Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

Åsne Stige

The Introduction of Machine Learning in the Design Process

A Study of Norwegian Design Consultancies

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
Co-supervisor: Cristina Trocin
May 2022

NTNU
Norwegian University of
Science and Technology

Åsne Stige

The Introduction of Machine Learning in the Design Process

A Study of Norwegian Design Consultancies

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
Co-supervisor: Cristina Trocin
May 2022

Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

NTNU
Kunnskap for en bedre verden

Preface

This master thesis was written at the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway, during the Sprint of 2022 as part of the subject TDT4900 Computer Science, Master's Thesis. This work builds on previous work conducted in Fall 2021 for the subject TDT4501 Computer Science, Specialization Project.

Associate Professor supervised the writing of this thesis in Data Science and Information Systems at the Department of Computer Science Patrick Mikalef. The project was conducted within the same department at NTNU.

I want to give special thanks to my supervisor, Patrick Mikalef, for guiding me through writing the specialization project and this thesis. He has been available with advice throughout the entire process. Additionally, I would like to thank Cristina Trocin for providing invaluable help preparing for, holding, and analyzing the interviews and for helping me write this thesis.

Abstract

Traditionally, the design process is performed by human designers with the support of traditional tools. However, the continuous advancements of new technologies are opening opportunities for automating parts of the design process using Machine Learning (ML). This includes simple automation tools for digitizing written text and also more complex solutions, like prototyping tools for guiding designers in creating innovative solutions. However, the introduction of ML in the design process is still in an early stage, and there is limited knowledge about how such technology can be used in the design process. This thesis explores the intersection of design and ML through four in-depth case studies. Gioia methodology guided the analysis of semi-structured interviews of Norwegian organizations operating in the design industry. Valuable insights have been identified about what designers think about introducing ML in the design process. This study developed six propositions, structured according to the TOE framework, and identified relevant enablers and inhibitors for introducing ML in the design process.

Sammendrag

Tradisjonelt blir designprosessen utført av menneskelige designere som får støtte fra tradisjonelle verktøy. Den kontinuerlige utviklingen av nye teknologier fører imidlertid til muligheten for å automatisere deler av designprosessen ved hjelp av maskinlæring (ML). Dette inkluderer enkle automatiseringsverktøy for digitalisering av tekst, og også mer komplekse løsninger, som verktøy for prototyping som kan hjelpe designere med å lage innovative løsninger. Innføringen av ML i designprosessen er imidlertid fortsatt i en tidlig fase, og det er begrenset kunnskap om hvordan slik teknologi kan brukes i designprosessen. Denne oppgaven utforsker skjæringspunktet mellom design og ML gjennom fire dyptgående casestudier. Gioia-metodikk guidet analysen av semistrukturerte intervjuer av norske organisasjoner i designbransjen. Det er identifisert verdifull innsikt om hva designere tenker om å introdusere ML i designprosessen. Studien har også utarbeidet seks proposisjoner, strukturert i henhold til TOE-rammeverket, og identifisert relevante muliggjørere og hemmere for introduksjonen av ML i designprosessen.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
NSD	Norwegian Social Science Data Service
TOE	Technology Organization Environment
UX	User Experience

1 Introduction

This chapter introduces the thesis and presents the structure of the report. First, the problem statement and motivation for the thesis are described. Second, the goal for the thesis and the related research questions are presented. The final section includes an overview of the structure of the thesis.

1.1 Problem Statement and Motivation

Creating user-friendly and innovative design solutions is linked to following an iterative design process focusing on the end-users and having qualities of creativity, problem-solving, sense-making, empathy, and collaboration (Oulasvirta et al., 2020). This is time-consuming and complex when creating tailor-made digital solutions for customers. Through gaining insight, prototyping, and evaluation, the solution designers need time for complex tasks. The complex tasks include translating requirements into functionality that meets user needs (Silva-Rodríguez et al., 2020). Today, designers also spent a lot of time on less challenging and tedious tasks, e.g., transcribing notes from interviews.

Throughout the design process, a variety of tools are used. The tools are analog and digital and help the designers create better solutions while also saving resources. Analog tools like sticky notes and whiteboards help the designers structure thoughts and find patterns. Digital tools like Figma can help designers create realistic and immersive prototypes of the product. The tools constantly evolve and allow designers to work even faster while still making more user-friendly solutions. However, a lot of the tools available lack desired functionality.

Introducing ML tools to the design process has the potential to solve many of the problems designers face by freeing up time, automating tedious tasks, and generating new creative ideas. According to Verganti et al. (2020), even simple ML tools can provide significant results. However, the use of ML for design is still in an early stage. As the technology improves, internal and external pressure to use the new ML tool will likely grow. Today, we have limited knowledge about the introduction and use of ML in the design process. Previous studies show that the use of ML is often driven by data availability and leaner performance, not a user-centered vision (Buschek et al., 2020). Therefore further research into how to systematically integrate ML into the design process is needed (Buschek et al., 2020). To accomplish this, it is important to identify how designers work and what problems they face.

As the introduction of ML tools can result in unwanted consequences, it is essential to choose the correct tools and make sure the time spent introducing the new technology is earned back. Previous research presents the main challenges of ML is related to a lack of trust in ML, technological competence and data (Davenport & Ronanki, 2018; Glikson & Woolley, 2020; Ransbotham et al., 2017). In addition, Koch (2017) suggests creating tools that collaborate with the designers instead of fully automating the process. Researching how designers feel about these new technologies can give valuable insight into what tools should be developed and what enablers and inhibitors designers face regarding ML tools.

Introducing new technology into an organization requires the designers to accept this change. Studying how organizations introduce new technology and how designers react to this can give valuable insight into how ML tools will be received. In addition, what designers think about ML, and their ideas for how it can be used can also identify how and when to use ML tools.

Lastly, as designers start using more ML tools, it is important to study its effect scientifically and identify if the evolving trends add value to the field of design.

1.2 Research Questions

This study aims to answer the following research questions

Research Question 1: What do designers think about introducing ML in the design process?

Research Question 2: What are the enablers and the inhibitors of introducing ML in the design process?

1.3 Overview of Research Methodology

To gain insight into the intersection of design and ML, four in-depth case studies were conducted. Each case study involved interviewing a Norwegian organization operating in the field of digital design. Eisenhardt's (1989) guidelines guided the research setting and data collection. The interviews resulted in rich empirical data describing the phenomenon central to the introduction of ML in design phases (Eisenhardt, 1989). Gioia methodology guided the analysis of semi-structured interviews (Gioia et al., 2013). The process included identifying exciting research questions, the selection of relevant cases, and the collection of relevant data with semi-structured interviews. The interview protocol encompassed questions inspired by the Technology – Organization – Environment Framework (TOE) to identify factors that enable and inhibit the implementation and use of ML in the design process (Tornatzky et al., 1990).

1.4 Thesis Structure

The thesis is divided into chapters, including this chapter the introduce the problem statement and motivation for the thesis, the goal and research questions, and the method used. Chapter 2 introduces related work and defines concepts related to the design process and ML. Chapter 3 presents the research methodology, and the approach followed to collect and analyze the data. The case studies and the corresponding findings from the interviews are presented in Chapter 4. Chapter 5 introduces six propositions based on a cross-case analysis of the findings. In Chapter 6, the findings and the study's limitations are discussed. To conclude, Chapter 7 presents some final concluding thoughts.

2 Theoretical Background

This chapter presents relevant studies that investigated the phenomenon of introducing ML in the design process. First, key notions of the design process, such as design thinking, and its core principles like user-centered design is presented, followed by a presentation of the main design phases and the trend called computationalism. Lastly, a brief historical evolution of the ML field and its implementation in the three design phases is provided.

2.1 The Design Process

Design is the decision-making process of innovation used to create new ideas and solve problems (Verganti et al., 2020). The term *design* is often defined in relation to its processes and principles. The design process unfolds along with different phases and involves the use of analog and digital tools as well as specific methods and collaborations in order to create a final product or service (Verganti et al., 2020). Design principles create the ontology of the design and describe the perspective and philosophy that inform the act of designing, such as design thinking or a user-centered approach (Verganti et al., 2020). Considering this, designers can produce anything ranging from physical objects to digital products, services, or visual identities. However, they aim to create solutions with high standards, which requires being aware of the biases of the people involved in the process, including their own. To meet high standards and minimize biases as much as possible, specific frameworks and design techniques are used (Wallach et al., 2020).

Design thinking is a paradigm for dealing with complex problems that use theories and models from design methodology, psychology, education, and other fields to emulate how designers think, work and drive innovation in organizations (Dorst, 2011). This approaches is particularly useful for thinking strategically and solving crucial problems before the development process starts (Brown & Katz, 2011). This goal resulted in an iterative human-centered approach. It focuses on including end users' needs while utilizing the possibilities offered by new technologies, fulfilling the requirements along with three core activities: inspiration, ideation, and implementation (Brown, 2008). Design thinking helps designers build empathy during the insight phase (Kelley & Kelley, 2013), which plays a pivotal role in design thinking, as Brown and Katz (2011) highlighted

> *"In contrast to our academic colleagues, we are not trying to generate new knowledge, test a theory, or validate a scientific hypothesis. The mission of design thinking is to translate*

> *observations into insights, and insights into the products and services that will improve lives."*

Another approach is the *user-centered design process.* In an effort to help designers build empathy, the steps involved in the *user-centered design process* are closely linked to the activities included in design thinking (Norman, 1986). The process focus on keeping the user at the heart of design, as this facilitates the designers to satisfy users' needs by analyzing the usage context, goals and requirements before starting the design process (Verganti et al., 2020).

The Double Diamond is another popular framework that consists of four actions: discover, define, develop, and deliver, split into two diamonds (Design Council, 2015). The first diamond represents the action of widely exploring the issue and ending up with a clear definition of the problem. The second diamond represents diverging again by generating many ideas to solve the problem and then taking focused actions to create the final solution (Design Council, 2015). This process is also linked to the design thinking approach.

As each project is different, there is not one design process or framework that fits every situation, but the designers can use relevant aspects from different approaches. For example, a common denominator of design thinking, user-centered design process, and the double diamond is their focus on iterations. In this way, the designers are encouraged to go back to previous parts of the design phases to ensure all requirements are met to design innovative results.

Regardless of the approach or framework followed, the *design process* usually consists of three main phases, the insight phase, the prototyping phase, and the evaluation phase (Preece et al., 2015). The *insights phase* can help to balance possible biases and includes understanding and specifying the context of use, the user requirement and other important aspects (Weller, 2019). In-depth knowledge of the domain, the end-user, and potential stakeholders is collected with qualitative methods such as interviews, workshops, observations of end-users' work, and any other archival documentation to create functional requirements. Zhou et al. (2020) affirmed that designers need to

> *"Place particular emphasis on obtaining, specifying, and documenting software requirements, which are based on normative, social, and technical aspects and must be transferred into functional requirements for system development."*

In the *prototyping phase,* the solution is designed in line with users' requirements through iterative processes. The designers create prototypes with different levels of complexity: low-, medium- and high-fidelity. Low fidelity is the most basic prototype with simplistic, cost-efficient mock-ups, usually sketched on paper and do not include much detail (Dave et al., 2021). It follows a creative approach to create key structural aspects (Buschek et al., 2020, p. 2; Sermuga Pandian et al., 2020). Mid-fidelity is the most used type as it is similar to the final product in terms of complexity and detail, without too many aspects like images or full text (Dave et al., 2021). The mid-fidelity prototype is often created digitally, using online tools, and includes a general layout and visual elements (de Souza Baulé et al., 2020). The most complex and detailed is the *high-fidelity* prototype, which is digitally made and typically includes actual images and content that is planned to be included in the solution (Dave et al., 2021). De Souza Baulé et al. (2020) describe this prototype as a "wireframe enhanced by visual design", which allows a better understanding of the design opportunities (Buschek et al., 2020).

The *evaluation phase* assesses whether the solution meets the requirements. This is done through usability testing, summarizing the feedback from the testing, and analyzing what is found (Technical Commitee ISO/TC, 2019). If the solution does not meet the requirements, new iterations of the design process should be initialized.

Traditionally, the three design phases are performed by human designers with the support of simple technologies. However, the continuous advancements of new technologies are opening new opportunities for automating parts of the design phases. Designing a solution requires a level of creativity and a knowledge of what is aesthetically pleasing. Creativity is, according to Sarkar & Chakrabarti (2008), a process where an agent uses its ability to generate ideas, solutions, or products that are novel and valuable. How and why humans possess these abilities is a complex question. The theory of *computationalism* state that the human mind can be understood as a computer (Scheutz, 2002). With the introduction of new tools that aid the design process, the question of what creative and aesthetic capabilities machines have raised. According to Scheutz (2002) computationalism is based on the conviction that

> *"There are program descriptions of mental processes and at least in principle, it is possible for computers, that is, machines of a particular kind, to possess mentality."*

Computationalism has shaped how we think about the mind, but has also evolved the understanding of technologies like AI and their capabilities (Scheutz, 2002). The notion of computationalism suggests the meaning of beauty, and creating beautiful solutions could be legible to algorithms because it is to humans (Kaiser, 2019). Kaiser (2019) explains that cybernetic systems can self-regulate if given the proper feedback at the right time.

2.2 Machine Learning (ML) for the Design Process

The field of *Artificial Intelligence* (AI) technology is complex and constantly evolving. AI is described as the frontier of computational advancements that references human intelligence in addressing complex decision-making problems (Berente et al., 2021). The nature of the changes driven by AI is different from those triggered by traditional information technologies since AI takes over complex reasoning and analysis tasks, which were previously performed mainly by human experts (Tschang & Almirall, 2021). Moreover, AI embodies assumptions that would have been made by human workers (Anthony, 2021). Thus, in the near future designers can produce solutions not only by drawing on distinctive expertise and by communicating with other professionals, but also by combining AI's analytical, predictive and decision support capabilities (Strich et al., 2021). Mikalef and Gupta (2021) defined AI as

> *"The ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals."*

The term AI was introduced in the 1950s with the aim of creating machines with intelligent human behavior, including the ability to sense, reason and think like humans (Benbya et al., 2021). However, in the 1960s, this ambition largely failed, mainly due to a lack of computational power. From the 2000s until today, new digital systems, sensors, and access to more data evolved under the umbrella of AI technology. AI is emerging as one of the top technological priorities of organizations (Mikalef & Gupta, 2021). For example, Gartner reported that the implementation of AI is growing rapidly as it tippled in the last year (*2019 CIO Survey*, 2019; Mikalef & Gupta, 2021).

The field of AI is broad and includes many technologies, where ML is one of the most used. *ML* is composed of a series of computer programs that learn from experience to improve its performance without getting new instructions (Koza et al., 1996). ML is often used to automate tasks that previously required human expertise (Benbya et al., 2021). Unlike traditional technologies, ML can find undetected patterns in the data (Berente et al., 2021) and create new knowledge, which is particularly valuable for making informed decisions (Anthony, 2021). With the automation of manual tasks, humans also have more time to engage in creative activities such as developing stronger ties with their clients and identifying new market segmentation (Trocin et al., 2021). In addition, AI can assist designers in creative activities by enhancing the input information and by providing multiple suggestions (Mikalef & Gupta, 2021). AI also appears to be able to enact popular design principles, being people-centered, abductive, and iterative (Verganti et al., 2020). Introducing ML involves changing how the responsibility is shared between the human users and ML (Martin, 2019). Kaiser (2019) affirmed that ML would automate parts of user experience by mimicking human designers given enough data and good models. However, Buschek et al. (2020) believe that if ML is used to complement designers' work instead of replacing them, they will augment their capabilities and create better solutions.

Previous research has uncovered multiple challenges related to ML, which inhibited its introduction in organizations. For example, the amount of data is increasing, and ML can be trained on data from multiple sources (Winter & Jackson, 2020). However, this leads also to new challenges such as low quality of data collected, and a lack of trust in the ML output (Glikson & Woolley, 2020). Indeed, the lack of trust is one of its main challenges, together with issues of safety, security, and negative consequences (Berente et al., 2021). Next, technological competence is another important inhibitor (Davenport & Ronanki, 2018; Ransbotham et al., 2017). This is strictly linked to the fact that organizations do not know exactly which data is necessary to collect to use ML or do not know how to make sense of the data already in large databases. Moreover, organizations also lack knowledge about the technological infrastructure necessary to store and transport the data (Ransbotham et al., 2017).

ML continues to evolve exponentially, and today it can do far more than automating simple tasks (Verganti et al., 2020). To investigate the phenomenon of ML in the design process, a literature review was conducted before starting the work on this thesis. The literature review found where ML is used in the insight, prototyping and evaluation phase.

In the *insight phase*, ML was used to generate automatic persona profiles (Salminen et al., 2019). ML provided accurate results about potential users' behavior in a few hours so that designers could get periodically updated profiles of potential end-users. Koch (2017) presented using AI to help designers check the requirements using an ML system. For example, the system would suggest ideas, similar projects, or inferred information, and based on the designer's feedback the system would adapt its understanding and present new results to the designer. This process allowed the system to collect important information to perform repetitive tasks and provide a better understanding of the initial requirements. This shows ML can perform redundant tasks such that designers can focus more on sense making and understanding what problems should be addressed (Verganti et al., 2020). Yang (2017) also stated that designers would become experts in knowing what problems ML needs to solve, implying the designers will work as problem setters, while the ML would work as a problem solver. Indeed, the focus on problem-solving can be linked to the challenge of understanding the relationship between tacit knowledge and machine (Berente et al., 2021). As ML can struggle with understanding tacit knowledge, working together with designers can result in more creative and efficient solutions (Koch, 2017).

Most articles included in the literature focused on the *prototyping phase*. According to Verganti et al. (2020), powering weak AI with ML can result in significant results without using too much time and resources when developing new solutions. One such use is creating tools capable of automatically transforming lower fidelity prototypes into higher fidelity, as the prototyping workbench Eve allows for (Suleri et al., 2019). This tool inputs sketches and uses ML to automate the software prototyping. Another use of ML is to suggest improvements to prototypes. An example is the tool DesignScape creating interactive layout suggestions (O'Donovan et al., 2015). This tool has an option for automatically changing and improving the design, which was perceived negatively by designers as they felt they lost too much control from the prototyping. Instead, the designers would prefer to not automate the entire prototyping phase (O'Donovan et al., 2015). Next, ML allows designers to easily create high-fidelity prototypes using automatic code generation. The coded prototypes are more dynamic and interactive then the traditional prototypes. Beltramelli (2018), Chen et al. (2018) and Latipova et al. (2019) suggested to use automatic code generation as a supplement to save time before tweaking and finishing the product themselves. The use of ML to generate code represents the trend of using ML in design to automate tedious and lengthy processes (Dave et al., 2021). In addition, most of the solutions managed to create code that preserved the hierarchical structure of the graphical elements (Beltramelli, 2018). However, many of the solutions could only identify a small number of components and were not trained on large data sets. Suleri (2020) also state that the use of ML to generate code based on sketches does not allow for enough control. In response to this, Nguyen and Csallner (2015) presented a less invasive tool – REMAUI. It identified interface elements with the support of computer vision and character recognition. The tool converted a screenshot into a digital user interface.

The literature review also uncovered tools used to *evaluate final solutions*. Swearngin and Li (2019) showed that ML could be used to evaluate a finished design by creating a solution that score how likely a human user is to perceive a component as tappable. Automating this small task helped the designers cut costs. The designers saw high potential in ML, but at the same time, they needed more functionality. Wallach et al. (2020) presented an extension of a prototyping tool that simulated human behavior and acted like the designers' “best friend”. The designer asked for help in some tasks and got quantitative performance predictions for given scenarios. The tool’s goal was not to replace user testing, as this gives important qualitative data, but to give qualitative insight from quantitative data. For example, Yang et al. (2020) collected user data from mobile applications and used it to measure the user experience (UX). This can help designers realize whether or not the design needs more iterations. One of the notable findings from this research is that even though the solution was able to simulate UX to a certain extent and improved the efficiency of optimal designs, it was not able to improve learning and effectiveness. Therefore, this suggest ML cannot take over the evaluation process, but is suited for assisting designers in evaluating final solutions.

3 Research Methodology

It was conducted four in-depth case studies to try to answer the research questions. This relied on rich empirical data to describe a phenomenon central to generating new insights (Eisenhardt, 1989). Specifically, I focused on idiosyncratic dynamics within each case, such as the interactions between designers and AI technology, i.e., ML, to better understand the new phenomenon. Gioia methodology guided the analysis of semi-structured interviews (Gioia et al., 2013). The process included identifying exciting research questions, choosing relevant cases, and conducting semi-structured interviews. The interview protocol encompassed questions inspired by the Technology – Organization – Environment Framework to identify factors that enable and inhibit the implementation and use of ML in the design process (Tornatzky et al., 1990).

3.1 Research Setting

The selection of cases plays a pivotal role when conducting this type of research. This defines the sample population that will be analyzed and will create the basis of findings related to design and ML (Eisenhardt, 1989). This is not a random choice. On the contrary, I relied on theoretical sampling when selecting the organizations for this project. Specifically, I included extreme cases and polar types to investigate the process of combining ML with design. First, I interviewed key actors from organizations that have not implemented ML into the design process. All the companies were positive about introducing ML tools in the future, even though some were more skeptical than others. In addition, two of the companies had tried to use ML tools as part of the design process but had not included them as a standard part of the process. I collected the interviewees' thoughts, limitations, and challenges in the pre-implementation phase.

The goal was also to include companies that implemented ML in the design process. This turned out to be more challenging than expected, as I could not identify companies advertising that they used ML tools. Multiple design firms designed solutions that included ML but did not use it as part of the design process. However, a few companies were identified, but I was not able to get in contact with them. To still get a better perspective of how ML is introduced in the design process, I collected information from the podcast "Design For AI" by Mark Bailey[1]. The findings extracted from the podcast were used to

[1] http://www.designforai.com/podcast/

triangulate important concepts the designers from the four organizations shared with me.

To narrow down the scope of this project, I have chosen to focus on organizations that operate in the design field and create tailor-made digital solutions. Through choosing these organizations, the goal was to get an insight into the process of creating more complex and unique solutions, as this requires more resources, time, and experience. This means the designers have the prerequisite to experiment with tools that can save resources. Further, Buschek et al. (2020) described that ML's implementation is often driven by data availability and performance. He stressed the importance of not using ML just because it is possible to do so. Therefore, I found it interesting to research how designers identify a need for new tools and how they can include it as part of the design process. Next, I focused on enablers and inhibitors of introducing ML in design.

To research this topic, it was necessary to find organizations with the following characteristics. I only contacted companies that created tailor-made digital software solutions for external customers. These were identified through LinkedIn and companies' Websites. To help minimize the cultural and theoretical differences that could influence the findings, only companies situated in Norway were included. In contrast, the podcast was produced in the United Stated. Moreover, to get a broader perspective, I included companies with different sizes and working in difference market segments. Only companies with a well-established reputation and working for renamed customers were chosen to ensure credible results. To summarize, I used specific selection parameters, such as organizations located in Norway which operate in the field of design, to create digital solutions with a well-established reputation in the field (Table 3.1).

Table 3.1 - Organizations included in this study.

Case	Industry	End Users	Digital Services	EU Size Classification[2]
Company A	Design Agency	Professionals Consumers	Websites for the general public, expert tools, visual Identities	Micro-sized <10
Company B	Design Consultancy	Professionals	Digital Product design, service design, complex systems	Micro-sized <10
Company C	Design Agency	Consumers	Digital products, service design, visual identities, facilitation, and guiding	Micro-sized <10

[2] https://ec.europa.eu/growth/smes/sme-definition_en

Company D	Design Consultancy	Professionals Consumers	Expert tools, complex systems, digital product design	Medium-sized <250

3.2 Data Collection

In line with Eisenhardt's (1989) guidelines, the first step is to define relevant research questions. I conducted a literature review for the course "TDT4501 Computer Science, Specialization Project", where I identified possible research areas. For this work, I elaborated a research agenda for future studies, which created the basis of the research questions for this project. Then, I collected semi-structured interviews as the primary source of data.

Before contacting companies and starting the data collection, I conducted preliminary activities. I applied to the Norwegian Social Science Data Service (NSD) to get approval for conducting this study. Included in the NSD application were a consent form and an information document containing information about the description of the project, such as the purpose of the project, data collection, data storage, and others. The consent form can be found in Appendix A, and the information document in Appendix B.

After having identified companies satisfying specific selection criteria, I contacted experts such as designers, CEOs, creative leaders and developers. It was important to get the experience of designers as they are directly involved in the design process. In addition, leaders, and people in the company responsible for introducing and researching recent technologies were included as they could contribute with relevant insight regarding the process of introducing them. I contacted them by email, where I described the project, as well as what it would mean to participate. After initial contact with the people interested in contributing to this study, I asked them to suggest other experts in the field I could contact, hoping for a snowball approach. The goal of this was to include more than one perspective from each company. The consent form and information document were sent to the participating people. Four companies ended up contributing to the study, interviewing ten people presented with pseudonyms.

The interview protocol was created after the identification of the research questions, which were continuously updated as the project unfolded based on the findings extracted. The questions were inspired by the Technology – Organization – Environment Framework (Tornatzky et al., 1990). Pumplun et al. (2019) state the *TOE framework* can be used to examine different aspects of IT development in organizations. It has already been used to research the adoption of AI in organizations (Pumplun et al., 2019; Schaefer et al., 2021). The TOE framework is suitable for investigating innovation adoption at an organizational level, and "suggests that human, enterprise, and technology resources are critical factors for AI-readiness" (AlSheibani et al., 2018). Therefore, it is a promising choice for structuring the identified enablers and inhibitors of introducing ML in the design process. The framework considers how the technological, organizational, and environmental dimensions influence the process of adopting a new technology such as ML in an organization (Tornatzky et al., 1990).

The interviews started with a brief introduction of the interviewee, the company they work for, and their typical customers. The full interview protocol is available in Appendix C, and the following themes were discussed

- The design process
- Involvement of customer, end users and colleagues
- The use of digital tools and techniques
- The future use of ML

I conducted semi-structured interviews. The interviews lasted from 46 minutes to 1 hour and 44 minutes, and the average time was 1 hour and 4 minutes. Each interview was recorded and automatically transcribed using a tool in Microsoft Teams. To save time in the transcription phase, and because my supervisor and co-supervisor do not speak Norwegian, the interviews were held in English. As the interviews were semi-structured, follow up questions were asked when needed, but an interview guide was followed, referred to as the interview protocol.

The interviews were conducted digitally through Microsoft Teams, and they were recorded with video and sound. All the interviews were conducted by me alone, except for one interview that was held together with my co-supervisor Cristina Trocin. The interviews were automatically transcribed through a built-in tool in Teams to ensure I was present in the interviews. In addition, it helped saving time on the analysis. The interviews resulted in ten word-files containing the transcriptions. In addition to the automatic transcriptions, notes were taken during the interviews to highlight important aspects and write down initial thoughts. Table 3.2 includes a summary of the interview objects and the associated interviews.

In addition, episodes 3, 5, 7, and 8 of the podcast "Design for AI" were listened to while simultaneously reading a transcription of the episodes. The episodes mainly focused on designing tools that include ML technology instead of using ML to aid the process of designing. However, some relevant information was extracted, and these statements were highlighted.

Table 3.2 - Summary of collected interview data.

Organization	Respondent	Position	Experience in the Field	Date and Duration of Interview
Company A	A1	Web developer (Background in design)	10 years	25.02.22 – 50 min
	A2	CEO and project leader (Economy)	6 years	23.02.22 – 1 h 22 min
	A3	Designer (Founder)	14 years	04.03.22 – 52 min
Company B	B1	UX and UI designer	1 year	22.02.22 – 1 h 1 m
	B2	Senior designer (Founder)	10 years	23.02.22 – 1 h 13 m
Company C	C1	UX designer	16 years	24.02.22 – 1 h 2 m
	C2	Digital and UX designer	3 years	24.02.22 – 46 min
Company D	D1	Creative leader of digital base/design	8 years	23.02.22 – 1 h 14 min
	D2	Digital designer	1 year	22.02.22 – 1 h 29 min
	D3	Creative director for digital design	20 years	24.02.22 – 52 min

3.3 Data Analysis

Gioia method (2013) was used for analyzing the data collected with interviews. Data analysis was conducted by uploading the transcribed interviews to NVivo. The automatic transcription of the interviews resulted in a file with short sentences divided by time stamps and who had made the statement. To create codes that were easy to analyze, I removed this metadata to create a coherent text. Important terms were categorized as 1st-order codes, focusing on using informant terms (Gioia et al., 2013). As my first time using NVivo, the first interviews were coded together with co-supervisor Cristina Trocin. The process resulted in approximately 300 1st-order codes. The extracted information from the podcast was also included as 1st order codes. To make it easier to structure the codes, a few high-level categories were created early in the process. These categories focused on structuring the findings according to the TOE framework. In addition, other categories were included, such as

- company information, e.g., the type of organization
- the design process, e.g., which phases were included
- ideas for ML tools

When conducting the interviews and creating 1st order codes, Gioia points out the importance of not being too familiar with the related literature. Not having extensive knowledge of theory makes it less probable not to have prior hypothesis bias or confirmation bias (Gioia et al., 2013).

4 Presentation of The Case Studies

Each case study includes a Norwegian organization working in the design industry. This chapter presents the companies, the services they develop, how they design them, how they collaborate with the end-users, and their ideas and expectations about introducing ML in the design process. All companies follow a design process that illustrates the steps involved in creating innovative solutions, starting with the insight phase, then prototyping, and concluding with the evaluation phase. Each company follows a process inspired by traditional frameworks, design principles, and personal experience. Even though the companies mentioned they usually follow the same general steps for each process, they highlighted how it changes from project to project.

4.1 Company A

Company A operates as a design agency creating tailor-made solutions. It offers multiple digital services to both consumers and other businesses. Consumers refer to ordinary people that do not possess any special domain knowledge and rely on personal experience while using the services (Cambridge Dictionary, n.d.). For this user segment, the company creates mostly visual identities and digital products such as Websites. This can also include the creation of the entire digital presence in the digital world to attract potential clients. For businesses, it creates more complex tools that are used by professionals in their field. The tools can be used internally by the customer or tools that the customer's clients use. Therefore, the complex nature of the solutions requires the designers to gain more domain knowledge.

The company is micro-sized and consists of a CEO, designers, and developers. They stand out as every employee owns a part of the company, which is an incentive to develop the company, do good work, and stay curious and experimental. Respondent A2 pointed out they are lucky because their designers have development knowledge, and the developers have design experience allowing them to collaborate efficiently.

4.1.1 The Design Process

This section explains a general process for creating websites for both consumer groups. The process includes an insight phase and a prototyping phase. The next step is to evaluate the solution before handing it over to the customer or developing it themselves. However, the details of the process are adapted depending on the solution created.

The design process is based on *design thinking* to ensure high-quality results. At the same time, respondent A2 explained the importance of not spending too much time on each step as this is expensive. Therefore, designers pay attention to both the cost and the value while designing a solution.

The *insight phase* is the first part of the process. The designers focus on collecting as much information and input as possible from their customers, the end-users of the solution, and its context. Respondent A1 explained that if the solution is for internal use by experts, the designers need to have an extra focus on jargon and specific terms to satisfy the end-users needs and expectations. The company uses around a month on the insight phase. It consists of multiple workshops, where the goal is to identify the solution's what, how, and why. This phase is challenging as respondent A3 explained that the customers often do not know what they need. The respondent adds,

> *"We start digging at why they need the app, 90% of the time it's that they need to send push notifications. That is a stupid reason to build an app."*

Workshops are particularly useful for identifying core functionalities and creating a data workflow. The last workshop usually focuses on creating a good UX. Whiteboards and sticky notes are used to aid the workshops. Respondent A3 explained the importance of creating a shared mental model with the customer from the first meetings. Another important aspect is the analysis and extraction of meaning from the collected information. This is described as a journey, where the process is as important as the result. Respondent A3 explained,

> *"We can't always document everything. Some key pieces might be missing, but that we just having in the back of our minds. We tried to write down everything that we've learned, but some nuances might be missing."*

Therefore, company A collaborates closely with its customers by organizing meetings at each phase. The designers have experienced the importance of the physical environment where the meetings occur. They have created an informal space with a couch and bean bags. Removing the setting where the designers and the customer sit on opposite sides of a formal table can help remove the opposing roles. Instead, they try to become a team. This helps with creativity and makes it easier to ask questions and create innovative ideas. Weekly or biweekly meetings with the customer throughout the project also assure continuous communication. This allows the designers to match the solution with the customers' expectations even after the insight phase.

The designers use a qualitative approach by conducting interviews and workshops and collecting paper-based or digital information that represents the end-user. Respondent A2 highlighted their need for more data. Therefore, they ask the client to get access to everything available early on. However, it is very seldom that they get anything specific enough to be helpful. The creation of solutions that meet customers' needs requires a lot of guesswork with the client. Respondent A2 thought they did not get access to data because most of their customers are medium-sized companies and lack a culture for data collection. In addition, it is not uncommon that the solutions created by Company A are not the primary mission of their customer but tools to achieve secondary goals.

The *prototyping phase* occurs after the insight phase. The designers use Figma, a collaborative design tool for creating prototypes. However, Figma lacks some desired functionalities. For example, the creation of prototypes that automatically responds to different screen sizes. Because of this, it can be challenging and time-consuming to enter necessary information suitable for the screen of a computer, a mobile phone, and everything in-between.

Company A usually follows its own version of the Google Design Sprint to create a prototype. The designers have customized the process to include more aspects of the design thinking approach. One of the most significant changes was changing the process's length, extending the process from five days to around six weeks. During the design sprint, they conduct multiple new workshops with the customer to find out what the customer wants out of the prototype instead of only focusing on pixels and layout. A common challenge is not jumping to conclusions. Respondent A2 explained that a new client or project could be similar to what they have worked on before and then need to adapt it to the clients' specific needs. It requires awareness to start from the beginning and get to know each customer and each project, ensuring the choices are based on relevant facts for the end-users.

Designers need to create consistent solutions that follow industry standards. Therefore, respondent A3 questioned if web designers need to be creative. The respondents followed industry standards by looking at what others have done before and researching other solutions. Respondent A3 explained that the designer becomes inspired by prior work instead of making a copy of other designs. There is a universally accepted view on what good design is, according to respondent A3, who stated good design is not very subjective, as 20% of good design is the designer's opinion, while 80% is achieved by following industry standards.

Moreover, respondent A3 stated that designers should think like developers when they create a prototype to know both the limitations and the possibilities. This also ensures the designers do not promise something they cannot deliver. In addition, the developers in the company are often involved in the design process. However, respondent A2 emphasized the importance of the developers not focusing on the limitations from the beginning to ensure the process stays creative and not restrictive. This requires developers that have an open mind, even when ideas are suggested that will be challenging to develop.

Sometimes, the company is only involved in developing a solution instead of designing the solution first. They have experienced only being handed over a prototype in Figma. Respondent A1 explained they spent some time before starting the development phase to understand the problem better themselves and talk to the designers to get a complete vision. This underlines the importance of designers and developers working together.

According to respondent A1, during the final product's *evaluation phase*, a few weeks are used to ensure the prototype and developed solution match. This is done by assessing all details created, such as layout, fonts, and colors. At clients' request, the company is also involved in further development improvements, which include redesigning parts of the solution. Respondent A1 explained that redesigning some parts of the solution often involves changing functionality they thought the users wanted that ends up not being used.

4.1.2 Introducing New Technologies and ML in the Design Process

The company recently switched from Adobe XD to Figma as its primary prototyping tool. The switch was an executive board decision made primarily due to the high cost of Adobe licenses, which is presented as an important factor for micro-sized companies. Respondent A3 suggested making this switch multiple years ago but experienced internal resistance. The reason for the resistance was that everyone was familiar with the Adobe tool, and many employees thought it would catch up with Figma, which did not occur. Figma offers similar features as Adobe XD but has the advantage of being more developer friendly, collaborative, less analog, and less old school.

Although ML technology can improve the design process and complement other traditional tools, company A did not embrace this opportunity. It experienced several challenges in the preadoption phase. First, the term Machine Learning is perceived as a buzzword and a "hype" according to respondent A1. In addition, they wish for more information about what ML and ML tools entail. Indeed, the designers highlighted that they do not know enough about the current state of AI and ML in the design industry. This can be due to the lack of design communities to share ideas and tools, making it harder to stay updated. Respondent A1 thought designers keep their cards closer to their chest than developers. However, these concerns have been diminishing in the last years with a positive trend of more new design communities. Secondly, the need to be a part of the majority is another issue highlighted by respondent A1. It refers to ML working well only when writing or speaking English or with specific handwriting. Thus, its implementation might be difficult, e.g., in countries speaking other languages. Third, the lack of consistency and predictability of the outputs elaborated by algorithms concerns the designers during the prototyping phase, especially when ML is used to create components that need to follow specific styles. Therefore, the company prefers to use a component pack made by a well-known designer. Fourth, although several employees think ML has the potential to facilitate and streamline the process, they are concerned with the time necessary to learn to use this new technology. Because of this, the company is skeptical about introducing ML in the design process as it can result in wasting time. This is explained by respondent A1 stating,

> *"I think the reason we don't use it is because right now it feels like a steep learning curve, and it still feels a bit immature, where I think our fear would be wasting time because we're such a small firm. If one or two of us were to sit down and try to figure this stuff out and find new tools, it would take up a lot of time and would reduce our working capacity."*

The need for a challenging work environment is presented as a prerequisite for thriving. ML is particularly useful for automating repetitive and tedious tasks. However, most website builders are not targeted at creating tailor-made solutions, according to respondent A2. Indeed, the company is not interested in tools that automate the entire design process because they feel most websites are too similar and are built in exactly the same way. On one side, creating websites with this type of tool is cost-effective and satisfies the needs and expectations of many companies. On the other side, most of Company A's customers require specialists that design the solution based on specific needs. Linked to this, respondent A3 was also concerned with the trend that ML would substitute designer for the creation of wireframes,

> *"The designer's role could be completely removed from the wireframe generating. So, if you have 10 different designs machine learning created, and user test all 10 you can find this is the best one. Then my role as a designer would simply be, I don't know. My responsibility would be just gone."*

Lastly, respondent A2 explained that their focus is not on the tools themselves but on the joy of creating new solutions that better satisfy their clients' needs. If and when a new technology contributes to this mission, they want to embrace this technology. For example, respondent A3 perceived ML as a way to help designers follow universally accepted design conventions and improve prototype responsiveness. The respondent suggest that tools should provide multiple suggestions allowing the designers to select the best option. This ensures that the designer is in control of the design process. Even though most of the employees are skeptical about the introduction of ML in the design process, respondent A2 hoped ML would become part of the design process in the future because it has the potential to make the process easier and faster. Respondent A3 stated,

> *"I should say we're not in general negative to that kind of technology, as long as it can make the end product better".*

Interesting reflections and ideas about the introduction of ML in the design process along the three design phases emerged during the study. For the *insight phase*, respondent A1 suggested the creation of a tool to save time on tedious parts of the process, such as saving the information on a whiteboard with sticky notes. At the moment, it is taken a picture of the whiteboard multiple times as the board fills up. After taking a photo of the whiteboard, additional work is required, like zooming in on the picture and rewriting the text digitally. In the future, this process could be done by an ML that automatically translate the content into text. For the *prototyping phase*, ML could be beneficial for taking pictures of the hand-drawn sketches and having them converted into wireframes. Another idea presented is to use ML to generate designs based on rules and factors inputted by the designer. In this way, ML would provide multiple wireframes-ideas of the same solution. The goal is to give the designers a direction at the beginning of the prototyping phase. Another example of an ML application is to help the designer create easier responsive solutions for mobile and desktop by providing suggestions for any other desired size, based on which the designer can make desired changes and customization. For the *evaluation phase*, ML could be useful for accessing more complex user patterns in relation to what operating system the user has, e.g., using ML for checking if Android users signed up more or less to a newsletter than iOS or desktop users. When redesigning the solution, this information could result in a better user experience. Moreover, ML can be used for comparing the final version of the developed website to the design prototype to save time and create more targeted solutions. The functionality could include a ghosting image on top of the website and supply suggestions of placement, colors, and other differences.

4.2 Company B

Company B is a micro-sized design consultancy, but it is not a typical consultancy that works from its customers' offices. Instead, most employees sit together in their own office, collaborating with their customers through web meetings or working as semi-in-house designers for technology companies. The company solely focuses on design, creating digital products, and service design. Their end users are primarily businesses, created for the customers' employees or sold to their client's customers. Respondent B2 stated they prefer to work on more complex systems that require a more methodical approach to design.

The company consists of only designers. One of its founders, respondent B2, explained that it was created because they felt there was no other existing design consultancy that worked the way they desired. The process of growing the company was described as an organic learning-by-doing process. In the foreseeable future, they aim to remain a micro-sized company and continue building a design community.

4.2.1 The Design Process

The company follows the iterative framework of the double diamond. The designers divide and explore different ideas before converging by selecting a few concepts. Then the solution diverges and converges again during the prototyping phase. The design process has evolved from a process where they contact the client, deliver a proposal, and follow a design process consisting of insight, concept, and detailing. Today, they work more as an embedded part of the team, with less clearly defined processes, and continue to collaborate with the customer for multiple projects and more extended periods. This also allows them to be involved while improving the solution later. Overall, they go through the following design phases.

During the *insight phase*, employees collect quality user insights through interviews and sometimes workshops. The phase traditionally involves the use of post-its and whiteboards to structure findings during meetings and workshops with customers, designers, and end-users. Sometimes, Miro is also used for presentations, drawing, and as a whiteboard. Respondent B2 mentioned how it could not replace paper and sometimes uses a drawing board directly into Miro to not think about building an idea with the shapes available in the tool. Respondent B1 also used notes on the computer to write down thoughts.

They bring the team together and try to define the problem, involving the clients and end-users as early as possible. In addition to defining the problem, they also identify potential constraints and technical limitations. The aim is to not spend time to create the wrong solution but to translate the problem into something tangible. Despite this, the clients often preferred to wait until the solution was more finished, to include end-users. Respondent B2 explained it is a maturing process to get the client to involve the end-user by specifying,

> *"Usually, you see the effects of involving the end user really quickly once you get there. What you take away from having a workshop or a user test is that you should have done this sooner. It clears up a lot of stuff."*

Next, they proceed with idea generation, which consists of brainstorming and coming up with ideas for several hours. It is a very creative yet complex task when starting on a new project, and they try to get involved in the process as early as possible. The goal is to ensure a continuous dialogue with the customer and the development team to avoid big surprises towards the end of the project. In addition to the double diamond, they also usually follow a user-centered-design process as outlined by respondent B1,

> *"Sometimes the thing that you're making is very specific for one person, or one type of user, and that's the end user for everything. Other products or services are supposed to accommodate different people at different stages, for example. So, I feel you need to be very flexible in the way that you structure your work so that it can fit the situation because it's very different from project to project."*

It can be challenging to get a hold of users. This is especially hard when the product is for experts, or the end-user is another business. In addition, the product is sometimes for a potential user group, not existing customers. In this case, the client takes on the role of the end-user by giving insight into what they want the solution to deliver. However, respondent B2 pointed out the importance of also including multiple other end users, as it is not ideal to base decisions on "a single source of truth". Company B explains that this also can result in guesswork. As the company prefers to develop more complex solutions, the designers explain that this requires a more methodical approach to design with more domain-specific knowledge. The complex nature of the project can lead to designers getting imposter syndrome feeling overwhelmed by the amount of information. In addition, as the solutions are so different, each case introduces new challenges. In order to avoid big consequences from negative results, the designers need to be mindful of the changes introduced in each solution.

Respondent B2 explained that the *prototyping phase* is where they feel most confident and empowered because of their vast expertise. For most prototyping, the company uses the tool Figma. In addition, respondent B2 used Framer to create more high-tech prototypes. The process entails iterating through different levels of detail for the prototypes. According to respondent B1, they usually start with the lowest fidelity paper-based prototypes to remove details. This is because the digital tools tend to result in end-users that get caught up in the details. Respondent B1 preferred starting on paper to signal that the prototype is unfinished, which makes it easier for people to give honest feedback and start from scratch if big changes need to be made. The next step is to create high-fidelity digital prototypes. As many designers spend the majority of their day using digital tools, people have many inbuilt expectations, and the users are familiar with patterns and certain behavior. Therefore, respondent B2 explains that they try to follow these standards when designing and staying updated on standards, which requires resources.

The designers work both alone and collaborate with other designers from the company. Regardless of the number of people working on a project, respondents B1 and B2 explain the importance of sparring with others as a security net. In addition, sparring with someone can uncover if they are off track. Respondent B2 highlighted the importance of the ability to ask for feedback, which requires having someone reliable and trustworthy to ask. The designers use their colleges for feedback but experience the downside of having to use time explaining the solution and its context. The colleges' lack of knowledge about the project can also lower the quality of the feedback. Respondent B1 preferred to work as part of a design team as this allows more communication. In addition, the respondent explained that it could be easier to formulate thoughts when talking to someone. In addition, respondent B1 stressed the importance of also communicating well with the developers and how hard this can be.

After the prototyping phase, company B *evaluate* the solution to check that it meets user requirements. The next step is to deliver it to the client. However, with a close relationship with the customers, many projects never really end as many solutions have the first launch and are redesigned through many iterations. Other times the company hands over the design to the company. In that case, the solution is developed and further tested without company B.

4.2.2 Introducing New Technologies and ML in the Design Process

As tools are an essential part of the design process, it can be challenging to agree on what tools to use. Before using Figma, the designers used Sketch and other tools to design and prototype. The files were stored locally, and it was required to document pixel measurements by hand. Respondent B2 explained that Figma allows easier collaboration with designers, developers, and customers. In addition, it has removed many mundane tasks related to documenting the design for the developers. In recent years, they have seen more low code and no code tools for creating a website. The tools try to bridge the gap between design and web development. However, they experience not being the target end-users of such tools. As they create tailor-made complex solutions, the new solutions lack too much functionality and customizability.

Company B has some experience working on creating products that include ML functionality. Because of this, the designers have a basic understanding of the capabilities of ML products. However, the company has never intentionally used ML tools as part of its design process. According to respondent B2, multiple AI-driven automatic page builders have promised a lot and failed to deliver. Bailey found the same inhibitor. His podcast states that multiple ML tools have not delivered what they promised, e.g., the website designing tool The Grid. Bailey explained that this has influenced how humans react to new tools, increasing a lack of trust in ML. In addition, the need for high-quality data can also be a challenge for getting good results when using a tool. This can be even more challenging as there is less relevant training data for a Norwegian company. The same problem can be seen when designing complex and tailor-made solutions. As the domains are unique for each project, it can be hard to get enough relevant data. Respondent B1 associated the term ML with a buzzword that people brag about, often without misusing it. In addition, the designers are unsure if they would trust the feedback or suggestions given by an ML tool. As ML tools can act unpredictably, respondent B1 found it scary to leave too much responsibility to an ML tool. Another concern is the possibility of losing control during the design phase, which is also linked to the responsibility they feel for the end product. Respondent B1 affirms,

> *"If something is not good, then, in the end, it's my fault. So, if I want to save time by using this Machine Learning thing and then it turns out it wasn't right. It's going to be my fault."*

Despite having multiple concerns, the company is willing to use new ML tools and explore new options. Respondent B1 thought it would be interesting to use ML. However, it is not a topic often discussed among designers. The designers are more likely to try tools when not having to commit to using them, which can be achieved by having easy access to an online version or a free trial period. Respondent B1 mentioned that ML tools should provide suggestions. However, to feel safe while using the tool, it is important to be able to override decisions made by the ML. This also makes the tool more useful and allows for more customizability. Even though it feels scary that ML can act unpredictably, respondent B1 thought this could be a good property of the tool for creating prototypes. This is because it has the potential to add something entirely new to the design and help the designers think outside the box.

The designers shared multiple ideas and thoughts for introducing ML in the design process. For the *insight phase*, ML would be beneficial for analyzing qualitative data collected with the support of giant whiteboards with sticky notes, which needs to be documented and sorted. Creating groups of similar notes and looking for patterns is time-consuming and a complex task. If an ML tool was able to analyze this data and possibly see new correlations, this could improve the results. During the *prototyping phase*, ML would be useful for idea generation and help visualize and explore many different options per solution. A helpful tool would also make suggestions based on universal design conventions. The need for easier creation of dynamic prototypes is something respondent B2 wished for. Creating more responsive prototypes without having to redesign all the different screen sizes would save a lot of resources. This could include an ML tool able to suggest the layout for, e.g., desktop-based on the prototype for the mobile app. Another idea is to use ML to transition between physical and digital design. Making a sketch digital could automate a tedious task. When designing, respondent B1 mentioned it could be easy to create the products with an end-user similar to yourself in mind. A solution to this problem in the *evaluation phase*, is a tool for suggesting improvements to suit a more diverse user group better. Respondent B2 also described the wish to integrate accessibility considerations into a design tool.

4.3 Company C

Company C is a micro-sized design agency composed only of designers. Different from the other companies, it solely creates solutions for consumers. The company focuses on digital product design, service design, and visual identities for both the private and public sectors. They also offer facilitation and guidance to their customers. Respondent C1 explained that solutions for consumers have the most potential for enabling the customer to gain money, thus such customers invest a bigger budget for creating the solutions.

4.3.1 The Design Process

Design thinking guides the creation of digital products for consumers with iterative procedures.

In the *insight phase*, the designers collect as much information as possible from their customers with a qualitative approach and workshops to understand the goal, the domain, and the customers' specific needs. Most of their clients are startups. According to company A, they do not have the skills or time to collect and analyze user data to provide the designers. In addition, respondent C1 explained they do not do this themselves as this is a task outside designers' scope and more appropriate for developers. Instead of using quantitative data, the goal is to involve the client as much as possible in their team, allowing for parallel work and better communication. On the one hand, the customer becomes a sparring partner, which lowers the threshold for showing unfinished work, especially if the customers have experience in that specific domain. On the other hand, the customers lack knowledge about design practice, which requires them to pay more attention to what to show and share. Because of this, the company customizes customer involvement based on their knowledge.

In this phase, analog tools are primarily used, such as whiteboards, sticky notes, pens, and paper. The employees avoid using laptops during customer meetings because it limits the connection between the designers and the customer. Moreover, respondent C1 mentioned preferring to not always use tools like Miro in this phase because it creates sketches that are "*too perfect*", as the creation of a box automatically becomes a "*perfect box*". This makes it hard not to focus on the details. The designers also add notes and transcriptions just are relevant for a limited time before relevant information is extracted. In addition, the notes can be used for consulting later also during other phases. The insight is used to pitch an idea. This idea is based on the information collected from the end-users, the design principles, and best practices.

However, it is not good to spend too much time on the insight phase before they start the *prototyping phase*. Creating something helps them to understand the problem. Therefore, company C usually conducts a Google Design Sprint. This includes a first iteration of the insight, prototyping and evaluation phase. Respondent C1 explain the sprint as follows,

> *"A four- or five-days process, with some work in advance of the process and some afterward. The outcome of that is a digital prototype and a test on users that has been interviewed for 45 minutes. We make a report of this and some suggestions about how to move forward."*

Respondent C1 affirmed that the most important thing is to work with agile approaches and deliver the final solution to the market as fast as possible. This allows for user feedback and real-life testing of the solution. Waiting too long to release the product can result in spending too much money on the wrong functionality. The Google Design Sprint allows them to work fast and collect data to improve the solution. The next step is a new iteration of the prototyping phase. Despite moving fast, it is important to make something that looks professional as it takes less than a second for a user to figure out whether they like what they see or not. An unprofessional design can affect the user experience even though the functionality meets the desired requirements. One of the main challenges for a designer is to solve the specific problem requested by their clients. Respondent C1 explained that designers could easily create a solution that looks good, but good design is much more than good-looking. Consequently, a designer's work is not only about the creation of solutions that works, but they also need to follow best practices and apply appropriate tools to solve specific needs. Respondent C2 stated,

> *"You steal a lot of ideas from others, which is something you should do, because it's the right thing to do."*

Teamwork was the most preferred approach among the designers. However, respondent C2 thought it sometimes was easier to work alone, especially in the beginning, because it allows more time to explore options and be creative. After landing on the idea, it can be good to introduce others to the problem to get new perspectives. In addition, respondent C2 adds the importance of always having colleagues available, which can help get an assurance of being on the right track or getting a fresh set of eyes to look at the solution.

In the prototyping phase, respondents C1 and C2 usually created a high-fidelity prototype after identifying an idea for the solution and creating its initial structure. For creating prototypes, the company uses Figma because it is easier to create interactive prototypes that feel real to the end-user. Respondent C1 added that the tool is better than others for easily involving developers. However, Figma does not suit every situation, for example, when creating sitemaps and flow charts. Respondent C1 explained that company C switched to high fidelity earlier because it works with consumers that are not professionals,

> *"If you are going to make an internal system for experts, you don't need that high fidelity part because you're talking to experts. You could draw this on a napkin. Right? Because they know what they want."*

However, when creating solutions for consumers, respondent C1 has experienced users who lack expertise in the field and good imagination. Therefore, they prefer to show the customers and the end-users something that looks like the final product. It is even better to create functional prototypes that act like the developed version, which helps end-users give better feedback. It also helps them explain what they need and want, making it easier to understand what to improve. Respondent C1 explained that it is worth taking the time to create something detailed.

When *evaluating* the solution, respondent C1 explains it is important to think about how the user test is framed, as this affects the results. It is also crucial to assess what questions are asked or how the information is displayed. The designers also need to know that digital products and web pages' design work never really ends because these solutions can always be improved. Multiple iterations are necessary to develop a solution that meets all user requirements. However, the company is often not involved in the phases due to a combination of budget and the customers' requests for building an in-house department for development and design.

In Norway, the market is small, and the customer's budget is also relatively small, even when creating solutions used by consumers. Thus, the budget allocated for the design process is often related to the potential income of the final product. A smaller budget ironically often requires a senior designer, who can work faster, but is more expensive. However, the solutions with a lower budget are not created with as many iterations as the design process ideally should follow.

4.3.2 Introducing New Technologies and ML in the Design Process

Company C recently started to use a new system for monitoring tasks. Respondent C2 experienced that not everyone used the new tool as instructed. It is mentioned how this is not a big problem because of the company's small size. However, respondent C2 thinks it would cause a problem if more people were involved.

Introducing new technology in the organization is described as a teamwork approach. The employees share when they find new tools. In addition, respondent C2 subscribed to multiple newsletters about design and technology. They claimed to have a low threshold for trying new things. The active search for new technology has led respondent C2 to introduce ML technology into the design process. Multiple simple ML tools were used, such as an abstract blob called blobmaker[3] that creates a figure based on how many edges and how abstract the designer wants the blob to be. This simple tool saves time as well as creates blobs that are different but have a similar design style. In addition, the respondent used the tool khroma[4]. When selecting 50 colors, the tool uses ML to create palettes of color combinations, which provides more inspiration. On one side, this tool can be hard to fit into the design process, as many customers already have a color palette. On the other side, it can be very useful for creating design identities for new customers. Company C elaborated interesting insights about the introduction of ML in different phases as follows.

The company identified some requirements for introducing more ML tools into the design process. Respondent C1 stated they are more likely to stop using a tool that is too rigid, including tools that require following a specific process without the ability to override the output created by the tool. ML should provide suggestions for the next step instead of finished output. The goal for both respondents C1 and C2 was to use tools that could support them to work in a better way. Instead of providing a finished design, they prefer more tools that automate parts of the process. For example, the spelling function on Android and iPhone helps the user finish writing sentences and work together with the user instead of trying to produce something independently. Creating tools that automate parts of the process is also suggested in the podcast by Bailey. He explained the future of AI should be in human-AI hybrids. As both humans and AI systems make shortcuts, the best results are achieved by filling in for each other. In correlation with company C, Bailey suggested that future AI tools should not replace designers but instead collaborate with them. One of the challenges the company experience is a lack of time, and this is the aspect to which ML can mostly contribute. However, If the tool is

[3] https://www.blobmaker.app/
[4] http://khroma.co/

too complicated, it is often not worth the time to learn, especially for tools solving a very specific problem.

In the *insight phase*, ML can be used to automate tasks, but respondent C1 felt that existing tools do not deliver what has been promised. For example, automatic transcription tools use AI to translate speech to text. However, they do not work very well in languages other than English, which is a recurring challenge for a Norwegian design agency. In addition, the respondents experience that several designers feel threatened by ML tools as they do not understand this new ML technology, feel insecure, and are afraid of being substituted and losing their job. Despite some concerns about introducing ML, they are positive towards ML tools and, in general, open to new things. Respondent C2 stated they always want to do better and to improve. Respondent C2 was positive towards ML tools, even when they are "*simple and stupid*" because they are often created by independent teams that introduce diversity into the process.

ML can be used during the *prototyping phase* to save time while generating design ideas, and according to the respondents, it should be trained on best practices. According to respondent C2, designers spend a lot of time searching for best practices. A tool where designers can type in a description of components or flows and get design options together with pros and cons could save resources. Another great feature would be functionality for making designers aware when they change the style of a component so that it does not fit in with the rest of the prototype. Another idea is a tool that allows for the automatic creation of different states for elements, such as a button being disabled or active.

When *evaluating the solution,* respondent C1 stated that sometimes it is easy to forget to check that every detail is properly designed. A tool for assisting the evaluation of the design could solve this problem as ML could help with checking all requirements, including spell checking and layout.

4.4 Company D

Company D is a design consultancy creating digital products. They create solutions for customers that are used by both consumers and businesses. However, Respondent D3 stated that almost all their projects are internal tools used by professionals in businesses. These projects are often highly complex, including many stakeholders and handling large amounts of information and data. The common denominator of their solutions is that they are for screens. This includes mobile phones, the bridge of a ship, or the screen of a heat pump in an industrial setting.

Unlike companies A, B, and C, the company is medium-sized. Despite its larger size, respondent D3 stated the company consists of approximately

95% designers. This means they do not have employees with degrees in product management and sale. Instead, almost everyone is a designer. Even though the organization consists mostly of designers, they do not all have the same background. Respondent D1 has a background in IT and no degree in design. Respondent D2 has an art background as well as a design degree. Based on this, respondent D3 explained that being a designer in the company is a very broad title, including people with different backgrounds. They believe this leads to more curious people, open to learning technical skills.

4.4.1 The Design Process

Even though the design process is adapted to fit the customer, the segment of end-users, and the type of solution, each process has similar features presented in this section. Company D has created a design process based on the double diamond. The designers state they have "*this double diamond sort of way of working*".

The *insight phase* traditionally involves post-its and whiteboards to structure findings while in meetings and workshops with customers, designers, and end-users. Instead, Company D often uses Miro for presentations, drawing, and a whiteboard. When starting the project, the customer is often unsure what the result will be. The goal is often something technical, but how much technology is included in the final solution is something they try to figure out during the project. Sometimes the customer asks for an app, but during the first stage of the double diamond, the designers discover something else is needed. Other than identifying the project's end goal, the insight phase also helps build empathy. Even though the clients already have really good insight, there is no way to transplant the empathy for the project and its end-users from the client into the heads of the designers. According to respondent D1, that is a very important reason to do the insight.

After getting the raw insight, they look for underlying patterns and recurring topics. In addition, they also usually follow the iterative user-centered design process. Respondent D3 explained they develop some products in sprints, while other processes are more up in the air. The company involves the customer throughout the whole process. As respondent D3 explained,

> *"We never have a project brief, and then we do our magic in the backroom and meet up six months later, and it's a ta-da moment. I don't really believe in those kinds of processes in complex projects because the clients, they are the experts of their own domain, and they know the category, their company, and their own users."*

In addition, respondent D1 mentioned that as a consultant, their job is not only to end up with the best product. They also need to entertain the client and develop a good relationship. This also encourages close collaboration with the client. Respondent D1 explained the importance of working with a design-mature customer,

> "Low maturity, I would say, is when a client comes to design agency and says, "this is the spec we have for the application we want to be made. Can you make it look pretty?". That's, in my opinion, not a very good use of design resources. Of course, we do that as well and try to make things pretty. But we are trained in making things usable, trained in connecting needs to functionality."

Respondent D3 also mentioned that the end-users are significant throughout the whole process. The end-users are, according to respondent D3, included because,

> *"We are making products and services for our clients, but in fact, we are making it for the end users, because if they don't see any value in it, then it has no value for the client either, so they are kind of the most crucial part of the projects."*

Despite this, it can sometimes be hard to get a hold of end-users because the product is new. Other times the end-users do not know they need the solution before it is done. In those projects, the choices are partially based on assumptions. Respondent D3 stated their biggest challenge is to understand and simplify the needs of the end-user.

When collecting data about end-users working for a business, meeting at their location is very important, according to respondent D1. This reveals crucial facts about how the users work and what solution is needed. The respondent explained this importance through a scenario from the fish farming industry. The project's goal was to digitize a process that was previously done using a walkie-talkie, pen, and paper. The customer's initial wish was to create an app to use instead. When visiting the facility, they uncovered that the employees had to keep one hand on the rail to not risk falling in the water. In addition, the cold weather conditions often required the employees to use gloves. These made it hard to use an app. Having just talked to the customer could have resulted in not uncovering these constraints, resulting in a useless solution.

In addition to visiting the facility, the designers would conduct interviews with employees with different roles in the organization. This includes everyone from facility managers, to the people tasked with feeding the fish. Through this process, data is collected about the domain. In an effort to understand the users, a qualitative approach is followed. Based on the findings, recurring topics are discovered. In addition, constraints and opportunities are agreed upon with the customer. When creating solutions for experts it can be an added challenge to understand the scope. Because of the complexity, respondent D3 explained that a lot of the projects last for a very long time. In addition, multiple teams of designers and many stakeholders are involved. These projects require a lot of resources to learn about the domain. Often, the clients themselves do not have a clear picture of what the end product is going to be. A reason for the complexity in a lot of the projects, is the amount of data available. Respondent D3 explained there is a huge change in the amount of available data. The company experience the customers not knowing how to create value using the data. In those situations, company D tried to help their customers analyzing the data as part of the insight phase. In large industries like renewable energy, oil and ocean, the technical infrastructure is skyrocketing. This results in more data gathered from physical sensors and digital solutions.

The *prototyping phase* includes creating the overall layout and structure of the solution. This is often done by creating a very low fidelity prototype. By using just paper and a marker, the overall concepts are agreed upon. This process allows for easy and fast feedback from the customer and end-users without focusing on design choices. The designers do not spend much time creating low-level prototypes. As soon as details are added to the low-level prototype respondent D3 experience the users focus mainly on the details. Related to this, respondent D1 often felt the time used on a paper prototype was not worth the effort. Instead, they started to create high-fidelity prototypes early. For them, data was important when prototyping, as it could be used to feed the prototypes or create developed prototypes that are more interactive. Respondent D3 explained that they are not able to extract all the information from the data but are using it more and more. Three years ago, they were not creating these types of prototypes, but it is becoming more common.

Even though there is a risk of developing high-fidelity prototypes early, respondents D1, D2, and D3 preferred this approach. In addition to using Figma, the company often uses programming to develop prototypes because this allows them to store values and create an interactive prototype. However, they mentioned that the majority of the designers in the company use more traditional methods and tools. Despite this, the respondents felt this worked better than Figma. The respondents said Figma felt more like a presentation tool than a prototyping tool. It also takes time to add complexity and connect frames in Figma.

Respondent D2 added that high-fidelity prototypes could improve the value of evaluating the solution when working with consumers with special needs. Especially children that lack the ability to imagine concepts. However, it was a problem that instead of focusing on the navigation and layout, small details felt important. Respondent D1 explained this is related to a lack of domain knowledge,

> *"Sometimes, there's a gap between what the designer knows and what the domain expert knows. That can really distract them when doing the testing. So, it's important to keep track of those."*

Even though details are important, designers sometimes get stuck fixing details. Respondent D1 mentioned a lot of designs use too much time making the prototype look perfect, even going back to parts that are developed to update them in Figma. Having others can help to ensure the correct progress. When prototyping, respondent D2 explained there is a big difference between working alone and in a team of designers. Working alone is more complicated, as it is easy to question if the ideas are the correct ones. This results in using a lot of time finding inspiration from other designers online. Therefore, it is important to collaborate and help each person improve.

In company D, developers are not introduced after the prototype is finished but are involved in the creative design process. This allows the designers to learn and expand their knowledge of available opportunities and ensures the prototypes are within the limits of what is possible. Before, it was more usual to deliver sketches in Figma, and the customer would get an IT consultancy to develop the solution based on the sketches. Respondent D1 reiterated that doing it like this indicates the customer is not designs-mature. However, respondent D1 pointed out that not everyone is open to the technical aspect of design,

> *"I love technology and I know that's some other of my colleagues do as well, but I know that there are also people who are very skeptical to the thought that designers should know code, HTML and CSS. It becomes too high a threshold to get into. I think just by being code, it's a bit scary."*

Related to this, it is pointed out that the company does not have a goal of being an expert within technology. The developed high-fidelity prototypes are very simple as the designers only have a basic understanding of programming. They also mentioned that code is not used when developers create the final solution later. The goal is not to create good code but to create a responsive prototype. Instead, they should be able to ask the right questions to the client. As respondent D3 affirmed,

> *"I don't think there is any project where we don't have a discussion regarding what technology can do to make a better product or service."*

4.4.2 Introducing New Technologies and ML in the Design Process

Respondent D2 claimed to be "*one of those people that tend to push technology as part of the design process*". In addition, multiple respondents describe the employees as very curious and willing to sacrifice some productivity to learn something new. However, respondent D1 pointed out how busy people are, working on multiple projects and having a lot to do, which increases the threshold for making time to learn new tools.

The company stated it is important to improve constantly, especially for companies that sell their competence. Respondent D3 pointed out that nobody can know everything, but most people are good at something. This requires the organization to find smart ways to share this knowledge. To ensure the designers stay updated on the newest technology, they only work 80% of their time on projects for customers. The remaining time is spent on improving and learning new things. In addition, the company arranges workshops and talks multiple times a month to ensure people are up to date on what happens in the design field. Respondent D3 also mentioned how taking time to talk to people, and remind them of the available resources and tools, has shown to help the designers keep exploring. However, they have experienced how easy it is for people to feel they do not understand if what is presented becomes too technical. Therefore, they focus on just talking about what can be achieved by using the technology. Respondent D3 was clear about how important new technology is for the company,

> *"I think that design companies who don't embrace technology will die because they won't be relevant in the future. You can't base design on only creative minds and thoughts. We need to understand the opportunities and possibilities within technology. And also, loads of the things we're making for our clients is driven by technology, so I think tech is probably more important now than ever."*

Despite the focus on improvement, respondent D2 felt it could be difficult for other designers to embrace new tools because they are not used to them. When Figma was introduced, there was a lot of skepticism in the industry. Now it is the standard tool for designing prototypes. This shows that it sometimes takes time for people to get used to new things. In addition, working as consultants for customers adds limitations to each project. Respondent D3 explained that the technical maturity of the customer is important. Some projects use outdated technology, while others are highly technological, e.g., using sensors and smart endpoints to collect data. The respondent thought it was their role to educate their customers,

> *"The clients need to get more mature about how these processes work, and I think that is also a huge, important role for designers as well, to make the clients understand why we need to do as we do and why it will create value in the long term."*

As the company uses a lot of resources to introduce new tech, it is not surprising that respondents D1, D2, and D3 tried to use ML during the design phases. Respondent D3 mentioned having tried to use different tools but not having found tools worth introducing as part of every process. The tools used include an ML tool they created that was trained on their design library of icons. The tool generated new icons, but they were not useable for real solutions, despite being a fun and interesting experience. In addition, they used a tool for creating synthetic human faces. This was also an experiment with the new technology. Respondent D1 has used a mobile application for digitizing sticky notes and other text. The tool translated the handwritten text into digital text that could be imported into Miro. This was described as a tool that helps the designers to summarize the workshops. Trying transcription tools has not been as helpful, according to respondent D1, as the results could not be trusted. In addition, before joining the company, respondent D2 created a small tool for brainstorming as an icebreaking exercise when creating physical products. The ML was trained on different physical objects and created new abstract objects with a corresponding text description. The tool's goal was "*to kind of move people's ideas. Try to get people to start talking and open a conversation*".

Respondent D1 questioned whether there is a need for all ML tools today. When the designer has gained insight into the end-users and developed a good understanding of what should be created, introducing another tool can feel like an unnecessary step. It feels easier to transform the knowledge into the design because it is complicated to bring ML into the project in a reliable way. When introducing ML, there is a need to translate the designer's knowledge into something that ML can understand. According to respondent D1, a lot of the information collected was based on a gut feeling. An example could be knowing the solution should be used from a distance in low lighting. This signals to the designer a need for a minimum contrast and a big font size. Because of this, it can also be a challenge to document every requirement. Another challenge related to ML is the trust in its output. Respondent D3 believed it is normal for humans to think of themselves as the only ones with the ability to solve intricate problems,

> *"We humans have always been skeptical, and it takes time before we give it our trust, but we will get there."*

Respondent D3 mentioned how ML, in many ways, still is a buzzword. In addition, the ML tools do not deliver what they promised. According to respondent this is related to the theory of the Gartner Hype Cycle. This show that people start with enthusiasm for new technology, but then they get disappointed when the technology does not deliver what it promised. Respondent D3 thought companies today are in the phase of collecting data, which will result in an environment for ML tools in the future. Access to quality data allows for ML technology to mature. When the technology slowly matures, it will eventually start to deliver what was promised. When the tools that revolutionize the design process are developed, respondent D1 is sure ML will be used.

The uncertainty towards ML is also related to many ML tools being treated as a black box. Not knowing what part of the data the ML is trained on creates uncertainty. It also makes it harder to trust the output, according to respondent D3. The black box approach also makes it hard to dig into what is happening within the algorithms, according to respondent D2. This adds to the uncertainty of what the ML delivers as the output. According to respondent D2, introducing an aspect of randomness into the equation feels like a risk. The output is also closely related to the quality of training data. Respondent D1 explained that they, as designers, lack the knowledge of data quality and ML to build and train models themselves. They require the use of tools to use ML. Another challenge related to data quality is the risk of developing a tool that inherits the biases from humans, as respondent D2 explained,

> *"Machine Learning is often trained on biased data. What the database is based on is very important to what the outcome is going to be, and that's very problematic when it comes to a lot of social issues."*

All ML tools tried by the company are relatively simple. They automate one task, not the entire process. Respondent D3 explained that they often feel technology is an important part of the process. Despite this, the technology is really simple, e.g., using a tool to reduce the number of input fields for the user. The respondent explained that simple tools could feel like magic and contribute a lot. In addition, one of the main qualities of future ML tools is access to understandable quantitative data. As respondent D2 stated,

> *"You could start to have qualitative level information on a quantitative scale."*

Using properly trained ML tools could make it possible to analyze large amounts of data. According to respondent D3, this can create valuable predictions and assumptions that would take a human brain so much more time to do. The respondents had a clear idea of what a good ML tool should deliver. According to respondent D1, the tools should be transparent about how ML is used. This makes it easier to know how to utilize the tool. With little transparency, the user can feel they need to outsmart the tool as the ML does not solve the problem the designer wants to. Respondent D1 also states that prototyping tools should create output in a format that can be imported into multiple tools. Having the output created as an SVG gives the designers more freedom and adds flexibility. Respondent D3 believed ML could help get the design process started or generate new ideas. Working as an inspiration for the designers could result in better and new types of solutions.

For the *insight phase*, respondent D1 desired a tool to support data analysis of information collected prior to their involvement. An idea is for the tool to act as an assistant, contributing with domain knowledge. As respondent D1 stated, gaining empathy is an important reason for the insight phase, and they still want to stay involved. The same point was raised by Bailey, who stated in the podcast that ML has problems with humanness and empathy, which is an important attribute of designers. ML tools also inherit human biases as the applications are built by people and use data from people's actions, implying some tasks in the insight phase should be done by designers. Another idea is for the tool to summarize textual information to help the designers understand the domain. This could also include help to research other related information about the customer and the solution. To help designers analyze interviews, a tool for cross-referencing information from the interviews is suggested by respondent D1.

In the *prototyping* phase, a tool for matching new components with what is already designed would be helpful, according to respondent D1. Another idea is a tool for improving the navigation in the solution. According to respondent D3, this could include automatic suggestions for new placements and styles for the navigation components. The different options for navigation could be presented to the designer, such as suggesting switching from a hamburger menu to a menu bar.

In the *evaluation* phase, designers need help with the identification and adherence of standards for accessibility, which are changing continually, and this makes the interpretation of colors slightly different. It would be helpful to be notified by an ML when the solution is no longer considered accessible. It would be even more helpful with a suggestion on what and how to make the change. After delivering the finished design to the customer, it can be challenging for the designers to experience the solution not matching the finished design. Respondent D1 explained the customer sometimes does not understand that it is important to negotiate developers' and designers' standards and requirements. However, the company sometimes experiences the developers protesting against parts of the design. Often, developers create their own interpretation of the design and overlook details in the design prototypes. To make this process easier, respondent D1 suggested a tool for matching the design, e.g., a Figma file, with the implemented version. ML could analyze the two solutions, identify their components, and suggest what should be changed to match all requirements.

5 Propositions

Based on the four case studies, six propositions were identified and are presented in this chapter. The codes related to the propositions are presented as a table in each section. The tables present what the company stated in the format (A, B, C, D). The tables are structured according to the TOE framework, dividing the codes into either the technological-, organizational- or environmental-dimension. The technological dimension describes the technologies relevant to an organization, including both those used and those introduced through external forces that have the potential to open new possibilities. The organizational dimension includes characteristics and recourses, e.g., size of the firm, structure, how decisions are made, and communication, that can influence the adoption process (AlSheibani et al., 2018). The environmental dimension describes influences from external environments like pressure and competition from stakeholders, end-users, or competitors (Schaefer et al., 2021).

Proposition 1 Current ML Tools do Not Meet Users' Needs

Even though ML has the possibility of automating repetitive tasks, the designers included in this study feel the existing ML tools do not meet their needs. The employees from company A stated that they do not know any helpful ML tools available. In addition, the companies list limitations of ML. As Norwegian design firms, companies A, B and C present the challenge of most tools they know of being trained on English data. This is primarily a challenge in the insight phase, where the existing documentation, notes, and data from interviews and workshops are not in English. Languages and other geographical issues can be seen as an inhibitor to introducing ML as part of the design process. Companies A, B, and D all present ML's unpredictable output as a challenge, mainly linked to prototyping tools. However, it is also suggested that this unpredictable output can be positive if used for other parts of the process. For generating ideas, something outside the box can result in new and interesting solutions. Another challenge with existing tools is how many website builders are designed to automate the process without allowing for much customization. This is perfect for many users, but companies A and B agree it is not made for design firms creating complex and tailor-made systems. However, as technology evolves, company D believes more useful tools will be created. Table 5.1 present the enablers and inhibitors of ML tools not meeting user needs.

Table 5.1 - Enablers (+) and inhibitors (-) of ML tools not meeting user needs.

1st Order Code	TOE Framework
- Most ML tools are not trained on Norwegian data (A, B, C)	Technology
- Most writing ML-tools only work well with specific handwriting (A)	
- ML can inherit out biases (D)	
- Existing ML tools lack design functionality (A, D)	
- ML does not provide consistent output (A, B, D)	
+ The unpredictability of ML can produce unique results (B)	
+ ML can automate repetitive tasks (A)	
+ Believe more valuable tools will be created in the future (D)	Organization
- Complex tailor-made systems are not the target use of ML tools (A, B)	Environment

Proposition 2 Technological Knowledge Help Designers Embrace New Tools

All companies state that technology is a more significant part of the design process today than earlier. However, it varies how much focus the companies have on staying updated on the latest trends. Companies C and D had an extra focus on learning new technology. Company D states that technological advancement is crucial to staying relevant in the business. The focus on knowledge resulted in more time to research and learn new tools. In this regard, companies C and D stand out, stating it is a team effort to improve and learn new things.

On the other hand, company A has too few employees to use the time to explore new technology. Because of this, they want to learn more about ML and technology. Company B also lacks knowledge of ML and states they have not talked to other designers discussing the topic. The lack of a design community presented by company A makes it more challenging to stay updated on new technology, as opposed to company C learning from other designers through newsletters and conferences. The different focus on new technology and tools can indicate a link between technological competence and having a lower threshold for trying ML tools. The technological focus can be a driver for companies C and D, having used ML tools and having a low threshold for trying new technology. This makes a focus on technology, and actively working towards embracing new knowledge, an enabler for trying ML tools. However, it is still stated by company D many designers are skeptical of the technology. The designers also mention that it is important to not focus on the technological aspects of a tool when introducing it to designers. They have experienced that this helps people not give up. In addition, it is important to constantly remind the designers of what tools are available to make the tools less unknown.

As company D has a medium size, this could be one of the reasons that allow them to try new things, despite employees acting skeptical. On the opposite side, micro-sized companies A and C had more significant problems introducing new tools because of internal resistance. In addition, working as a design consultant, the technical competence of their customers is closely related to how the designers create solutions. The customers add limitations to the process, setting the budget and designing when the designers are included in the process. Companies D and C state that many customers lack both technical maturity and design maturity. As all companies involve the customers in the design process, introducing ML tools when working with people who lack technical competence can act as an inhibitor. Table 5.2 summarize the enablers and inhibitors from the findings related to the proposition.

Table 5.2 - Enablers (+) and inhibitors (-) of the correlation between technological knowledge and ML tools.

1st Order Code	TOE Framework
- Lack of ML knowledge (A)	Organization
- Designers do not have time to learn new tools (A, C, D)	
- Majority of designers prefer to use traditional tools (A, B, D)	
- Focusing too much on technological aspects result in designers giving up (D)	
+ Designers know of new technology (B, D)	
+ Designers want to improve constantly (C, D)	
+ Team effort to improve and learn new things (C, D)	
+ Low threshold to use new technology (C, D)	
+ Designers use new tools more when reminded it exists (D)	
+ Want to learn more about ML (A)	
- Many customers lack technical maturity (D)	Environment
- Many customers lack design maturity (C, D)	
- There is a lack of a design community to share knowledge (A)	
- ML is not talked about among designers (B)	
+ Need to learn new technology to stay relevant (C, D)	
+ Newsletters and forums introduce ML tools (C)	

Proposition 3 The Availability and Use of Data Varies

Although company C created solutions for consumers only, all the design firms follow a similar design process. All the companies collect qualitative data to gain insight through in-person interviews, workshops, or meetings. As company C mentioned, it is easier to support decisions based on data. Having access to ML tools to see new patterns and uncover new insight can complement qualitative work. However, creating and using such tools require much high-quality data. The amount of data available for creating ML tools varies according to the companies. Companies A, B, and C experience their customers lacking data or the resources to collect it. This is mainly related to smaller customers or customers in a startup phase. However, company D has experienced their customers create more and more data, especially when working on projects related to renewable energy, oil, ocean, and technical infrastructure. Despite the large amounts of data, companies A, B, and D agree that complex projects require unique data. In addition, future solutions using ML to aid the process will need to be trained on specific use cases to add value because of the complexity of these projects, according to companies B and D.

As technology is a more significant part of the design process today, an enabler of introducing ML can be understanding how solutions are developed. All four companies agree that development knowledge improves the end product, allowing the designers to be aware of limitations. However, they add that many designers are skeptical about learning to code. When prototyping, the companies do not agree on switching to high-fidelity prototypes and what tools to use. Company C, designing solutions for consumers, thinks a high-fidelity prototype is necessary to get the correct feedback from end-users, as they often lack imagination and design knowledge. Therefore, they use Figma to create prototypes and sometimes use programming to create functional prototypes. When creating more complex solutions for businesses, companies A, B, and D agree to start using low-fidelity prototypes to save money and ensure the end-users do not get too focused on details. This is also related to how time-consuming it is to create prototypes for solutions with a complex domain. In addition, Company C also starts creating low-fidelity sketches in the beginning. However, companies C and D use more technology to aid their design process early. Both companies have experienced getting better feedback when coding high-fidelity prototypes early. This can imply that the companies focusing more on technology also are more willing to use ML prototyping tools for more extensive parts of the process. Table 5.3 summarize the enablers and inhibitors from the findings related to the proposition.

Table 5.3 – Enablers (+) and inhibitors (-) of data availability and use.

1st Order Code	TOE Framework
- Complex projects require unique data (A, B, D)	Technology
- Complex projects require analyzing more data (B, D)	
+ Develop functional prototypes using data (C, D)	
+ Technology is a more significant part of the design process today (A, B, C, D)	
- Collects qualitative data to gain insight instead of quantitative data (A, B, C, D)	Organization
- Start creating non-digital prototypes to create complex structures (A, B, D)	
- Start creating non-digital prototypes as digital tools create too perfect outputs (C)	
+ Designers want help to stay updated on all standards for design and technology (A)	

+ Easier to support decisions when based on data (C)	
+ Switch to high fidelity prototypes early to get better feedback (C, D)	
+ Positive when designers have some development knowledge (A, B, C, D)	
- Customers lack high-quality data (A, B, C)	Environment
+ Customers have a lot of data (D)	

Proposition 4 Designers Do Not Trust Existing ML Tools

Companies A, B, and D explain that the designers' do not trust ML tools. To explain this phenomenon, Company D explains the Gartner Hype Cycle theory and points out the disappointment humans feel when the technology does not deliver what it promised. Existing tools not living up to the expectations lead to a lack of trust in new ML tools. This attitude can be attributed to both the media coverage of ML tools and the experiences the designers have had when trying tools. This lack of trust affects the willingness to use future ML tools. Because of this scepsis, designers from all four companies also state thinking of ML as a buzzword. Findings from company C present that many designers also feel threatened by ML. In addition, the lack of trust is also closely related to ML tools are not a talking point among designers, and many lack knowledge and experience. According to companies A and B, this lack of knowledge is linked to being scared of losing control if using ML tools. For a respondent from company B, the need for control is closely related to feeling responsible for the end product. Not being able to control the output of an ML tool increases this stress. Another inhibitor of trusting ML is related to the consistency of what the ML outputs. The unpredictability of ML outputs makes it hard to trust its suggestions. To make it easier to trust tools, Company D stresses the importance of transparency about how the ML algorithm works and where it is used. ML tools that work like a black box make it harder to feel in control and trust the output. Another reason for the lack of trust in ML tools is linked to a preconceived notion that traditional tools are better to use presented by companies A, B, and D. In addition, it is also related to a lack of technological knowledge, presented in Proposition 2. This phenomenon is exacerbated mainly in companies A and B by too little time available to try tools and the lack of style presence in a design community that focuses on ML. Table 5.4 summarize the enablers and inhibitors from the findings related to the proposition.

Table 5.4 - Enablers (+) and inhibitors (-) of trust in ML tools.

1st Order Code	TOE Framework
- ML do not provide consistent output (A, B, D)	Technology
- Existing ML tools lack design functionality (A, D)	
- Think ML is buzzword (A, B, C, D)	Organization
- Do not trust ML tools (A, B, D)	
- Scared of losing control (A, B)	

- Feel threatened by ML (A, C)	
- Lack of ML knowledge (A, B)	
- Some people fear being replaced (A)	
- Majority of designers prefer to use traditional tools (A, B, D)	
- Many designers are skeptical to technology (D)	
- Designers do not have time to learn new tools (A, C, D)	
- There is a lack of a design community to share knowledge (A)	Environment
- ML is not talked about among designers (B)	

Proposition 5 Designers Are Willing to Try ML Tools

Despite not trusting existing tools and feeling the tools lack necessary functionality, all companies state they are favorable to trying ML tools. The willingness can be related to existing traditional tools lacking desired functionality, e.g., Figma not working well for creating responsive designs. In addition, the organizations want to embrace new technology that improves the design process and its result. Company D is even willing to sacrifice time to learn to use new tools to accomplish this. The designers agreed on multiple requirements for what makes a good ML tool. The main focus of companies A, B, and C was to keep the designers in control. They see themselves using ML tools that provide suggestions and act as a guide. In addition, companies A and C do not wish for tools that automate the entire process without allowing the designers to stay involved in important decisions. The designers also wish for tools that are easy to use. There is a possible correlation between this wish and the designers' lack of time to learn new tools in companies A, C, and D. To make the tool easier to use, company B also wants tools that are possible to try without having to commit to using it. Despite the respondents of this study being positive about new ML tools, companies A and C experienced challenges when switching to new design tools. This internal struggle could imply that it would be challenging to start using ML tools. Table 5.5 summarize the enablers and inhibitors from the findings related to the proposition.

Table 5.5 - Enablers (+) and inhibitors (-) of willingness to try ML tools.

1st Order Code	TOE Framework
- Some employees do not want to switch to a new tool (A, C)	Organization
- Scared of losing control (A, B)	
- Designers do not have time to learn new tools (A, C, D)	
+ Low threshold to use new technology (C, D)	
+ Existing non-ML tools lack design functionality (A)	
+ Positive to trying ML tools (A, B, C, D)	
+ Willing to sacrifice time to try a new tool (D)	
+ Newsletters and forums introduce ML tools (C)	Environmental

Proposition 6 New ML Tools Should Assist Designers

During this study, it was uncovered a need for ML tools that assist the designers in the process instead of just automating it. Companies A, B, and

C desire ML tools that provide suggestions and link this to the need for feeling in control of the process. The wish for assistance is also linked to company D’s notion that ML tools should not work as a black box. Instead, the tool should be transparent about where and how the ML is used. The need for this is apparent in the tasks associated with the insight phase. Companies A, B, and D suggested ML tools to aid the insight phase. This uncovered a need for tools to help analyze user data and automate tedious tasks related to transcribing interviews and meeting notes.

However, company C mentions the empathy and insight gained through tedious tasks like transcribing interviews. In addition, this study mostly uncovered inhibitors of introducing ML tools for automating this process. All four companies wished to collect qualitative data to gain insight through in-person interviews, workshops, or meetings. However, the companies added it could be helpful to use ML tools as an addition to get insight from quantitative data. They still wanted to collect qualitative data as they emphasized the importance of being actively involved in this phase. Companies A and D agreed on the need for physical meetings with the customer and end-users. This is important to them as the customers often do not know what they want to end up with. Starting with physical meetings allows the designers to gain a lot of insight. According to company D, meeting at the end user’s location is also essential to learn about the environment in which they work. However, as companies B, C, and D state, it can be challenging to get a hold of end-users.

Companies A, B, and D also focused on the need to be involved in the process themselves, as it is challenging to document everything they learn in the process. Insight conducted by someone else lacks tacit knowledge about the problem and its users. The uncertainty and complexity of the insight phase can make it challenging to translate the scope of the project into something an ML algorithm could use to aid the insight. In addition, company D stated it feels like an unnecessary step to have to translate the findings from the insight to a tool.

Because of this, there is a need for tools assisting this part of the process, not automating it. In relation to tools for prototyping, companies B and C underlined the importance of tools where the designer can override decisions. The wish for tools to assist the designers is also reflected in the ideas for tools. This can also be related to the need of the designers in companies B, C, and D. They wanted to work together with other designers to spar and ensure they made sufficient progress. However, it was mentioned that it sometimes takes a lot of time to explain the situation to a designer that does not work on the project. Using ML as an assistant to spar during the process has the potential to cut down this time and save resources as fewer designers can work on the task. However, this requires an ML tool that can acquire the context of the project through analyzing data.

In addition, all companies agree that it is essential to include the customers, end-users, and developers throughout the entire process. This includes using tools that are easy to share and use for everyone. Having ML tools that automate significant parts of the process, e.g., a drawn sketch to a finished high-fidelity prototype, can make it challenging to include all the stakeholders. Company D suggests a tool that acts as an assistant, and company C describes a tool providing suggestions. Table 5.6 summarize the enablers and inhibitors from the findings related to the proposition.

Table 5.6 - Enablers (+) and inhibitors (-) of creating ML tools assisting the design process.

1st Order Code	TOE Framework
- Need for informal physical meetings with customers and end-users (A)	Organization
- ML tools feels like an unnecessary addition to the insight phase (D)	
- Important to meet end-user at their location (D)	
- Important to feel in control (A, B)	
- Collects qualitative data to gain insight instead of quantitative data (A, B, C, D)	
- Designers want to be involved in insight process themselves to understand the scope (A, B, C)	
- Designers gain insight when transcribing tools (C)	
- Challenging to document everything they learn (A, B, D)	
- It takes time to explain the situation when sparring with designers (B)	
+ Feedback and sparring help with ensuring sufficient progress (D)	
+ There is a need for help available for sparring (B, C, D)	
- Design consultants must create a solution that entertains the customer (D)	Environment
- Customers do not know what they need (A, D)	
+ Hard to get a hold of end-users to collect data (B, C, D)	

6 Discussion

This chapter discusses the theoretical and practical implications of this study and the limitations and further work identified. This includes the similarities and differences that emerged from the four case studies presented as a cross-case analysis of the findings.

6.1 Theoretical Implications

This research contributes to further investigation of the field of AI-related to design. In line with Berente et al. (2021) and Glikson & Woolley (2020) a lack of trust in ML is found as an inhibitor of introducing ML. Our findings are also consistent with the statement from Bailey, the notion that the lack of trust in ML has increased in line with the creation of ML tools that have not delivered what they promised, e.g., the website designing tool The Grid.

Companies A, B, and D explain that it is hard to document everything the designers learn about the customer, the domain, and its end users. This is because the insight includes large amounts of data and lets the designers gain tacit knowledge. Previous studies (Verganti et al., 2020; Q. Yang, 2017) suggest that designers should focus on sense-making and understanding what problems should be addressed, working as problem setters. As problem setting also includes inputting the correct information into an ML tool, the challenges designers face with translating the information into something tangible can be seen as an inhibitor of ML.

Based on the findings from this study, it is proposed that new ML tools should assist designers. This was also suggestions by Bailey, explaining that the future of AI should be in human-AI hybrids. This finding is also in line with the findings of O'Donovan et al. (2015) and multiple other articles that focus on the importance of having the designers lead the process and choosing what input to use. Pandian and Suleri (2020) underline this when explaining solutions where the designer sketches a UI, and ML is used to generate code based on this sketch does not allow for enough control. In addition, Koch (2017) explains that systems should suggest ideas, and Buschek et al. (2020) add ML should be used to complement the designer instead of replacing them. Another similar finding is presented by Wallach et al. (2020), where the ML tool simulates human behavior and acts as the designer's "best friend".

In addition, this study found inconclusive results regarding the amounts of data available. Company D states that large amounts of data are available, while the other companies experience a lack of data. According to Winter & Jackson (2020), the amount of data is increasing but point out a new challenge is the lack of high-quality data. It is possible the designers feel there is a lack of data because it is of a poor quality.

Furthermore, Davenport and Ronanki (2018) and Ransbotham et al. (2017) find that a significant inhibitor of getting value from AI is a lack of technological competence. This corresponds with the findings in this study, linking technological competence to having a lower threshold for trying ML tools.

6.2 Practical Implications

The findings presented in the thesis also provide valuable insight into what designers think about introducing ML in the design process.

It was found that designing digital solutions includes gaining insight into the domain, the customers, and the end-users involved in the process. Designers focused on actively including both customers and end-users to ensure better insight. In addition, they found it important to be actively involved themselves. However, it was found that ML tools still have the potential to aid this part of the process. This included tools for automating tedious tasks like transcribing notes and gaining domain knowledge. It also included more advanced tools for gaining a qualitative understanding of quantitative data.

The insight was followed by prototyping the solution, either going through many different prototype fidelities or creating a dynamic and realistic-looking high-fidelity prototype as fast as possible. The designers were favorable to trying tools that could provide new ideas and think outside the box for prototyping.

In the evaluation phase, designers checked if the solution met requirements, industry standards, and national regulations, e.g., accessibility. For this step, the designers wished for ML tools to suggest improvements or automatically evaluate if the solution follows design standards. When working, the design companies tried to get involved as early as possible and wished to stay involved after the prototype was created. This active involvement can inhibit the use of ML tools that restrict the process or limit the inclusion of the customer, end-users, and developers. Multiple designers also introduced more technology into the design process today than a few years ago.

However, the designers did not feel the ML tools available today met their expectations. This uncertainty made it challenging for designers to stay updated on what tools were available, as they did not feel they had time to search for new technology. It seemed interacting with a design community or subscribing to newsletters focusing on technology made it easier to stay updated on what new tools were created. In addition, the study found that the companies that prioritized time to develop new skills were more likely to try new tools. Figure 6.1 illustrates a summary of what types of ML tools the designers wished for.

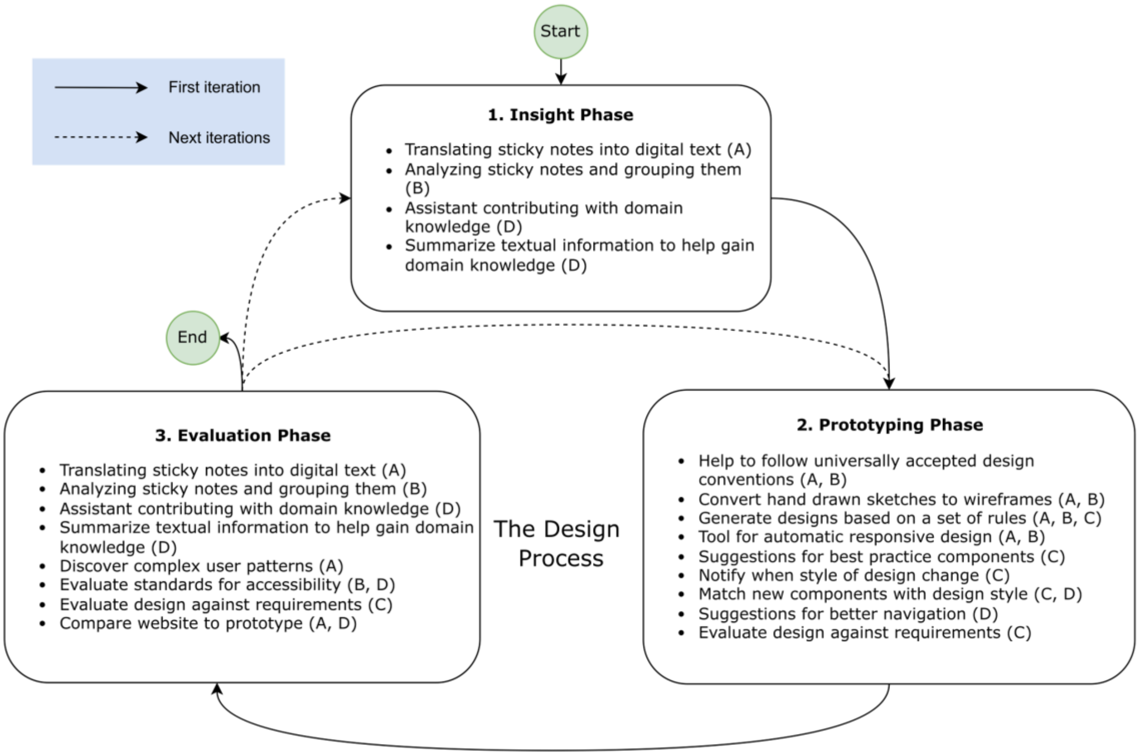

Figure 6.1 - Ideas for ML tools.

6.3 Propositions

The propositions identified support the finding that the majority of design firms did not use ML tools to aid the design process. The tools used by the designers had resulted in mediocre results, even though company C found that a few simple tools helped save resources.

The lack of use of ML tools can be related to the six propositions identified in Chapter 5. It has been found that the lack of available tools to meet user needs is an important reason for most designers not using ML tools. It is worth noting that the claim that a lack of tools does not mean no tools exist, only that the designers are not aware of any. As presented in Proposition 2 the use of ML tools is also closely related to the designers, customers, and end-users technical knowledge. The lack of knowledge about ML is linked to a lack of trust in the tools and an aversion to switching out familiar tools and techniques. The study also found a correlation between development knowledge and the use of ML tools. In addition, when working as a consultant, and especially on a complex solution, the environmental factors of the customers are important for being able to use ML tools. This is linked to the possibility of including the end-users and customers in the process and the data the customers have available. However, it is an important finding that designers are willing to try using new tools. If tools are created to assist designers and help them create better end products or save resources, the designers claim to be willing to sacrifice both time and change the process of learning the tool.

6.4 Evaluation of Method, Limitations and Future Work

The thesis contains limitations it is important to address. Firstly, it is worth noting that this study is researching Norwegian companies, and the theoretical background consists of literature from other countries than Norway. Because of this, future research is needed to study other Norwegian companies and identify what cultural differences affect the design process concerning ML use.

To gain insight into designers thoughts on ML in the design process, a qualitative study was chosen. Through interviews, the goal was to gain in-depth insight and uncover new aspects of the field. Because of this, semi-structured interviews were held. This allowed for flexibility to discover what was important to the designers. However, flexibility also has the potential to influence the results indirectly. It is possible the respondents talked in more detail about the questions that engaged them the most. Despite trying to stay neutral, it is also possible that preconceived ideas influenced my wording and descriptions of the questions. An observation related to this is how every company focused more on describing the insight phase than the other parts of the process. It is hard to identify why this happened. It could be because this is the most similar process for all projects, or it is a possibility that the questions were written in a way that encouraged this focus.

As not everyone interviewed was a designer, and the designers had different backgrounds, the respondents had different prerequisites for answering the questions. It is reasonable to assume this prerequisite influenced their thoughts on the design process and the use of ML. A designer with a good understanding of ML will likely identify different inhibitors and enablers than a designer with no knowledge of the field. In addition, some of the respondents presented themselves as tech enthusiasts and described being the ones introducing new technology to the organization. It is worth noting that the respondents who agree to join this study may be more interested in ML and new technology.

Another limitation related is related to language. Due to a lack of resources and because the supervisors of this study do not speak Norwegian, it was decided to conduct the interviews in English. As this is not the language the respondents use when working, it is possible this affected their response.

There was no budget to travel to visit the companies or invite them to our location. Therefore, the interviews were held digitally over Teams. Digital interviews also allowed for recording and automatic transcription. This saved many resources when analyzing the data. However, it was harder to interpret body language, possibly leading to misunderstandings. In addition, two interviews were temporarily paused due to technical issues. As the respondents had booked a room to participate in the interview at their office, we ended up with too little time towards the end of the interview. It is possible this affected the answers of the two respondents.

When analyzing the interviews, 1st order codes were created. These were categorized after discussing the findings with Mikalef and Trocin. If given more time, it would be interesting to continue the work by creating 2nd order codes and relating the findings to more similar findings from previous studies. The task of analyzing ten interviews alone took a lot of resources. If more time is used in the future, it is likely more interesting findings will be uncovered.

Conducting a qualitative study where ten participants from four companies were included has resulted in interesting findings and multiple propositions. However, there is a need to research this field by collecting more data to support the findings. This has the potential to uncover new relations between the design process and the use of ML. As the study included few companies, it can be seen as a limitation that only ¾ of the companies were micro-sized, and ¾ mostly created complex systems for business end-users. This diversity could have influenced the results, making it harder to conclude. Future research should try to identify further how the size of the company and the types of solutions created to affect the use of ML.

Lastly, there is a need for more research into how companies that use more ML tools as part of the design process experience this. As none of the companies included in this study used ML tools for every design process, it would also be interesting to get the respondents to try ML tools and research how using these tools would affect their thoughts on ML.

7 Conclusion

This thesis aimed to gain a deeper understanding of what designers think about introducing ML in the design process and identify enablers and inhibitors of this introduction. To accomplish this, four case studies were analyzed and compared. The methodology included following Eisenhardt's (1989) guidelines for the research setting and data collection. The Gioia methodology (2013) was followed to analyze the data, resulting in codes structuring the interview data. Through semi-structured interviews of ten Norwegian designers, developers, and leaders working in the design industry, it was uncovered how designers work and who is involved in the design process. Their thoughts on ML and the introduction of new technology were also researched, resulting in six propositions presenting the findings from a cross-case analysis. Conducting a qualitative study has provided a rich insight into this field. The study contributes insight into where in the design process there is a need for ML tools, and what types of tools should be created.

It was found that the use of ML when designing is still in an early stage. Because of this, the tools available today do not meet user needs. A correlation between technological knowledge and the willingness to embrace new ML tools was also found. Most of the companies also experienced a lack of high-quality data available. This was linked to working for smaller and less established customers. The lack of available tools, technological knowledge, and data was the biggest inhibitor to the introduction of ML tools. It was also found that these factors were linked to a lack of trust in existing ML tools. Despite the inhibitors identified, the designers are willing to try new ML tools and want to learn more about the technology. This is especially true for tools that can assist the designers and allow for control when working.

References

2019 CIO Survey: CIOs Have Awoken to the Importance of AI. (2019). Gartner. https://www.gartner.com/en/documents/3897266

AlSheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. 8.

Anthony, C. (2021). When Knowledge Work and Analytical Technologies Collide: The Practices and Consequences of Black Boxing Algorithmic Technologies. *Administrative Science Quarterly*, *66*(4), 1173–1212. https://doi.org/10.1177/00018392211016755

Beltramelli, T. (2018). pix2code: Generating Code from a Graphical User Interface Screenshot. *Proceedings of the ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, 1–6. https://doi.org/10.1145/3220134.3220135

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research. *Journal of the Association for Information Systems*, *22*(2). https://doi.org/10.17705/1jais.00662

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, *45*, 1433–1450. https://doi.org/10.25300/MISQ/2021/16274

Brown, T. (2008). Design Thinking. *Harward Business Review*, 10.

Brown, T., & Katz, B. (2011). Change by Design. *Journal of Product Innovation Management*, *28*(3), 381–383. https://doi.org/10.1111/j.1540-5885.2011.00806.x

Buschek, D., Anlauff, C., & Lachner, F. (2020). Paper2Wire – A Case Study of User-Centred Development of Machine Learning Tools for UX Designers. *Mensch Und Computer 2020 (MuC'20)*, *20*, 19–32. https://doi.org/10.1515/icom-2021-0002

Cambridge Dictionary. (n.d.). *The General Public*. Cambridge Dictionary. Retrieved April 19, 2022, from https://dictionary.cambridge.org/dictionary/english/general-public

Chen, C., Su, T., Meng, G., Xing, Z., & Liu, Y. (2018). From UI Design Image to GUI Skeleton: A Neural Machine Translator To Bootstrap Mobile GUI Implementation. *Proceedings of the 40th International Conference on Software Engineering*, 665–676. https://doi.org/10.1145/3180155.3180240

Dave, H., Sonje, S., Pardeshi, J., Chaudhari, S., & Raundale, P. (2021). A Survey on Artificial Intelligence Based Techniques To Convert User Interface Design Mock-Ups To Code. *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 28–33. https://doi.org/10.1109/ICAIS50930.2021.9395994

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. *Harward Business Review*, 10.

de Souza Baulé, D., von Wangenheim, C. G., von Wangenheim, A., & Hauck, J. C. (2020). Recent Progress in Automated Code Generation from GUI Images Using Machine Learning Techniques. *J. Univers. Comput. Sci.*, *26*(9), 1095–1127.

Design Council. (2015). *What Is the Framework for Innovation? Design Council's Evolved Double Diamond*. Design Council.

https://www.designcouncil.org.uk/news-opinion/what-framework-innovation-design-councils-evolved-double-diamond

Dorst, K. (2011). The Core of 'Design Thinking' and Its Application. *Elsevier*, *32*(6), 521–532. https://doi.org/10.1016/j.destud.2011.07.006

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, *14*(4), 532–550.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Kaiser, Z. (2019). Creativity as Computation: Teaching Design in the Age of Automation. *Design and Culture*, *11*(2), 173–192. https://doi.org/10.1080/17547075.2019.1609279

Kelley, T., & Kelley, D. (2013). Creative Confidence: Unleashing the Creative Potential Within Us All. Crown.

Koch, J. (2017). Design implications for Designing with a Collaborative AI. *The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems*. The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems.

Koza, J. R., Bennett, F. H., Andre, D., & Keane, M. A. (1996). Automated Design of Both the Topology and Sizing of Analog Electrical Circuits Using Genetic Programming. In J. S. Gero & F. Sudweeks (Eds.), *Artificial Intelligence in Design ’96* (pp. 151–170). Springer Netherlands. https://doi.org/10.1007/978-94-009-0279-4_9

Latipova, A., Gasenko, A., & Sim, G. (2019). On ‘Artificial Intelligence-User Interface’ Approach. *2019 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*, 0446–0451. https://doi.org/10.1109/SIBIRCON48586.2019.8958406

Martin, K. (2019). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, *160*(4), 835–850. https://doi.org/10.1007/s10551-018-3921-3

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Elsevier*. https://doi.org/DOI: 10.1016/j.im.2021.103434

Nguyen, T. A., & Csallner, C. (2015). Reverse Engineering Mobile Application User Interfaces with REMAUI (T). *2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, 248–259. https://doi.org/10.1109/ASE.2015.32

Norman, D. A. (Ed.). (1986). User Centered System Design: New Perspectives on Human-computer Interaction. CRC Press.

O’Donovan, P., Agarwala, A., & Hertzmann, A. (2015). *DesignScape: Design with Interactive Layout Suggestions*. 1221–1224. https://doi.org/10.1145/2702123.2702149

Oulasvirta, A., Dayama, N. R., Shiripour, M., John, M., & Karrenbauer, A. (2020). Combinatorial Optimization of Graphical User Interface Designs. *IEEE*, *108*(3), 434–464. https://doi.org/10.1109/JPROC.2020.2969687

Pandian, V. P. S., & Suleri, S. (2020). BlackBox Toolkit: Intelligent Assistance to UI Design. *CHI’20, Workshop on Artificial Intelligence for HCI: A Modern Approach*. https://doi.org/10.48550/arXiv.2004.01949

Preece, J., Sharp, H., & Rogers, Y. (2015). Interaction Design: Beyond Human-Computer Interaction, 4th Edition | Wiley (4th ed.). Wiley.

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A New Organizational Chassis For Artificial Intelligence—Exploring Organizational Readiness Factors. *Research Papers*.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping Business With Artificial Intelligence: Closing the Gap Between Ambition and Action - ProQuest. MIT Sloan Management Review.

Salminen, J., Sengün, S., Jung, S., & Jansen, B. J. (2019). Design Issues in Automatically Generated Persona Profiles: A Qualitative Analysis from 38 Think-Aloud Transcripts. *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, 225–229. https://doi.org/10.1145/3295750.3298942

Sarkar, P., & Chakrabarti, A. (2008). Studying Engineering Design Creativity. *Proceedings of The International Workshop on Studying Design Creativity.*, 21.

Schaefer, C., Lemmer, K., Samy Kret, K., Ylinen, M., Mikalef, P., & Niehaves, B. (2021). Truth or Dare? – How can we Influence the Adoption of Artificial Intelligence in Municipalities? *Proceedings of the 54th Hawaii International Conference on System Sciences*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2021.286

Scheutz, M. (2002). *Computationalism: New Directions*. MIT Press.

Sermuga Pandian, V. P., Suleri, S., Beecks, C., & Jarke, M. (2020). MetaMorph: AI Assistance to Transform Lo-Fi Sketches to Higher Fidelities. *32nd Australian Conference on Human-Computer Interaction*, 403–412. https://doi.org/10.1145/3441000.3441030

Silva-Rodríguez, V., Nava-Muñoz, S. E., Castro, L. A., Martínez-Pérez, F. E., Pérez-González, H. G., & Torres-Reyes, F. (2020). Classifying design-level requirements using machine learning for a recommender of interaction design patterns. *IET Software*, *14*(5), 544–552. https://doi.org/10.1049/iet-sen.2019.0291

Strich, F., Mayer, A.-S., & Fiedler, M. (2021). What Do I Do in a World of Artificial Intelligence? Investigating the Impact of Substitutive Decision-Making AI Systems on Employees' Professional Role Identity. *Journal of the Association for Information Systems*, *22*(2). https://doi.org/10.17705/1jais.00663

Suleri, S., Sermuga Pandian, V. P., Shishkovets, S., & Jarke, M. (2019). Eve: A Sketch-based Software Prototyping Workbench. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–6. https://doi.org/10.1145/3290607.3312994

Swearngin, A., & Li, Y. (2019). Modeling Mobile Interface Tappability Using Crowdsourcing and Deep Learning. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–11. https://doi.org/10.1145/3290605.3300305

Technical Commitee ISO/TC. (2019). ISO 9241-210:2019, Ergonomics of human-system interaction—Part 210: Human-centred design for interactive systems. Standard Norge.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The Processes of Technological Innovation*. Lexington Books.

Trocin, C., Hovland, I. V., Mikalef, P., & Dremel, C. (2021). How Artificial Intelligence affords digital innovation: A cross-case analysis of Scandinavian companies. *Technological Forecasting and Social Change*, *173*, 121081. https://doi.org/10.1016/j.techfore.2021.121081

Tschang, F. T., & Almirall, E. (2021). Artificial Intelligence as Augmenting Automation: Implications for Employment. *Academy of Management Perspectives*, *35*(4), 642–659. https://doi.org/10.5465/amp.2019.0062

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and Design in the Age of Artificial Intelligence. *Journal of Product Innovation Management*, *37*(3), 212–227. https://doi.org/10.1111/jpim.12523

Wallach, D. P., Flohr, L. A., & Kaltenhauser, A. (2020). Beyond the Buzzwords: On the Perspective of AI in UX and Vice Versa. In H. Degen & L. Reinerman-Jones (Eds.), *Artificial Intelligence in HCI* (pp. 146–166). Springer International Publishing. https://doi.org/10.1007/978-3-030-50334-5_10

Weller, A. J. (2019). *Design Thinking for a User-Centered Approach to Artificial Intelligence* [Daffodil International University]. https://doi.org/10.1016/j.sheji.2019.11.015

Winter, M., & Jackson, P. (2020). Flatpack ML: How to Support Designers in Creating a New Generation of Customizable Machine Learning Applications. In A. Marcus & E. Rosenzweig (Eds.), *Design, User Experience, and Usability. Design for Contemporary Interactive*

Environments (pp. 175–193). Springer International Publishing. https://doi.org/10.1007/978-3-030-49760-6_12

Yang, B., Wei, L., & Pu, Z. (2020). Measuring and improving user experience through artificial intelligence aided design. *Frontiers in Psychology*, *11*, 3000.

Yang, Q. (2017). *The Role of Design in Creating Machine-Learning-Enhanced User Experience*. The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems. https://www.aaai.org/ocs/index.php/SSS/SSS17/paper/view/15363

Zhou, J., Tang, Z., Zhao, M., Ge, X., Zhuang, F., Zhou, M., Zou, L., Yang, C., & Xiong, H. (2020). Intelligent Exploration for User Interface Modules of Mobile App with Collective Learning. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 3346–3355. https://doi.org/10.1145/3394486.3403387

Appendices

Appendix A: Consent Form

Appendix B: Information Document

Appendix C: Interview Protocol

Appendix A: Consent Form

Consent form

- ☐ I have received and understood information about the project “Machine Learning Aiding the Digital Design Process” and have been given the opportunity to ask questions.
- ☐ I give consent to participate in an interview
- ☐ I give consent to the interview being recorded and transcribed
- ☐ I give consent for my personal data to be processed until the end date of the project, approximately December 2022

First name ____

Last name ____

Date ____

(Signed by participant, date)

Appendix B: Information Document

Information About the Project: Enablers and Inhibitors of Machine Learning in the Design Process

This is an inquiry about participation in a research project. In this letter, we will give you information about the purpose of the project and what your participation will involve.

Purpose of the project
We are conducting a study identifying enablers and inhibitors of using machine learning as a tool in the design process of software products.

Who is responsible for the research project?
Norwegian University of Science and Technology (NTNU) – Department of Computer Science (IDI) is the institution responsible for the project.

Why are you being asked to participate?
We are interested in interviewing designers and other key people involved in the design process working for firms creating digital design solutions.

What does participation involve for you?

If you chose to take part in the project, this will involve taking part in a semi-structured interview. It will take between 30 and 90 minutes, and will with your consent be recorded to allow us to analyze the data properly.

The interviews will focus on

- how the design process at your company works.
- what types of customers and types of projects you work on.
- thoughts on the introduction of new tools and techniques.
- experience with learning to use new digital tools
- using "The Technology – Organization – Environment Framework" to identify the factors that enable and inhibit the implementation and use of machine learning as a tool in the design process.

If necessary and with your agreement, it is possible to conduct a second interview. The interviews, including your identity and what company you work for, will be kept strictly confidential.

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 choose 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 in this information letter. We will process your personal data confidentially and in accordance with data protection

legislation (the General Data Protection Regulation and Personal Data Act).

Data collection
During the data collection process, no personal data of the participant will be stored. In fact, only their position within the company, years of experience, and email addresses will be retained in the raw data set. The raw datasets will be accessed only by the principal researcher Åsne Stige, and will be stored in a personal Google Drive folder. The curated dataset will not contain any personal or company information, making it impossible to be traced back to the individual or the firm they work in.

In the case where companies or other organizations agree to hand over any type of information that has been collected by them, there will be a thorough examination that data is in compliance with national and EU personal data regulations. In all cases, processing and publishing results that are an outcome of this type of data will be completely anonymized, as with primary data collected.

Storage
Storage of raw data will be done in a Google Drive folder owned by Åsne Stige, while curated data will be saved on NTNU's servers, with limited access rights to Åsne Stige and Prof. Patrick Mikalef. During the implementation of the open data pilot all curated data will be carefully reviewed by the two scientists in order to confirm that there is no way to trace back information. As such, no personal data will be retained or analyzed. The datasets will be analyzed at an aggregate level, so no individual firm-level results will be derived. Consequently, publications resulting from the analysis of such data will not include personal respondent or firm information, establishing full anonymity. The only person with access to the raw files will be Åsne Stige who will also be responsible for curating datasets in the appropriate format. In the case that participants want to withdraw their provided information, at any time during the data collection, the principal researcher will be in charge of removing entries in the dataset and delivering new curated ones with the omitted data.

Protection
From any type of raw dataset, the curated dataset that will be used for the analysis of results will remove any identifiers of personal data. These identifiers include:

- Names (if provided)
- The geographic location of company/respondent (Except for country)
- All elements of the date
- Telephone numbers
- Email addresses
- IP address numbers

The raw datasets will be in the possession of Åsne Stige, stored on a password-protected Google Drive folder. Once the raw data files have been curated, the anonymized datasets will be the only source on which analysis will be conducted. To ensure compliance with national and European Union data protection regulations, an application for each study will be submitted to the Norwegian Social Science Data Service (NSD). At the current point in time, an application has not been submitted since it requires that the exact questions of interviews and/or surveys are submitted. Nevertheless, once the study design has been completed and granted approval, there will be continuous updates towards the European Commission.

Retention and destruction
This project will participate in the open access to research data by providing accessibility to curated versions of datasets. Hence, curated datasets will be retained and made publicly available even after the project has ended in order to promote accessibility to other researchers and the academic community. Nevertheless, the raw datasets will be destroyed following the completion of the project to prevent unauthorized access to them. Participants will be informed that they are able to retract their participation in the study up to the date the project formally ends.

What will happen to your personal data at the end of the research project?
The project is scheduled to end in December 2022

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 Data Protection Officer or 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 Norwegian University of Science and Technology (NTNU) – Department of Computer Science (IDI), NSD – The Norwegian Centre for Research Data AS has assessed that the processing of personal data in this project is in accordance with data protection legislation.

Where can I find out more?
If you have questions about the project or want to exercise your rights, contact:
- Norwegian University of Science and Technology (NTNU) – Department of Computer Science (IDI) via your name and Patrick Mikalef.
- Our Data Protection Officer:
- NSD – The Norwegian Centre for Research Data AS, by email: (personverntjenester@nsd.no) or by telephone: +47 55 58 21 17.

Yours sincerely,
Project Leaders
Patrick Mikalef and Åsne Stige

Appendix C: Interview Protocol

Interview protocol

1. Introduction

We are conducting a study to identify enablers and inhibitors of using Machine Learning in the design process of software products.

- The interview today will be kept anonymous.
- The data from this interview can be saved and processed until the end of the project in December 2022.
- The interview will last approximately 60 minutes.
- You can at any time choose to end the interview.

With your consent, I will now start to record the interview and start asking you the questions.

~ START TAPE RECORDER ~

2. Interview

I have now started the recording and wanted to ask for consent to record and transcribe the interview one last time so that we have it recorded.

2.1 A brief introduction

1. Can you introduce yourself?
    a. Your age
    b. Your position
    c. When did you start to work in this position?
2. Can you tell us a little about the company you work for (keeping in mind the name and other identifying factors will not be included in the study)
3. Approximate size of the company
4. What country do you work in?

2.2 The design process

1. What kind of solutions do you typically design?
    a. Internal or external
    b. Webpages, apps?
2. How do you identify the idea to design a new solution?
3. How does the budgeting of a project influence the way you work?
4. Can you describe the process for designing a solution from first contact with the customer, to delivering the finished product, including any maintenance?
    a. Which tasks are included in the process?
5. Do you get inspired by specific theories or templates?
    a. Which key principles do you follow?

2.3 The people involved in the design process

1. Can you introduce the typical customer you work with?
    a. What sector do they belong to? (private, public sector, combination)
    b. Their approximate size
    c. How involved are they in the design process of software products?
2. What is your role in developing the idea into the finished solutions?
3. Who else from your company is involved, and what is their role?
4. How do you involve end-users in the process?

   a. How many end-users?
   b. How and at what stages do you collect data about users?
   c. Do you collect feedback after finishing the solution, and use this to improve the design?

2.4 The use of digital tools and technologies

1. Do you use some technologies to support your work when designing a solution?
   a. Did you attend training courses to use the new technology?
   b. Why did you start to use the new technology? Which specific needs triggered the introduction of this technology?

2.5 Your understanding of machine learning

1. Can you explain your understanding of machine learning, and what you associate with this word?

I*f a new term is mentioned: Can you explain what you mean by the term.*

2.6 The future use of Machine Learning

1. Have you discussed the possibility to introduce ML as part of the design process?
   a. What did you discuss?
   b. Have you experienced any pressure from customers or competitors to introduce or not introduce ML?
2. Are there any design tasks or processes you wish to use ML for in the future?
   a. For example, as part of one of the tools you already use?
   b. If yes, can you say which features you wish?
   c. If no, why not?
3. Do you believe ML will become a part of your design process in the future?
   a. What needs to change for this to happen?
   b. What can make the transition easier
   c. What can make the transition harder?
   d. What are some constraints you have regarding introducing ML?
4. How do you think introducing ML would change the design process?
5. Do you ting introducing ML will change frameworks and theories?
   a. If yes, how?

3. Close and Summary

Thank you so much for your participation. I want to remind you that the interview is anonymous and that your answers will be combined with the others in this study. I will now stop the recorder.

~ STOP TAPE RECORDER ~

NTNU
Kunnskap for en bedre verden