies can sometimes lack focus and provide only partial support for theories. A common critique is their potential to be overly broad, failing to provide definitive answers (Dubois & Gadde, 2002). By employing the iterative method of abduction, integrating the structured TAM3 framework, this research aims to maintain focus within the case studies while using potentially divergent results to contribute to the theoretical

framework. Leaning on TAM3 ensures a balance between the rigidity needed to focus the study and the flexibility needed to adapt to emerging data and insights.

5.2.1.1 Data Collection for Case Studies

For the data collection, I utilized semi-structured interviews to balance the flexibility required to delve deeper into participants' perspectives with the need for a structured comparison framework across cases. I aimed for a length of one hour, consistent with Yin's (2014) description of a short case interview. These interviews serve as a tool for collecting information in context, providing insight into phenomena which might be difficult to observe (Easterby-Smith et al., 2015).

5.2.1.2 Selection Criteria for Case interviews

I applied a literal replication logic, meaning I anticipated and looked for similarities between the participants (Yin, 2014). As seen in the Ipsos and IOA reports, GenAI adoption is high among the workforces of Norway and South Africa respectively (Ipsos & Chernykh, 2024; IOA, 2023), hinting that GenAI adoption has some global similarities. To fit the research context, I set these criteria for the candidates:

- Founders are based in Norway and South Africa.
- Their startups must be under three years old, with fewer than ten employees.
- Startup is affiliated with an incubator or accelerator program

Criteria 2 ensures that the startups are small enough that the founders have to perform a broad range of entrepreneurial tasks suitable for GenAI capabilities. Instead of focusing on industry differences, we rely on Chen et al.'s (1998) general entrepreneurial tasks as similarities between the cases, in addition to being affiliated with an incubator or accelerator program, letting them participate in a larger network and subjective norm.

I contacted accelerator programs within the respective countries to compile a list of early-phase startups and their founders. After narrowing down the selection and asking for consent to participate, six founders remained. The participants are listed in table 3, together with GenAI usage inferred from interviews.

Participant	Role	Label	Interview Duration	Country	Industry
1	CEO	Founder 1	55 min	Norway	Educational Software
2	CEO	Founder 2	59 min	Norway	Health Hardware
3	CEO	Founder 3	54 min	Norway	Health Software
4	CEO	Founder 4	1 hour 2 min	South Africa	Mining Software
5	CEO	Founder 5	45 min	South Africa	Educational Software
6	General Manager	Founder 6	46 min	South Africa	Recruitment Software

Table 3: List of informants

The interview setting was chosen with a preference for in-person meetings, with digital meetings when necessary. According to Irani (2019), digital interviews through video chat are practical and might make the subject more relaxed, but they can also limit the breadth of data collected through visual cues when being present in the room, both from the participants body language and from their surroundings. Furthermore, connection issues might disrupt the interview (Irani, 2019).

All the interviews were audio-recorded and stored securely at the Western University of Applied Sciences, with consent obtained before and during the recordings. Consent forms detailing data security were also provided (see Attachment 1).

To keep interviews focused, I created an interview guide, initially leveraging the Resource Based View and Absorptive Capacity frameworks as theoretical lens (see Attachment 2). As I gained more insights I reworked the guide to fit better with ELT and TAM. Before the end of the interviews I ensured that we had touched on the most important themes from the frameworks, and other than that I let the participant control the flow of the interview.

5.2.2 Observation

As an extension of the case studies, I employed participant observation to deepen my understanding of the phenomenon. This method entails actively engaging with the research context, immersing myself in the environment, and participating alongside the subjects (Yin, 2014). I leveraged my first-hand experience in the field by conducting workshops in Norway and South Africa where I encouraged participants to explore the practical use of GenAI in entrepreneurship.

These workshops would provide me with firsthand insights into decision-making processes, collaborative dynamics, and creative GenAI tool utilization under real-time constraints. When combined with interviews, this method let me collect data that the participants might not mention in the interviews.

The workshops were planned in collaboration with two incubators, one in Bergen, Norway and one in South Africa. I promoted the Norwegian workshop by posting to my own network on LinkedIn. There were eight participants, half of them founders fitting into my case study criteria and the rest working with innovation in some way. The South African incubator promoted the South African workshop for me, as I did not have any personal network there. There I got three participants, two of them being technologically adept software developers and founders, and one of them being a professor on innovation.

Both of the workshops followed the same agenda (see Attachment 3). First, I presented the plan for my study and introduced a definition of GenAI tools. Then, I suggested a range of GenAI tools with different capabilities (see Attachment 3) which the participants could use and finally presented them with broad entrepreneurial tasks (see Attachment 3) which they had an hour to solve. The tasks were meant to be traditionally hard or impossible to solve in an hour.

I moved between groups and talked to the participants during the workshop, listening to their discussions and coming up with suggestions of tools to use to help them along the way. I took notes during the group work and filmed when the participants presented their experience and results at the end of the workshops.

5.3 Transcription and Analysis

In this section, I will be presenting how the data was transcribed and analyzed.

5.3.1 Transcription

After the interviews and workshops were recorded, I leveraged the University of Oslo's GenAI-based transcription tool Autotekst. This tool used the OpenAI Whisper V3 model to perform a rough transcription in a secure manner; locally on their servers (Universitetet i Oslo, 2024). Spoken language can be ambiguous, including elements like tone, pauses, and nonverbal cues in addition to words. These elements are crucial to consider for contextual understanding. (Bailey, 2008). These elements were hard for Autotekst to detect. Therefore, I used the auto-generated transcripts mostly as a searchable guide, verifying the relevant parts more rigorously myself by correcting mistakes and adding context from memory, audio or notes.

5.3.2 Coding and Analysis

As a method to structure findings, I used thematic analysis. In thematic analysis coding involves categorizing data segments that are relevant to the research questions, which are then organized into meaningful themes (Braun & Clarke, 2006). This process requires the researcher to be both systematic and creative, ensuring that the codes and themes accurately reflect the data while highlighting underlying patterns and insights (Guest, MacQueen, & Namey, 2012). In line with the abductive method, I iteratively leveraged TAM3 and GenAI capabilities together with intuition and observations to establish themes. I also went back and forth between writing and analyzing whenever I perceived something which could be insightful and relevant to be missing from the findings section.

5.4 Trustworthiness

To ensure trustworthy results, qualitative quality measures are considered and applied. These measures; credibility, dependability and transferability, will be introduced in this section.

5.4.1 Credibility

Credibility, similar to internal validity in positivist research, seeks to ensure that the study measures what it intended to measure (Shenton, 2004). To establish credibility, Shenton (2004) suggests several techniques, including triangulation, ensuring participant honesty, reflective commentary, and thick description of the phenomenon under scrutiny (Shenton, 2004; Yin, 2014).

In my study, I employ triangulation by integrating positivist, constructivist, and social constructivist methods to enhance the reliability of the results. This methodological triangulation helps to cross-verify data from multiple perspectives, reducing bias and providing a comprehensive understanding of the phenomenon. Ensuring participant honesty is another crucial aspect; I achieve this by assuring participants of their anonymity and

explaining the importance of their contributions to the research by ensuring them that all answers and opinions are helpful.

For reflective commentary, I write in a personal tone, striving to address any biases and limitations I encounter. This transparency allows for a more nuanced understanding of the data collection and analysis process, which might affect the findings. Additionally, I have provided theory-based descriptions of the entrepreneurial contexts of the countries studied, the GenAI technology, and the entrepreneurial tasks connecting the cases.

Furthermore, presenting citations from my transcripts alongside the results of my thematic analysis ensures a clear link between theory, data, and findings. This approach allows readers to see the direct connection between the raw data and the interpreted results.

5.4.2 Transferability

Shenton (2004) refers to transferability as the extent to which the findings of qualitative research can be applied to other contexts. He suggests that it is the reader's task to determine if the findings transfer to their context, while it is the writer's task to provide sufficient contextual information to enable this judgment. This approach ensures that the study can be repeated in similar settings. He specifically recommended providing details about number of participants and where they are based, restrictions in who could contribute to the data, number of participants involved in fieldwork, employed collection methods, length of data collection sessions and length of data collection time period (Shenton, 2004). Some of these details can be seen in Table 3.

Yin (2014) supports this view, adding that theoretical frameworks can enhance transferability through analytical generalization. Although case study findings are not intended to represent a larger population directly, they can contribute to theory development and application in similar contexts. By using theoretical frameworks to compare findings from different cases, researchers can develop broader implications and enhance the general understanding of

phenomena. This process involves rigorous case selection and clear articulation of the theoretical propositions guiding the study (Yin, 2014).

By leveraging TAM3, and providing context and the case selection criteria recommended by Shenton (2014), I enable other researchers and founders to leverage and build upon my findings, thus making them transferable in a qualitative manner.

5.4.3 Dependability

Furthermore, Shenton (2014) compares dependability to positivist reliability, meant to ensure that repeating a study under the same conditions yields similar results. He explains how this is problematic for qualitative research due to the changing nature of phenomena. Detailed reporting of the research process allows for repeatability and assessment of proper practices. This includes writing about research design, implementation, how data gathering was carried out, and final evaluation of the process effectiveness (Shenton, 2004). Yin (2014) also emphasizes the importance of transparency through meticulous documentation. This ensures that studies are replicable and methods assessable, reinforcing the dependability of the research findings (Yin, 2014). I ensure dependability by following Shenton's documentation recommendations, in addition to including the interview guide (see attachment 2), workshop agenda (see attachment 3) and participant consent form (see attachment 1).

By adhering to these strategies, I strived to ensure high trustworthiness for this study. I also referred back to these concepts when discussing limitations.

5.5 Ethical Considerations

Ethical considerations are crucial to maintaining the integrity and credibility of research (Resnik, 2011). To uphold proper ethical standards in my study, I ensured that my research

project complied with SIKT and the Western University of Applied Sciences (HVL) guidelines, which advocate for adherence to recognized ethical norms and the law (HVL, 2024; SIKT, 2024). While the data I collected was not sensitive, I made efforts to anonymize it by not mentioning specific companies or people. I did not include personal information. I made sure to store the anonymized data on HVL's encrypted cloud solution, and sent all participants a consent form detailing what their involvement entailed regarding privacy (see attachment 1).

5.6 Reflexivity Statement

In this research, my positionality as a Norwegian citizen without an inherent understanding of South African culture and norms posed potential challenges in interpreting data from a culturally sensitive perspective. Despite spending four months in South Africa to bridge this gap, I acknowledge the possibility of residual bias or misinterpretations stemming from potential cultural differences. This awareness reflects a commitment to cultural reflexivity, acknowledging how my background influences data interpretation (England, 1994).

My academic and professional experiences in Cognitive Sciences, including Machine Learning and software development, in addition to some entrepreneurial experience significantly informed the research design and data collection processes. While this expertise was beneficial for engaging with startup founders, it also introduced potential biases. My familiarity with the startup environment might have led me to project my experiences onto the participants, potentially skewing data interpretation towards my personal business challenges. Additionally, this background raised the risk of posing leading questions during interviews or unconsciously suggesting solutions during workshops.

Being an inexperienced interviewer might have influenced my ability to conduct the interviews properly. Sometimes it was hard to ask the right questions or follow up the right lines of conversations. Leaning on the interview guide helped address this, and I made sure to

transparently involve the interviewees in the process, explaining why I sometimes took breaks to make sure our discussions touched upon relevant themes.

This inexperience was also challenging when analyzing the data. Employing the abductive approach and consulting with my supervisors has been very helpful in addressing this issue. I continuously strove to remain open to data that might not conform to pre-existing theories or my own beliefs.

Emotionally, my optimistic view of generative AI technologies could have influenced my interactions with participants, especially when encountering views that did not align with my technological optimism. My enthusiasm for the potential of technology sometimes led me to want to tell the interviewees about the potential benefits, rather than listening. Such emotions were carefully managed to minimize their impact on data collection and interpretation, reflecting emotional reflexivity in the research process.

By maintaining an ongoing dialogue with these aspects of my reflexivity, I aimed to enhance the trustworthiness of the research findings, ensuring that they are a product of rigorous and ethically conscious scientific inquiry.

5.7 ChatGPT as a Research Asssistant

After consulting with supervisors and Western University of Applied Sciences guidelines (HVL, 2024) I have leveraged ChatGPT as a research assistant and writing aid. Among Generative AI applications, ChatGPT is the most used (van Rossum & FlexOS, 2024). It is able to generate and edit text, and is trained on a corpus sourced from the internet (OpenAI, 2024). This means that among its capabilities is generating scientific text, based on scientific articles.

I am using ChatGPT for creating and modifying text, in addition to suggesting papers that I should read. I am perceiving this as beneficial, as I spend less time on choosing words, rewriting text, looking for sources and attaining a general understanding of a theme.

While ChatGPT provides valuable assistance in handling and summarizing large volumes of information, it is important to note that the model has inherent limitations and potential biases, as highlighted in a study by Salleh (2023). This study discusses errors of commission (where incorrect actions are taken) and errors of omission (where relevant actions are not taken), both of which can impact the accuracy and completeness of the information processed by AI systems like ChatGPT (Salleh, 2023). This means that ChatGPT might generate fake sources or content and omit to mention crucial information. Additionally, contextual biases inherent in the training data of AI can lead to skewed or partial insights (Salleh, 2023).

To address these issues I have taken these precautions when using the tool in these ways:

- Asking for sources: I always ask ChatGPT to refer to sources while writing. As it predicts words from a context it will sometimes not be able to do this (OpenAI, 2024). In these cases, I cross-validate sources myself and rewrite the text accordingly.

- Providing a draft: I draft or make my mind up on what I want to write before prompting ChatGPT, and create detailed descriptions. This helps me spot biases outside of my own and I have experienced more accuracy when verifying results after using this method.

- Verifying results: I verify that the sources and the content generated by ChatGPT are real and coherent by finding and reading the cited articles and sources.

- Modifying: I go through the text and modify it to suit my own thoughts and ideas.

With these techniques, I validate and take responsibility of the generated content, which originates from my own ideas.

6 Findings

The findings are aggregated into three dimensions: Playfulness, Capabilities and Skill. This section will conclude with a conceptualization of this data structure, after a breakdown of the dimensions, relating them back into quotes to increase credibility. During the discussion I will also include some of the quotes which were used to form the themes.

6.1 Playfulness

This dimension is related to Computer Playfulness from TAM3 and is divided into two categories: High Playfulness and Low Playfulness.

6.1.1 High Playfulness

"I immediately tried it to see if it was a good tool for me" - Founder 2

High Playfulness refers to high interest or enjoyment in keeping updated on technology, learning new tools and creatively finding use cases, even when initial results are not perfect.

"So I do follow a lot of people on YouTube that gives weekly updates on new tools that's rolling out. And I'm always thinking, okay, could that be applicable to me?" - Founder 2

These individuals follow the development of new technologies and tools enthusiastically, and are open to trying tools even if they are not initially convinced by others' recommendations.

"I enjoy tech and I enjoy exploring new things. [...]. He came home one day [husband] and someone told him at work about ChatGPT [...] and he told me 'listen, imagine you can write a storybook with just like a prompt'. And I was still thinking this is weird. [...] I remember

starting to play with it to write a story, and I was blown away by the way it could write a story conversationally" - Founder 6

Founder 6 further explored how ChatGPT could debate for and against a claim and proceeded to use it carefully. They found a use for it in their company, even though they do not perceive its un-edited output as sufficient.

"When we use ChatGPT, it's when we write a copy for social media for the most part [...] So it helps, but we need to be so careful with those typical words from ChatGPT" - Founder 6

This pattern can be found across most of the participants who can be characterized as playful with technology. In conclusion, they try it themselves, are impressed, explore use cases and learn how to adopt it in a way which mitigates imperfections. All the participants with high playfulness have integrated GenAI into their workday since discovering it.

6.1.2 Low Playfulness

Interviewer: *"Are you exploring new tools?"* Founder 3: *"No, I can't be bothered"*

Low Playfulness refers to low interest or enjoyment in keeping updated on technology and learning new tools, in contrast to High Playfulness. I only categorized one of the participants as expressing Low Playfulness. This low representation might be due to a bias in the participant selection because participating in a study about GenAI might be more enticing for an individual which is interested in the technological theme. Founder 3 was introduced to ChatGPT by a colleague

"I arrived at work, and [colleague] asked me: aren't you going to use ChatGPT? [...] I input the whole application text and got the finished application text as output. And it was like wow! [...] then I go home [...] And I started looking at it, and I saw this is just bullshit!" - Founder 3

Following the same pattern as the High Playfulness individuals, Founder 3 tried it themselves and was initially impressed. However, they quickly noticed flaws in the output. Founder 3 did not continue to use the technology, other than once in a while.

"So that was the only time I used it. And yes, I also wrote the ending of my pitch, but I had to correct it. [...]" - Founder 3

Just like Founder 6, Founder 3 mitigated the flaws. However, Founder 3 did not integrate the tool into their habits. They did not seem to enjoy the process beyond detecting the first flaws.

"I think it would be the user interface. It is made for people who are interested, I think." - Founder 3

When asked what improvements would have to be made to make the tool useful to them, Founder 3 stated that the tool seems to be made for people with a special interest, implying that they were not especially interested in the technology. It is worth noting that Founder 3 leverages AI technologies in their company's product, and that they are adept at using computers even though they do not especially enjoy using technology.

In conclusion, Playfulness is divided into High Playfulness and Low Playfulness by interest or enjoyment in exploring and using new technological tools. They might discover a tool through similar processes, but Low Playfulness seems to halt adoption when the individual doesn't enjoy the learning process.

6.2 Capability Awareness

Capability Awareness describes the participants awareness of GenAI's capabilities, aggregated from Risk Awareness, Perceived Benefit and Use Cases.

6.2.1 Risk Awareness

Furthermore, Risk Awareness describes the participants perception of a GenAI tools limitations and dangers, which might damage their reputation, breach privacy and propagate bias and their awareness of how the output could be prone to error.

A participant from the Norwegian workshop said this after being tasked with AI-generating a strategy for establishing a company in Norway:

"It creates a good list of points we should be aware of. But you have to be critical of what it writes" - Norwegian Workshop Participant

The participant continued to explain how they had asked ChatGPT to identify business partners. Either it omitted relevant partners, or included irrelevant partners, which lines up with Salleh's (2023) results experimenting with GenAI as a research assistant. The participant worked in a Technology Transfer Office and could easily devalidate the output.

"As much as ChatGPT is really nice because it's helping you to come up with ideas, if she doesn't do a good job to edit it, it actually damages, in my opinion, my reputation. Because then you look lazy" - Founder 6

Founder 6 further supports the importance of validating output, as the raw output might damage the writer's reputation by being obviously AI generated, a sign of laziness.

"The risk of AI being biased is a huge risk. Because when it's biased, what happens then? Well, people believe what they read and what they see" - Founder 2

"...you give this to your employees, you have to understand that there's some agendas behind these LLMs from whatever the organization was that trained it" - Founder 4

However, being perceived as lazy is not the only risk being mentioned in the interviews. Bias is a recurring theme, where participants are afraid of receiving made up or even intentionally constructed misinformation.

"I wouldn't, for instance, ask to summarize my kids biography with their birth details and all of that kind of stuff." - Founder 6

There were privacy concerns as well, with Founder 6 explicitly stating that they would not trust GenAI with sensitive or personal data. The participants seem well aware of the inaccuracy risks discussed in GenAI theory, in addition to specific privacy risks which might have more to do with the implementations of the technologies themselves.

6.2.2 Perceived Benefits

Perceived benefits refers to the positive outcomes the participants experienced or expected from the use of GenAI. As mentioned in the Playfulness section, many participants were impressed with their first hands-on experience with GenAI, indicating that it provides them with quick results. When asked about benefits, participants answered:

"It's a lot quicker than having to go down and look for the problem on Stack Overflow" - Founder 5

"Well, mostly time. I mean, yes, money obviously, but mostly time because it takes me half the time or maybe like a 10th of the time that I would have to spend on image design" - Founder 6

"It's probably enhanced our productivity 10 times at least. Maybe more. It's such a time saver" - Founder 2

"I think it makes you 10% more efficient. Tools make you more efficient. That probably means that we need 10% less employees." - Founder 1

Founder 4 even instructed their employees to use GenAI to save time on tedious tasks:

"I told my engineers, like, look, your skill is in systems engineering and creative problem solving. Like, if you are going to try and be clever by sitting down and trying to work out how to write a shell script for Linux for two hours, I'm going to be angry" - Founder 4

Participants who utilized GenAI frequently expressed significant time and cost savings due to increased productivity for both themselves and their employees. They highlighted the complementary expertise provided by tools like ChatGPT, which acted as a virtual expert across various fields, offering summarized information and strategic advice. Additionally, participants in the South African workshop noted that GenAI helped alleviate writer's block by providing initial drafts of documents, which they could then edit, thus simplifying the writing process from the outset.

6.2.3 Use Cases

To reach these benefits, the participants told me how they applied GenAI to a myriad of use cases. Use Cases refers to categories of tasks that the participants are applying GenAI. I have already mentioned copywriting, summarizing, brainstorming, consulting experts, finding information and solving tedious and uncreative tasks.

"... my ultimate favorite is Midjourney because image generation is just crazy. And all of our social media is Midjourney. We don't take pictures. We don't do photo shoots. We have a prompt system that works" - Founder 6

"I was learning Russian about a year ago and the ability for you to ask it, 'what's the etymology of this word? Why does these two words look the same?' " - Founder 4

Participants also used GenAI for image generation, as a private teacher, to create videos.

A group of participants in the Norwegian workshop generated a realistic video pitch of their concept with an AI-generated person, powerpoint and voice, using only a free tool they found online and a prompt. They also generated a visualization of a decision tree, instructing ChatGPT to generate it as a markup language and pasting the output into a markup interpreter.

6.2.4 Summary of Capability Awareness

To conclude, Capability Awareness addresses founders' understanding of Generative AI's potential and limitations. This awareness encompasses "Risk Awareness," where founders note concerns about AI inaccuracies affecting their reputation and the necessity of critical engagement with AI outputs. Founder 6 also mentioned privacy concerns. Conversely, the "Perceived Benefits" highlight the significant time and effort savings AI tools offer, enhancing productivity. Finally, "Use Cases" detail practical applications of AI. The founders experiences depict GenAI as a versatile tool for entrepreneurial tasks with an emphasis on the importance of human oversight to manage potential risks effectively.

6.3 Skill level

In the context of the data collected for this study, Skill Level is the participants ability to mitigate risks and validate the input through Risk Reduction Techniques. While Skill Level in other contexts could point to an individual's ability to create something, the emphasis here is on controlling the process as GenAI is generating something on behalf of you. A recurring theme was that participants who used GenAI often learned to mitigate flaws in the generation process. I quoted the Norwegian workshop participant on omission and commission in the Risk Awareness section, and how Founder 6 had developed a prompt system to ensure quality images in the Use Case section.

> *“I constantly try and get my prompting to be better because I know version six [of Midjourney] relies on a lot of the information [from the prompt]” – Founder 6*

"... it's still garbage in, garbage out if you don't know what you're doing. It's probably an accelerator. So it either accelerates you down the slope or it accelerates you up the mountain. And it depends on how good the hands are that you have it in." - Founder 4

Interviewer: *"Is there anything to learn on how to use [GenAI tools]?"* Founder 5: *"Yes, prompting. So learn to learn. Yeah, there's a whole giving it a role, giving an example, and then asking what to do."*

While it seems to be easy to get results from day one with GenAI, the participants using GenAI often seem to agree that results improve over time while risk is reduced by learning prompt technique and understanding how GenAI processes information. There was a clear pattern where participants who had experience with prompt techniques mentioned more benefits.

6.4 Subjective Norm

Subjective Norm in these findings refers to how participants expressed influence from other people in the context of GenAI adoption and usefulness.

I previously quoted Founder 6, who shared that they first learned about GenAI from their husband, who demonstrated its capabilities to them. Despite initial skepticism, Founder 6 decided to try it and subsequently began using the technology frequently. Conversely, Founder 2 was uncertain about how they discovered GenAI but mentioned using YouTube to explore and experiment with new tools. Founder 3 was introduced to GenAI by a colleague and tried it out themselves but did not adopt it for frequent use.

"In general, it seems like they're all very positive. Like I see people adopting it all around me" - Founder 6

“When investors tell us, 'you can just use AI for that, it's good,' it's easy to say. Throw AI at the problem, and it'll solve itself. It's just a tool” - Founder 3

There seems to be some pressure on adopting GenAI, both in Norway and in South Africa. But the participants are reacting differently to this pressure. While Founder 6 uses it frequently, with a clear perception of reputational and privacy-related risks, Founder 3 is not particularly interested unless there is a clear use case. As previously quoted, they were not happy with the output from their first session.

In addition to these findings, the way the participants spoke of risks indicate that they might be influenced by others in that area too. The current public discourse on GenAI is polarized, with opinions shifting fast (Gerlich, 2023) This implies that media has a lot of influence. Unfortunately I did not dive deep enough into this topic in my interviews to identify any trustworthy patterns.

Figure 2 summarizes the findings, and Table 4 illustrates how the dimensions relate to quotes.

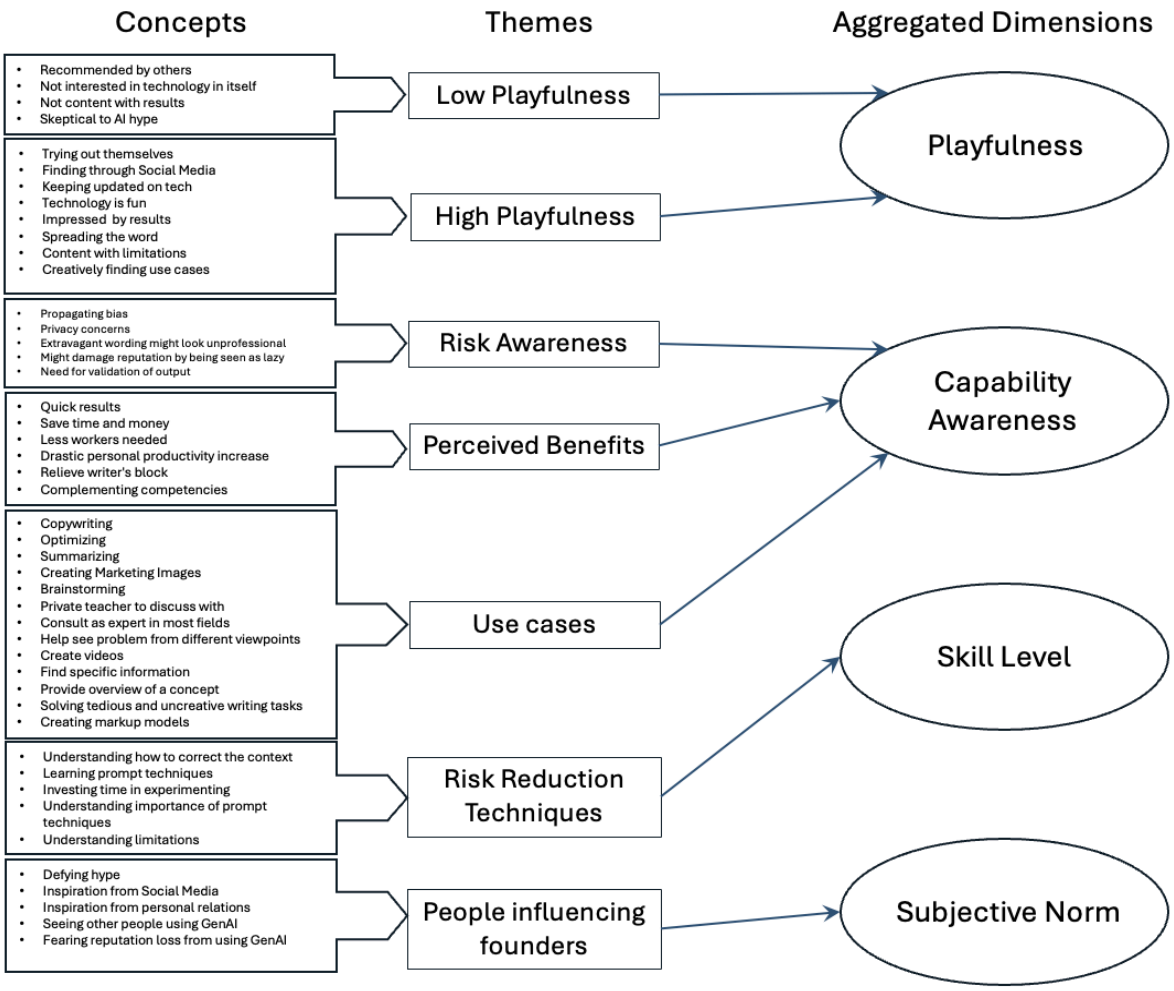

Figure 2: Data structure

Aggregate Dimension	Quotes
Playfulness	Interviewer: *"Are you exploring new tools?* Founder 3: *"No, I can't be bothered"* *"I'm one of those guys who likes playing around with new tools and really testing them out"* - Founder 5 *"I immediately tried it to see if it's a good tool for me"* - Founder 2
Capability Awareness	*"It creates a good list of points we should be aware of. But you have to be critical of what it writes"* – Norwegian Workshop Participant *"You can become very effective if you don't need to learn new languages and syntax"* – Founder 4 *"... my ultimate favorite is Midjourney because image generation is just crazy. And all of our social media is Midjourney. We don't take pictures. We don't do photo shoots. We have a prompt system that works"* - Founder 6
Skill level	*"I constantly try and get my prompting to be better because I know version six [of Midjourney] relies on a lot of the information [from the prompt]"* – Founder 6 *"... it's still garbage in, garbage out if you don't know what you're doing. It's probably an accelerator. So it either accelerates you down the slope or it accelerates you up the mountain. And it depends on how good the hands are that you have it in."* - Founder 4 Interviewer: *"Is there anything to learn on how to use [GenAI tools]?"* Founder 5: "Yes, prompting. So learn to learn. Yeah, there's a whole giving it a role, giving an example, and then asking what to do."

Table 4: Aggregate dimensions and quotes summarized

7 Discussion

The main goal of this study was to find out how founders adopt and leverage GenAI in their entrepreneurial tasks, exploring whether the promises of efficiency boosts hold true for the founders in question. I have defined this search in these research questions:

RQ1: How do startup founders perceive the usefulness of GenAI tools?
RQ2: How are startup founders adopting GenAI?

I leveraged in-depth interviews with founders in Norway and South Africa—six cases in total with a similar prediction logic—in addition to workshops to collect data for this inquiry. With a primarily abductive and qualitative research design, I leveraged TAM3 as a theoretical lens for planning the data collection, conducting interviews and analyzing findings. The data was analyzed using thematic analysis, resulting in the aggregated factors Playfulness, Capability Awareness, and Skill Level. In this section, I will discuss these findings in light of theory and use these insights to answer the research questions.

7.1 Findings Relation to TAM3

In this section I will relate my findings to the TAM3, discussing whether the framework can be used to interpret how the founders adopt and perceive the usefulness of GenAI. If the framework aligns well with my findings, it could be used for quantitative studies generalizing aspects of GenAI adoptions amongst startup founders. Discrepancies would indicate potential knowledge gaps for future research on TAM3 before applying it in a quantitative analysis. I will examine the aggregated factors identified from my findings individually. Results are summarized in Figure 3.

7.1.1 Playfulness

The first factor, Playfulness, was induced from the observations with the Computer Playfulness determinant from TAM3 as inspiration. Venkatesh & Bala (2008) refer to

Playfulness as "cognitive spontaneity in microcomputer interactions", meaning that the user experiments with the software spontaneously, inventively and imaginatively. (Venkatesh & Bala, 2008; Webster & Martocchio, 1992). This can be combined with Perceived Enjoyment to align with well with my own definition of Playfulness: "*high interest or enjoyment in keeping updated on technology, learning new tools and creatively finding use cases, even when initial results are not perfect*". The Playfulness dimension aligns well with TAM3, while indicating that these determinants might sometimes weigh heavier than output quality.

7.1.2 Capability Awareness

To put Capability Awareness in context with TAM3 I will break it down to the themes Computer Anxiety, Result Demonstrability, Job Relevance and Output Quality. I find that these align quite well with TAM3, however, its explanatory power is lacking in some cases, which might be attributed to differences between AI tools and traditional software.

7.1.2.1 Risk Awareness

My exploration of Risk Awareness highlights perceived limitations and potential dangers associated with the use of Generative AI, such as reputational damage, privacy concerns, bias propagation and a need for validating output that might be factually wrong. The founder who had the most apprehensions about using computer systems saw the initial output quality as too bad to continue using the tool. This partially aligns with the Computer Anxiety component in TAM3, which typically addresses users' apprehensions or even fear when faced with possibility of using computers, stating that this can affect ease of use (Venkatesh & Bala, 2008). This assumes that the goal of the use is to get a factually correct output and that this is possible with enough experience of using GenAI. An interesting finding is that even the most experienced founders had apprehensions and anxieties around GenAI usage. Weisz et al. (2023) suggests that, when working with technological systems, users form mental models of how to achieve desired outcomes. While traditional computer systems behave predictably (deterministic), GenAI is less predictable (non-deterministic), implicating the need for new design principles for GenAI systems (Weisz et al., 2023). GenAI output is prone to errors and depends on factors which might be out of the users control (Salleh, 2023). Lack of perceived

control is generally suggested to increase anxiety (Bowers, 1968). This implicates that GenAI applications might induce a new form of computer anxiety, which is triggered in another group of people than the original definitions would be applicable to. This seems to be attributed to lack of control over non-deterministic outputs. This finding could be explored and tested in further research.

While an extended definition of Computer Anxiety might explain the fear of not being able to mitigate risks like bias propagation and factually wrong output, reputational concerns might align more with the Image element. Image refers to how the user perceives that use of an innovation will enhance their status (Venkatesh & Bala, 2008). Founder 6 pointed to ChatGPT's tendency to write superficial text and use extravagant language if left unchecked. They claimed that obvious use of ChatGPT can be perceived as laziness, which might be interpreted as a risk to a person or a company's reputation.

The findings are inconclusive on whether the founder meant that general use of GenAI can be perceived as laziness, or if they meant that low quality output being shared with others without being improved was the root of the problem. While public perception about GenAI usage is generally positive, research communities are often more skeptical (Miyazaki et al., 2024). This implies that founders who keep updated on academia might have a more negative perception of how their own use of GenAI might affect their Image. Another possibility is that the founders fear being held accountable for their AI-generated content, which is prone to errors.

My findings on Risk Awareness can be partially explained by Computer Anxiety in TAM3 and by Image. However, further research is needed to extend the definition of Computer Anxiety to non-deterministic systems like GenAI, as this new phenomenon might cause anxiety in a larger group of users.

7.1.2.2 Perceived Benefits

The Perceived Benefits identified in my findings, such as time savings and enhanced productivity, align closely with both Result Demonstrability and Output Quality. Output Quality, evaluates whether users believe that the system performs their tasks effectively, while Result Demonstrability refers to the tangibility, observability and ability to communicate the results of using the system (Venkatesh & Bala, 2008). Many users had a high regard for GenAI's impact, with some users noting up to a tenfold increase in efficiency. These users were typically playful and experienced with GenAI tools, while everyone was impressed by the first results of GenAI capabilities. The founder who was less playful and experienced with prompting reported low quality output upon closer inspection, and did perceive GenAI to be less useful than the others. The benefits or lack of quality was perceived easily with tangible results like generated research papers or code. This suggests that the Perceived Benefits theme of Capability Awareness might be explained using existing definitions of both Result Demonstrability and Output Quality.

7.1.2.3 Use Cases

Use Cases in my findings illustrate the practical applications of GenAI across various tasks, and could be measured by the Job Relevance component of TAM3. This element evaluates the pertinence of a technology to an individual’s job responsibilities (Venkatesh & Bala, 2008). The diverse applications of GenAI described by the participants of the study—from code generation to language learning—showcase its relevance to different job functions and industries, aligning with theory on GenAI capabilities and Entrepreneurial Tasks.

7.1.2.4 Summary of Capability Awareness through TAM3

While Capability Awareness can be explained through TAM3, the factor needs to be broken down to its individual themes to do so. Risk Awareness can be measured by Computer Anxiety and Image, but the definition of Computer Anxiety would need to be extended to lack of control over non-deterministic systems. Perceived Benefits can be explained through

the Output Quality and Result Demonstrability determinants. Use Cases is relatable to Job Relevance, which aligns with how the founders GenAI usefulness.

7.1.3 Skill Levels

I have defined "Skill Level" as the participants' ability to effectively mitigate risks and validate outputs using risk reduction techniques when interacting with GenAI. This definition emphasizes the control over the generative process, reflecting the proactive engagement required to ensure quality and reliability in AI-generated outputs. While discussing lack of control earlier, my findings make it evident that the founders might be able to gain more control through experience, which also works as a moderator in TAM3 (Venkatesh & Bala, 2008).

There seems to be a strong pattern of time spent using GenAI resulting in increased perceived benefits due to increased understanding of capabilities and how to achieve good outputs. By mitigating risks and understanding limitations, founders learn something about the Objective Usability of the system, defined as “A comparison of systems based on the actual level (rather than perceptions) of effort required to complete specific tasks” (Venkatesh & Bala, 2008, p. 54). This aligns with how Venkatesh & Bala (2008) suggest experiences relationship with objective usability and ease of use in adoption of a technology (Venkatesh & Bala, 2008).

My findings do include founders' perception of their own skill level. Computer Self-Efficacy in TAM3 is related to an individual's belief in their ability to use the technology successfully (Venkatesh & Bala, 2008). The development of effective prompting techniques and a deeper understanding of GenAI's processing mechanics directly contribute to enhancing users’ self-efficacy. As Founder 5 mentioned, learning to utilize GenAI effectively—learning to learn—is crucial. Learning how GenAI applications learn, developing prompt techniques, give the founders more control over their output, in turn making the system easier to use in line with TAM3.

To summarize, skill level is related to experience, objective usability and computer self-efficacy from the TAM3 framework, which might be used to explain usefulness and adoption.

7.1.4 Subjective Norm

Furthermore, my findings indicate that Subjective Norm is relevant to GenAI adoption through the ways in which the founders perceived the influence of others regarding their adoption and use of GenAI. Most of them found out about the technology through recommendations from their personal network or social media, and they were very aware of how GenAI was discussed in public discourse, which propagates a generally positive image of GenAI, though also very polarized and quickly shifting (Miyazaki et al., 2024; Gerlich, 2023). This aligns with the TAM3 framework, where Subjective Norm refers to the degree to which an individual perceives that most people who are important to them think they should or should not use the system (Venkatesh & Bala, 2008). While social media might not have been accounted for in this definition, evidence supports that it should be included in the framework. Jiménez-Castillo & Sánchez-Fernández (2019) studied digital influencer recommendations and found that digital influencers can increase expected value and behavioral intentions of brands they recommend. Expected value and behavioral intentions increasing together align with PU's relationship with behavioral intention in TAM3 (Venkatesh & Bala, 2008). Baskin et al. (2023) found that social media has a strong relationship on subjective norm (Baskin et al., 2023). While this suggests that social media might be separate from the definition of Subjective Norm, it does seem to have a clear influence. I recommend future researchers to review TAM, finding out whether and how social media should be included in the model.

Founder 3 was not positively influenced by the subjective norm being positive about GenAI. They expressed how many people, both in their personal network and outside, were advocating for the use of GenAI, but they found the claims to exaggerate the usefulness of the technology. While they differed from the other founders in terms of computer playfulness and joy, a possible explanation is that their perceived ease of use weighed heavier on how

they perceived usefulness than Subjective Norm. They also expressed low enjoyment of using technology in general. This finding could be attributed to individual differences, but it would be interesting to conduct quantitative and generalizable studies on how the determinants should be weighed regarding GenAI.

7.1.5 Summary of Findings Relation to TAM3

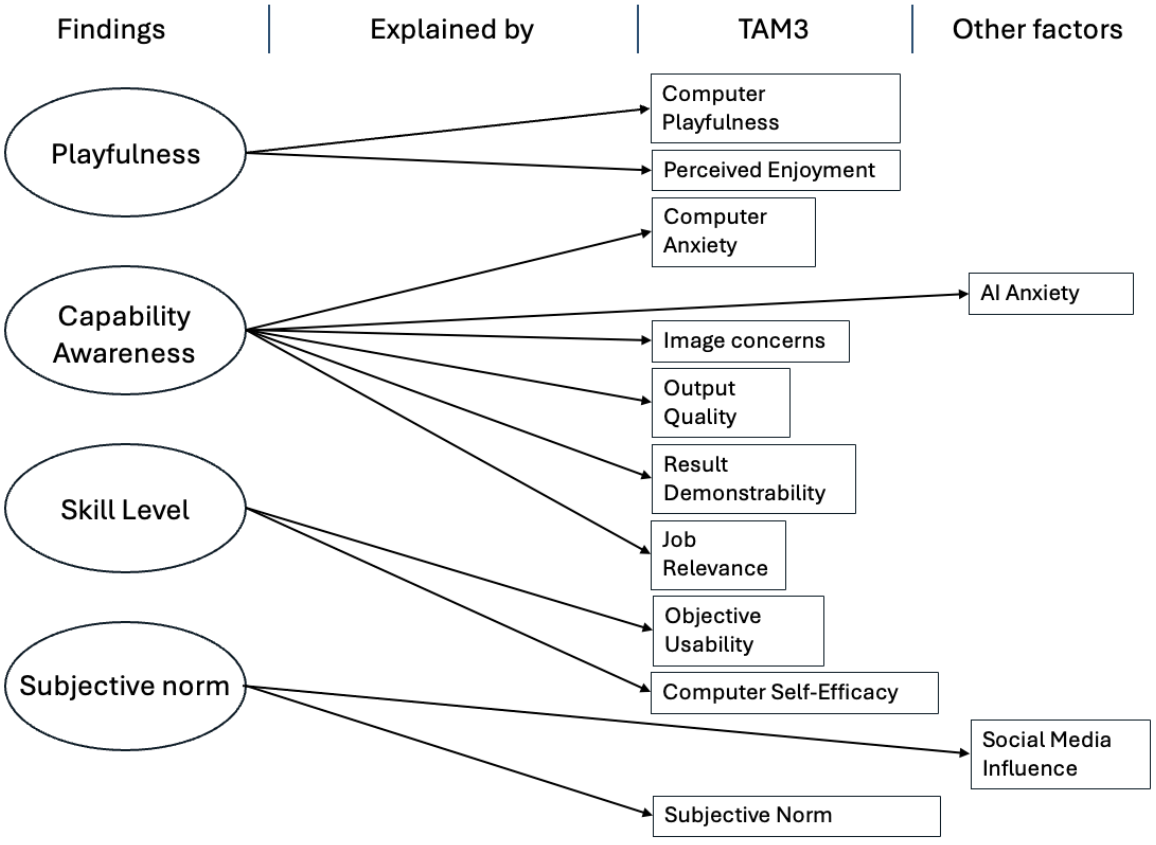

Figure 3: Findings explained by TAM3 and other factors

Most of my findings align well with the TAM3 framework. However, further research is necessary to understand AI's role in Computer Anxiety, particularly in relation to the loss of

control and anxiety experienced during the mainstream adoption of GenAI tools, which are inherently non-deterministic. Additionally, the influence of social media on TAM3, especially its impact on the subjective norm, warrants exploration. Finally, it remains undetermined how to prioritize the determinants in the context of GenAI adoption by founders. Both general patterns, such as Playfulness leading to more perceived benefits from the technology, and individual differences, such as a founder defying the subjective norm, emerged from my interviews and workshops.

While TAM3 provides a robust framework for understanding technology adoption, the unique characteristics and challenges associated with GenAI require further investigation to fully capture its impact on user behavior and acceptance

7.2 RQ1 & RQ2: Findings and their connection to adoption and usefulness

Given that TAM3 aligns with most of my findings, with the extension of AI anxiety and social media pressure, I will apply the terminology from the framework to patterns in my findings to interpret how founders are adopting and perceiving the usefulness of Generative AI.

The main pattern regarding usefulness is that founders first perceived usefulness from recommendations in their personal network or social media, through subjective norm. They were all initially impressed by its result demonstrability in doing tasks that they had typically not seen computer systems do before. Even though expectations of job relevance are not immediately met, founders with high computer self-efficacy, playfulness and enjoyment continue leveraging the technology. Risk-awareness through AI anxiety and Image concerns keeps the technology from being useful in more serious tasks. Over time they achieve more control of the technology through experience, resulting in higher output quality, job relevance and in turn higher perceived usefulness. The founder who did not enjoy the process stopped using GenAI after noticing flaws in the output, not sustaining enough interest to gain enough experience to overcome the risks and perceiving higher control of output.

In short, the answer to RQ1 is that while all the participants could be impressed by GenAI's capabilities from the first time that they tried it, perceived usefulness was much higher after they gained more experience with it. The pattern also explains RQ2, adding that when the founders find GenAI useful, they continue using it.

My findings generally support that TAM3 explains how founders are adopting GenAI. Playfulness, Capability Awareness, Skill Level and Subjective Norms were important factors, which could be mapped to TAM3 to conduct a more generalizable quantitative study. In the context of founders starting their companies in academic circles, my findings indicate no patterns of differences for GenAI adoption between Norway and South Africa.

Through an abductive approach, documenting my findings and relating them to existing theories, I ensure credibility, transferability and dependability. While results are not directly transferable to similar contexts, the study can be recreated and I have identified numerous areas where quantitative studies could be applied to achieve generalizable findings.

7.3 Limitations

While the results point to a strong pattern, there are some limitations to the study.

Firstly, the participant selection process may have impacted the credibility of the findings. Due to limited time and resources, I leveraged my own network to recruit participants for the Norwegian workshops. Consequently, approximately half of the workshop participants were individuals I knew well, which might have influenced their responses and my interpretation of the results. This potential bias was somewhat mitigated by the group setting of the workshops and anonymity in transcriptions.
Furthermore, there is a potential selection bias, as founders who participated in the interviews likely had positive experiences with GenAI adoption. With only one participant not having adopted GenAI, the patterns of non-adoption are less robust. Yin (2014) recommends a

minimum of six cases for multiple case studies, and while this study meets that minimum, a larger sample size could enhance credibility.

Regarding the interviews, my inexperience may have affected the quality of the data. For instance, I did not probe deeply enough into Founder 6's concerns about reputational risks, necessitating reliance on other sources to understand whether these risks were perceived as stemming from the output quality or the automation of work. Additionally, modifications to the interview guide might have impacted dependability, although this risk is reduced by the open interview structure, which led to the participants eventually discussing similar topics. The workshop data could also be more comprehensive, as my analysis primarily focused on the final presentations.

It is important to underline that my findings on usefulness are based on founders' perceptions rather than measurable outcomes. While the perceived usefulness and adoption of GenAI align with established theories, factors such as Image and Subjective Norm may play a significant role in shaping these perceptions. An alternative interpretation could be that founders are unconsciously influenced by the sunk cost fallacy, justifying the time spent learning the technology (Arkes & Blumer, 1985). Future research could either probe deeper into this qualitatively or aim to quantify the usefulness of GenAI tools for entrepreneurial tasks.

7.4 Practical implications

The main practical implications of this study stem from the finding that founders who adopt and gain experience with GenAI, will perceive it as very helpful over time. The general adoption pattern is strong throughout the findings, and is supported by the TAM3 framework. The finding that GenAI is mostly perceived as useful after gaining some experience with it, combined with the identified use cases for entrepreneurial tasks, might serve as an inspiration for founders who want to start new companies with less resources, or effectivize their startup with GenAI. This also applies to other stakeholders who work with entrepreneurial tasks. However, these findings are not generally applicable, and readers will have to decide for themselves whether the findings are transferable to their situations. I have identified

numerous areas for further research which could make the findings more generally applicable.

7.5 Future Research Proposals

In light of the findings from this study, I propose several directions for future research. GenAI as a tool is a rather new and unexplored phenomenon, with high perceived usefulness indicating that it might be an important technology for the future. The implications of this research would be to deepen our understanding of how to use and adopt GenAI constructively, providing stakeholders clearer pathways for developing and adopting GenAI applications, while managing risks. The research proposals are summarized in table 5.

Firstly, TAM's application for GenAI should be assessed quantitatively, further exploring the weight of the determinants identified in the Technology Acceptance Model 3 (TAM3). This can provide valuable insights to stakeholders on enhancing the overall user-friendliness of GenAI technologies.

A multiple case study approach with a prediction logic that contrasts GenAI adopters with non-adopters could nuance and strengthen findings of reluctance and reasoning to not adopt GenAI. This would contrast my study, which included an overweight of participants focusing on the positive aspects, while complementing credibility limitations.

Additionally, the suggestion that computer anxiety is more prevalent in relation to non-deterministic systems like GenAI might warrant closer scrutiny. Future studies should aim to define and quantify this new anxiety dimension, exploring whether it should be included in traditional Computer Anxiety definition, or if it is different enough to be its own determinant.

Lastly, the quantitative impact of GenAI on specific entrepreneurial tasks needs systematic examination. This could involve detailed case studies or time-motion studies to quantitatively

measure more precisely how GenAI tools affect efficiency and productivity in everyday startup operations. This could offer more definitive conclusions on the practical benefits and drawbacks of GenAI in early-phase ventures.

These proposed studies would not only extend the current understanding of GenAI's role in startup environments but also contribute to the broader discourse on technology adoption and resistance in modern business practices. Through such explorations, the field can better support startups in harnessing the full potential of GenAI technologies while mitigating the associated risks and anxieties.

Theme	Research Design
Weighing TAM determinants for GenAI adoption	Quantitative analysis leveraging operationalized TAM determinants.
Adopters vs. non-adopters of GenAI: What separates them	Multiple case predicting different results.
Differences of Computer Anxiety in deterministic vs. non-deterministic systems	Quantitative analysis leveraging the operationalized Computer Anxiety determinant.
Measuring the impact of GenAI in entrepreneurial tasks	Quantitative experiment measuring task efficiency with and without applying GenAI.

Table 5: Summary of research proposals

8 Conclusion

The aim of this thesis is to explore adoption and usefulness of Generative AI (GenAI) applications for startup founders working with entrepreneurial tasks. The results offer insights into founders' perception of using the technology, which can inform other individuals working with entrepreneurial tasks on whether it can be helpful to adopt the technology themselves. It also offers insights on adoption to developers and other stakeholders providing GenAI services, highlighting patterns that might be worth exploring to improve their

products. In addition to this, the exploration results in an array of research proposals on this new phenomenon.

The study was inspired by rich claims of the technologies revolutionary potential in social media. I systematically investigate the perceptions of startup founders in Norway and South Africa regarding the impact of Generative AI (GenAI) on their ventures' efficiency.

I find that founders who adopt and gain experience with GenAI, will perceive it as very helpful over time. GenAI is deemed useful in the study's context, because of its active use and helpfulness in their businesses' core activities. The use cases align with theory on entrepreneurial tasks and GenAI capabilities. Although not generalizable, the triangulation of two different national contexts, data collection through both case studies and observation, and abductive reasoning with TAM3 and other established theory strengthens the findings and conclusions of the study. I also identify areas where TAM3 could be extended.

The Technology Acceptance Model 3 (TAM3) serves as a framework to explain the determinants of GenAI adoption by entrepreneurs. The congruence between TAM3 and the study’s findings underscores the model's efficacy in explaining GenAI adoption factors, with only a few shortcomings resulting from newer phenomena. The explanatory shortcomings identified are Computer Anxiety for non-deterministic systems like AI specifically, and social media's influence on perception of Subjective Norm. Consequently, the research builds on existing literature supporting TAM3 while also proposing additions to it.

Despite its limited scope, this study is important for future research because it illustrates how some founders perceive great benefits from adopting GenAI, which can be partially explained by TAM3. However, the question remains which factors are the most important, and some determinants might need to be adapted. Researching this further can help those building generative AI-enabled services focus on the most crucial factors for startups to adopt generative AI more easily, and thus reap its benefits.

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10 Attachments

10.1 Attachment 1 - Information Letter to Informants

Might I use your contribution in a research project exploring how Generative AI is helping for founders?

Purpose of the project
You are invited to participate in a research project where the main purpose is to explore and describe how startups might leverage Generative AI applications to progress their ventures.

The objective is to explore user-friendliness, adoption, whether the technology enhances knowledge absorption, and whether the technology has the potential to be a central resource granting a competitive advantage.

Your data, collected through questionnaires, workshop participation and interviews, will be used in a 30 ECT master's thesis, which might also be rewritten and published as a P.hd. research paper. Your data might be stored and used for these purposes and will be deleted afterwards.

Which institution is responsible for the research project?
The Western University of Applied Sciences in Bergen, Norway, is responsible for the project (data controller). Affiliates from the UTFORSK program at The University of Pretoria might be granted insight and involved to aid the project.

Why are you being asked to participate?
You are being selected as you either have a central role in a startup in Norway or South Africa, or you're participating in one of the workshops. The total population size of the interviews will be between 6-14, and for the workshops it will be 10-40.

I have received your contact information either from an incubator, through a signup form or you're part of my personal network. If you're not in my personal network I've received approval to contact you, and you're welcome to ask me who specifically referred you to me. This can be done by sending an e-mail to my student mail account: 669285@stud.hvl.no.

What does participation involve for you?
If you choose to take part in the project, this might involve that you

- Fill out a form with general information about your startup, with the purpose of creating a profile and arguing how your startup fits in a homogenous sample of similar startups across countries. It will take approx. 5 minutes.
- Participate in an interview where you answer demographical questions and discuss how you and other people in your startup use Generative AI applications. The interview will be recorded, and takes approximately 1 hour.
- Participate in a workshop where you, me and other participants in the study explore Generative AI in a startup context by trying to solve relevant tasks. The workshop should take up to 3 hours, including a lunch break with networking opportunities and possibly guest speakers to add value for you. You are welcome to send ideas, requests and feedback to 669285@stud.hvl.no. The workshop will be filmed.

Participation is voluntary
Participation in the project is voluntary. If you chose to participate, you can withdraw your consent at

any time without giving a reason. All information about you will then be made anonymous. There will be no negative consequences for you if you chose not to participate or later decide to withdraw.

Your personal privacy – how we will store and use your personal data
We will only use your personal data for the purpose(s) specified here and we will process your personal data in accordance with data protection legislation (the GDPR).

The people who will have access to your data for a limited amount of time is the student writing the thesis, two mentors affiliated with the Western University of Applied Sciences, and supervisors from the Utforsk project at the Western University of Applied Sciences and the University of Pretoria.

To ensure that no unauthorized persons are able to access the personal data, I will replace your name and contact details with a code. List of names and contact details will be encrypted and stored locally on my personal computer. The rest of the data will be stored in my student account's Microsoft OneDrive folders, provided by the Western University of Applied Sciences. Read and write access will only be granted to mentors and supervisors of the project, and will be revoked when access is no longer relevant.

Persons and startups will not be directly recognizable in the publication, but might be inferred given previous knowledge of the startups core activity and participants. Age and occupation might be referenced categorically, e.g. a 21 year old founder might be referenced as "an executive between 18-25 years old participating in a startup company". While no startup names will be mentioned, attributes like amount of employees, country of origin, stage of progress and industry might be mentioned, like "Idea-stage Norwegian tech company with more than 5 employees". Activities performed might also be included, but will be generalized as much as possible. A startup using ChatGPT to create a pitch for investor y from fund X would be referenced as "Startup using ChatGPT to create a pitch for an investor from a fund".

What will happen to your personal data at the end of the research project?
The planned end date of the project is 29.06.24. All data collected from participants, including voice recordings, film and data sets, will be deleted at the end of the project. The transcriptions and thematic analysis might be kept longer to rewrite the master's thesis into a research paper, by one of the mentors from the Western University of Applied Sciences.

Your rights
So long as you can be identified in the collected data, you have the right to:

- access the personal data that is being processed about you
- request that your personal data is deleted
- request that incorrect personal data about you is corrected/rectified
- receive a copy of your personal data (data portability), and
- send a complaint to the Norwegian Data Protection Authority regarding the processing of your personal data

What gives us the right to process your personal data?
We will process your personal data based on your consent.

Based on an agreement with the Western University of Applied Sciences, The Data Protection Services of Sikt – Norwegian Agency for Shared Services in Education and Research has assessed that the processing of personal data in this project meets requirements in data protection legislation.

Where can I find out more?
If you have questions about the project, or want to exercise your rights, contact:

- The Western University of Applied Sciences via the master's student at 669285@stud.hvl.no or supervisor at inger.beate.pettersen@hvl.no.
- Our Data Protection Officer at Trine.Anikken.Larsen@hvl.no

If you have questions about how data protection has been assessed in this project by Sikt, contact:

- email: (personverntjenester@sikt.no) or by telephone: +47 73 98 40 40.

Yours sincerely,

Project Leader (Researcher/supervisor) Student

Consent form

I have received and understood information about the project "*Unlocking the Potential: How Generative AI Can Empower Startups*" and have been given the opportunity to ask questions. I give consent:

- ☐ to participate in a survey about the startup I am part of
- ☐ *to participate in an interview where the audio is recorded*
- ☐ *to participate in a workshop which is filmed*
- ☐ *for information about me to be published in a way that I might be recognised by people already familiar with me and my startups core activities and participants*

I give consent for my personal data to be processed until the end of the project.

(Signed by participant, date)

10.2 Attachment 2 - Interview Guide

Interview guide

1. **Personal Introduction and Startup Overview:**

- Collect missing data points
- Collect age and role
- Could you introduce yourself and describe your role in the startup?
- Briefly describe your startup – its main goals, current stage, and key activities.

I Define GenAI for this context, giving examples like ChatGPT, midjourney or built-in Notion language model.

1. **Individual Use of GenAI Applications:**
    - Do you use GenAI applications in your work?
    - If no: finne ut om det er spesifikke grunner eller bare generelt at det finnes 1000 verktøy og ting er greie som de er
        -

        <u>Questions if no</u>

        - Is there any reason you're not using them?
        - Have you tried any GenAI applications before?
        - Do you know anyone else doing startup using Generative AI? Can you put me in touch with them?
    - If yes:
        - What specific GenAI applications do you use in your work? Can you provide examples?
        - Have you solved tasks with substantial help from GenAI? What tasks?
        - How did you come across these GenAI tools, and what motivated you to start using them?

2. **Practical Applications and Utility:**
    - In what daily tasks or activities do you find GenAI applications most useful?
    - Can you share a recent example where a GenAI tool significantly aided you in your work?
3. **Decision-Making and Adoption Process:**
    - As a founder, what influences your decision to use or not use a GenAI application?
    - How do these tools work with your existing workflows and processes?
4. **Impact on Startup Operations and Efficiency:**
    - How have GenAI applications impacted the efficiency or effectiveness of your work?
    - Are there any areas of your startup's operations where GenAI tools have been particularly helpful?
    - Are there any areas where GenAI applications have not been helpful or disappointing?
5. **Challenges and Limitations in Usage:**
    - Have you encountered any challenges, limitations or risks while using GenAI tools?
    - How do you manage these challenges, and what improvements would you like to see in these applications?
6. **Cultural and Contextual Influences:**
    - If using GenAI applications, how did you start using them?
    - How are people around you using them?
    - How are people around you talking about them?
7. **Future Perspectives and Expectations:**
    - How do you envision the future role of individual GenAI tools in startup environments?

- Do you have any expectations or hopes for the evolution of GenAI applications in supporting startups?
- Do you have concerns about the evolution of GenAI applications in supporting startups?

8. **Eventual**
    - Do you have anything else you'd like to say?

Questions if no

1. **Background and Technology Use:**
    - Can you describe the current technological tools and solutions your startup employs?
    - How do you typically decide whether to adopt new technologies within your startup?
2. **Awareness and Understanding of Generative AI:**
    - What is your current level of understanding regarding Generative AI technologies?
    - Have you explored or considered the use of Generative AI tools? If so, what was your impression?

1. **Perceived Capabilities and Usability:**
    - Are you aware of any capabilities of Generative AI and how they might apply to your startup's needs?
    - What concerns or limitations do you perceive in the usability and user-friendliness of Generative AI tools for non-technical users?

    1. **Knowledge Acquisition and Application:**
        - How does your startup manage the acquisition and application of new knowledge?
        - Do you believe Generative AI could enhance your startup's capacity to identify, assimilate, and utilize valuable information? Why or why not?

Proposition 4: Resource Generation and Competitive Advantage

1. **Strategic Resources and Competitive Edge:**
    - How important is the generation of unique resources and maintaining a competitive edge for your startup?
    - In what ways do you think Generative AI might or might not contribute to creating strategic resources or offering a competitive advantage for startups?

Barriers to Adoption

1. **Adoption Barriers:**
    - What are the main barriers (e.g., cost, complexity, lack of knowledge) that prevent your startup from adopting Generative AI?
    - Do you perceive any ethical, security, or reliability concerns specifically associated with Generative AI that influence your decision not to adopt it?

Future Considerations:

- Under what circumstances would you reconsider the adoption of Generative AI technologies in your startup?
- What kind of support or changes (e.g., policy, market developments, technological advancements) might encourage you to adopt Generative AI in the future?

Agenda

11:00 - 11:20: Introductory presentation
11:20 - 11:50: Problem solving
11:50 - 12:00: Break
12:00 - 12:30: Problem solving
12:30 - 12:55: Groups present solution, observations and feedback
12:55 - 13:00: Wrap-up
13:00 - 14:00: You're welcome to stay for mingling and brainstorming

Create Transform Modify Reconstruct Reduce Predict

GenAI Tool Suggestions

ChatGPT

All types of text information processed by a chatbot
https://chat.openai.com/

Midjourney

Text-to-Images
https://midjourney.com/home

Ramblefix

Speech summarization
https://ramblefix.com/

Elevenlabs

Text-to-speech
https://elevenlabs.io/

Synthesia

Text-to-video
https://www.synthesia.io/

Verktøy & Oppgaver

ChatGPT
All types of text information processed by a chatbot
https://chat.openai.com/

Ramblefix
Speech summarization
https://ramblefix.com/

Midjourney
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https://midjourney.com/home

Synthesia
Text-to-video
https://www.synthesia.io/

Elevenlabs
Text-to-speech
https://elevenlabs.io/

1

Etabler en ny bedrift i Bergen. Identifiser aktører, identifiser et problem, lag strategi, planer, gjør så mye som mulig!

2

Søknadsskriving: Hva fungerer og hva fungerer ikke? Push grenser og vær kritiske, se om dere kan bruke KI til å finne ut hva som er KI-generert

3

Kan KI hjelpe din bedrift med å få fotfeste et annet land? Lag en strategi og så mye materiale som mulig.

4

Lag et nytt produkt! Så omfattende og innovativt som mulig

Verktøy & Oppgaver

ChatGPT
All types of text information processed by a chatbot
https://chat.openai.com/

Ramblefix
Speech summarization
https://ramblefix.com/

Midjourney
Text-to-Images
https://midjourney.com/home

Synthesia
Text-to-video
https://www.synthesia.io/

Elevenlabs
Text-to-speech
https://elevenlabs.io/

2

Create a whitepaper which summarizes Cybaretes technology.

Use AI tools to understand the task, requirements and process snippets of informartion