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Machine Learning (ML) diffusion in the design process: A study of Norwegian design consultancies

Cristina Trocin[a], Åsne Stige[b], Patrick Mikalef[b,c,*]

[a] Newcastle University Business School, 5 Barack Road, Newcastle Upon Tyne NE1 4SE, United Kingdom
[b] Department of Computer Science, Norwegian University of Science and Technology, Sem Sælandsvei 9, 7491 Trondheim, Norway
[c] Department of Technology Management, SINTEF Digital, S. P. Andersens veg 3, 7031, Trondheim, Norway

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ABSTRACT

Traditionally, the design process has been performed by designers and developers with the aid of digital technologies. The proliferation of Machine Learning (ML) during the last years has been argued to boost the creative process of design. This includes simple tasks such as translating handwritten notes, suggesting layouts options but also more complex action possibilities like generation of new ideas and prototyping for their visualization. However, the discourse about ML in creative industries is in an early stage, and there is limited knowledge about its diffusion in the design process. In our case study of four Norwegian design consultancies, we found that inhibitors (lack of ML knowledge, lack of trust in ML outputs, and poor results provided in languages other than English) overweighted the enablers (identifying patterns in the transcriptions, checking the requirements). This limited the intentions of design consultancies to introduce ML and undermined its diffusion in their design process.

1. Introduction

Machine Learning (ML) is part of Artificial Intelligence (AI) umbrella that can support the artists in their creative process in surprising ways (Davenport and Mittal, 2022) based on its ability to learn[1] from datasets with or without human supervision and to make predictions for multiple solutions (Padmanabhan et al., 2022). ML besides being introduced into non-traditional creative industries such as healthcare (Lebovitz et al., 2021), human resource management (Trocin et al., 2021), customer relationship management (Chatterjee et al., 2022), open source development communities (Shaikh and Vaast, 2022; Vaast, 2022), it is attracting more and more attention also in traditional creative industries such as design (Watkins, 2023), music (Bedingfield, 2023), fashion (Ginsberg, 2023), art (Hsu and Myers, 2023), film (Smith, 2023), radio (Rowe, 2023), photography (Grierson, 2023). For example, ML can support the design process by automating tedious tasks, generating new creative ideas, and providing suggestions for layout options (Verganti et al., 2020). The aim of ML is not to replace the key actors across the industries (e.g., the case of radiologists (Davenport and Keith, 2018)) but to support them with a new plethora of action possibilities that can be used by the experts, which in turn can lead to improved performance. Although the intention is to boost artists' creativity, the discourse around the diffusion of ML in the creative industries triggers disruption, disagreements that require changes, and most importantly is still in an early stage. Specifically, little is known about the enablers and the inhibitors of ML that emerge when it is diffused in the design process. As unintended consequences emerge regularly, it is essential to better understand the reflections, needs of the designers and developers in the diffusion phase.

Organizations often struggle to leverage the potential value of latest technologies due to issues that emerge while diffusing them into their operations (Mustonen-Ollila & Lyytinen, 2003). This is also the case with many applications of AI in organizations, where a plethora of factors relating to both technical and organizational aspects has resulted in a slow uptake of such technologies (Mikalef and Gupta, 2021). While literature has identified several barriers in the diffusion process of AI in non-creative industries, little is known about the issues encountered in the creative industries as many of these are highly dependent on the context in which AI is deployed. This has been argued to be primarily due to the fact that AI applications, and even those within the domain of ML, differ significantly based on the area of use (Collins et al., 2021). As a result, it is important to develop a holistic understanding of how the

* Corresponding author.
E-mail addresses: cristina.trocin@newcastle.ac.uk (C. Trocin), aasnesti@stud.ntnu.no (Å. Stige), patrick.mikalef@ntnu.no (P. Mikalef).

[1] Can machines really learn? The royal society.

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diffusion of novel technologies (e.g., ML) changes existing ways of operating in the creative industries (e.g., design).

Consequently, our aim is to understand how the diffusion of ML changes the design process by investigating the following research question: What are the enablers and the inhibitors of ML diffusion in the design process? We conducted an exploratory case study in four Norwegian design consultancies to investigate the benefits and the challenges experienced by the designers (Eisenhardt, 1989). Gioia methodology (2013) guided the collection and the analysis of semi structured interviews. The interview protocol was based on the categories of the Technology – Organization – Environment (TOE) framework to identify the aspects that enable and inhibit ML diffusion in the design process (Tornatzky et al., 1990).

Our results show that ML has the potential to support designers and developers along the three design processes, which are insight, prototyping, and evaluation. We developed a framework that shows the diffusion of the enablers and the inhibitors of the ML at each process and the interrelationships among them. ML can be particularly valuable for transcribing handwritten annotations, analysing transcriptions, identifying patterns invisible to human eyes, providing suggestions, checking the requirements, and making suggestions for multiple layouts, colours, and others. These enablers can improve the quality of the solutions designed, the creativity process of the designers or the idea generation after the data analysis. At the same time, the designers and the developers experienced several inhibitors that had a strong impact on their decision of introducing ML in the design process as follows. ML is still largely a buzzword that did not deliver the envisioned benefits, thus there is a strong lack of trust in ML outputs and in its use more in general because it lacks important design functionality such as poor results in languages other than English and most important it is not introduced into the design community; thus, the designers lack ML knowledge and do not perceive it as a tool that can improve their work. Our study shows that the inhibitors overweighted the enablers of ML diffusion in the design process, which undermined its introduction in the design processes.

The paper is organised as follows. First, we introduce the design process with its key processes, we continue with the role of ML in each phase and we present the diffusion innovation theory to interpret our case study. Next, we describe the research method based on which we wrote our findings. We conclude with the discussion, implications, limitations, and future research.

2. Theoretical background

2.1. Design process

Design is the decision-making process through which new ideas and solutions are created to solve specific problems (Verganti et al., 2020). The term *design* is often defined in relation to its principles, which create the ontology of the design and describe the perspective and philosophy that inform the act of designing, such as design thinking or user-centred approaches (Verganti et al., 2020). Designers can produce anything ranging from physical objects to digital products, services, or visual identities. The creation of solutions with high standards and quality requires to consider several aspects that range from technical specificities to mandatory regulations and rules, to users' preferences and others. To meet all these aspects, designers use specific frameworks and techniques. For example, design thinking deals with complex problems through the use of theories, models from design methodology, psychology, education, and other fields to foster innovation in organizations (Dorst, 2011). This paradigm can solve crucial problems before starting the development process and can help designers build empathy 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."*

Iterative user-centred approaches focus on keeping the user at the heart of the design, as this facilitates designers to satisfy users' needs by analysing the usage context, goals, and requirements before starting the design process (Verganti et al., 2020). At the same time, such approaches use the possibilities offered by new technologies, fulfil the requirements along with three core activities: inspiration, ideation, and implementation (Brown, 2008). Double Diamond is another popular framework that consists of four actions: discover, define, develop, and deliver, that are split into two diamonds (Design Council, 2015). The first diamond represents the action of widely exploring the field in order to create 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). Since each project is different, there is not one design process or framework that fits every situation, but designers can use relevant aspects from different approaches. For example, a common denominator of the approaches discussed above is their focus on the iterations. So, the designers are encouraged to go back to the previous design phases to ensure that all requirements are met.

Design is defined also in relation to its process, which usually consists of three main phases, the insight phase, the prototyping phase, and the evaluation phase (Preece et al., 2015). The *insights phase* includes understanding and specifying the context of use, the user requirements, and other important aspects (Weller, 2019). In-depth knowledge of the domain, the end-user preferences, and potential stakeholders are 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, technical aspects and must be transferred into functional requirements for system development.*" In the *prototyping phase,* the solution is designed in line with the users' requirements through iterative processes. Designers create a simulation or a sample version of the final product before actually developing the final product. It can range from simple models with sketches to functional, interactive digital prototypes. The *evaluation phase* assesses the final solution through usability testing, summarizing the feedback from the testing, and analysing the final result until the designers are satisfied with the final version of the solution developed (Technical Commitee ISO/TC, 2019). ML continues to evolve exponentially, and today it can do far more than automating simple tasks in the design process (Verganti et al., 2020).

2.2. Machine Learning (ML) diffusion in the design process

Artificial Intelligence (AI) technology is complex and constantly evolving. AI is defined 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 as AI takes over complex reasoning and analysis tasks, which were previously performed mainly by human experts (Tschang and Almirall, 2021). Thus, in the near future the 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 field of AI is broad and includes many technologies such as Machine Learning (ML). 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 segmentations (Trocin et al., 2021). In addition, AI can assist designers in creative activities by enhancing the input information and by providing multiple suggestions (Mikalef and Gupta, 2021). AI also is able to enact popular design principles, such as user-centred, abductive reasoning, and iterative procedures (Verganti et al., 2020). The introduction of ML in organizations involves changing the way the responsibility is shared between the human users and technologies (Martin, 2019). Although ML can mimic human experts, it is mainly used to complement designers' work instead of replacing them.

Prior studies identified interesting findings along the three design phases. In the *insight phase*, ML was used to generate automatic persona profiles (Salminen et al., 2019). ML provided accurate results about potential users' behaviour in a few hours such that designers could get periodically updated profiles of potential end-users. Koch (2017) showed that AI can help designers to check the requirements with 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. Consequently, 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, the guidance of the designers can result in more creative and efficient solutions (Koch, 2017).

Several studies 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 (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. Indeed, the designers 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. The use of ML to generate code represents the trend of using ML in the design field to automate tedious and lengthy processes (Dave et al., 2021). However, many of the solutions could only identify a small number of components and were not trained on large datasets. Pandian and 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.

Finally, some scholars investigated the introduction of ML in the *evaluation phase*. Swearngin and Li (2019) showed that ML could be used to evaluate the final product 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 to 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 behaviour and acted like the designers' "best friend". The designer asked for help in some tasks and got quantitative performance predictions for given scenarios. The goal of the tool was not to replace user testing, but to give qualitative insight from quantitative data. For example, Yang et al. (2020) collected user data from mobile applications for measuring user experience (UX) as it can help designers to understand whether the design of the solution needs more iterations.

Our literature review revealed two main gaps. First, extant literature uncovered either the enablers or the inhibitors of ML in organizations, which limits our understating about a more complete perspective of ML, which combines the enablers with the inhibitors. Second, although prior literature investigated the introduction of ML in some organizations such as healthcare, human resource management, finance, and others, little is known about the diffusion of ML in the design process. Specifically, some scholars examined the use of ML in one design phase, thus in isolation without considering the impact of ML across and its interrelatedness among the three design phases. Our research fills this gap by investigating what are the enablers and the inhibitors of ML diffusion in the design process. We adopted diffusion innovation theory to investigate our research question.

2.3. Diffusion of innovation theory

Diffusion of innovation theory has been used in the study of information systems implementation for more than three decades now. The theory posits that there are multiple often competing factors that influence the decision of organizations or their key decision-makers to adopt a novel technological solution (Rogers, 2003). A key point of the theory is that adoption or non-adoption are not entirely based on aspects of the technology, but include elements that pertain to organizational arrangements, the external environment, as well as the socio-technical system in which they are diffused. Furthermore, the structures and the norms of organizations, which encompass the established behaviour patterns for the members of a social system influence the types of operations in which technology is being diffused, as well as the nature of such deployments.

Furthermore, the theory describes how innovations are diffused over time, which follow an S-curve form. Based on this distinction of diffusion over time, the theory identifies five adopter categories are the innovators, early adopters, early majority, late majority, and laggards (Porter et al., 2016). This differentiation into categories of adopters highlights the fact that those that are within the first two categories face different challenges that ones that are laggards. This is due to the fact that while the technology has emerged as a potential solution for some challenges, it is still at an early stage of maturity, which entails a lot of tailoring and fitting the technological innovation to operational requirements. As this is also the case when it comes to ML use in the design process, it deemed as appropriate to use this lens when exploring the enablers and inhibitors of diffusion and through the phases this occurs. Furthermore, unlike most technology adoption models that focus on adoption and non-adoption of a specific technology, diffusion of innovation theory allows a more nuanced understanding of the different phases of diffusion a novel technology undergoes while becoming part of the organizational fabric (Gambatese & Hallowell, 2011).

3. Research methodology

We conducted an exploratory case study in four Norwegian design consultancies and we relied on rich empirical data for generating new insights (Eisenhardt, 1989). Specifically, we focused on idiosyncratic dynamics within each case, such as the interactions between designers and ML to better understand its enablers and inhibitors in the design process. Gioia methodology guided the analysis of semi-structured interviews (Gioia et al., 2013). Our interview questions were inspired by the Technology – Organization – Environment (TOE) framework to identify factors that enable and inhibit the introduction of ML in the design process (Tornatzky et al., 1990).

3.1. Research setting

The selection of cases plays a pivotal role when conducting an exploratory case study approach as this defines the sample population for the interviews and creates the basis for the interpretation of the findings (Eisenhardt, 1989). We focused on the diffusion phase of ML in design consultancies to develop a better understanding of the phenomenon. First, we interviewed key actors from organizations that have not implemented ML into the design process. Then, we interviewed two companies that tried to use ML in their design process but did not implement it. Lastly, we included valuable information from the podcast "Design For AI" by Mark Bailey.[2]

We focused on organizations that operate in the design field and create tailor-made digital 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 addition, we included a podcast that was based in the United Stated. Moreover, to get a broader perspective, we 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, we 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).

3.2. Data collection

We collected semi-structured interviews with several professionals such as designers, CEOs, creative leaders, and developers to gather relevant information about the introduction of ML in the design process. The respondents were contacted via mail and provided with information about our project (e.g., description and purpose of the project, data collection, data storage, and others). Each respondent signed the consent form. At the end of some interviews, we asked the contact of other potential respondents in line with a snowballing approach. We asked questions inspired by the Technology – Organization – Environment (TOE) framework (Tornatzky et al., 1990) to examine different aspects of ML technology in the design field. The framework considers how the technological, organizational, and environmental dimensions influence the process of introducing a new technology such as ML, which guided our data collection process.

The interviews lasted from 46 min to 1 h and 44 min, and the average time was 1 h and 4 min/please see Table 3.2). The interviews were conducted online with Microsoft Teams, they were recorded with video, sound and automatically transcribed. Notes were taken during the interviews to highlight important aspects and write down initial thoughts. In addition, we included in our dataset the episodes 3, 5, 7, and 8 of the podcast "Design for AI[3]".

Table 3.1
Organizations included in this study.

Case	Industry	End users	Digital services	EU size classification[a]
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
Company D	Design Consultancy	Professionals Consumers	Expert tools, complex systems, digital product design	Medium-sized <250

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

3.3. Data analysis

Gioia methodology (2013) guided the data analysis of semi-structured interviews and the conversation in the podcasts "Design for AI". NVivo software helped the organization of the codes and the interpretation of the companies. Open coding played a fundamental role in data analysis and allowed us to let the data tell the story that emerged from the four design consultancies (Gioia et al., 2013). The codes were strictly linked to the terms used by our respondents such as automating repetitive tasks, technologies to improve our joy of creating and others. The process resulted in approximately 300 1st-order codes. Then, the codes were grouped according to TOE framework. Moreover, other categories were included, such as company information (e.g., the type of organization), design process (e.g., which phases were included), ideas for ML tools. This allowed us to write the findings as follows.

4. Findings

In this section, we present the companies, their services, the design process they follow, and their reflections about ML along the three-design process. We conclude with a framework that shows the diffusion of the enablers and the inhibitors of the ML at each process and the interrelationships among them.

Table 3.2
Summary of collected interview data.

Organization	Respondent	Position	Experience	Date, duration of interview
Company A	A1	Web developer (Design background)	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

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

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

4.1. Company A

Company A is a design agency, which offers multiple digital services to both consumers and businesses. For consumers, it creates mostly visual identities, digital products such as websites and can include also the creation of the entire digital presence in the virtual world, which requires the designers to gain more domain knowledge. For businesses, company A creates more complex tools, which are used by professionals in their field (e.g., tools can be used internally by the customer or tools that are used by customer's clients). The company is micro-sized and consists of a CEO, designers, and developers. Each employee owns part of the company, which is an incentive to continuously develop the company, to work with high standards, to be 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

The design process is based on design thinking to ensure high-quality results within a certain budget and unfolds along three main phases. In the *insight phase,* the designers focus on collecting information from their customers, end-users, and the context of use. If the solution will be used by experts, the designers will collect additional information about the jargon and the specific terms to better satisfy the needs and expectations of the end-users. Usually, this phase lasts approximately a month and consists of multiple workshops. The creation of the final solutions requires considerable guesswork with the client. Several customers are medium-sized companies and lack a culture for data collection. The insight phase is challenging as the customers often do not know exactly what they need as respondent A3 explained:

> *"We start digging into why they need the app. For example, when customers ask us to develop an app, in 90% of the time they just need to send push notifications. We explain them this is not a good reason to build an app, there are other solutions for that."*

Qualitative approaches are used for conducting interviews, workshops and for collecting paper-based or digital information. Workshops are particularly useful for identifying core functionalities and for creating the data workflow with a focus on user experience. Whiteboards and sticky notes are widely used to create a shared mental model with the customer from the first meetings. The analysis and the extraction of relevant meaning from the collected information, which is described as a journey, where the process is as important as the result. Therefore, company A collaborates closely with its customers during each phase. To create a more creative and relaxed environment the company created an informal space with a couch, bean bags and removed formal tables where the designers and the customers sit in front of each other. Their aim is to become a team, which fosters creativity and innovative ideas. Weekly or biweekly meetings assure continuous communication even after the insight phase.

In the *prototyping phase,* designers use Figma, a collaborative design tool for creating prototypes. However, Figma lacks some desired functionalities such as the creation of prototypes that automatically respond to different screen sizes. Thus, 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. In addition, company A usually use 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, which resulted into extending the length of the process from five days to around six weeks. During the design sprint, they organise multiple new workshops to identify customers' preferences in the prototype instead of only focusing on pixels and layout. Designers avoid jumping to final conclusions as respondent A2 explained that even if some projects might be similar to prior work they did in the past, they need to adapt it to the clients' specific needs. This requires awareness and good understanding of each customers' preferences in order to personalise the solutions accordingly.

Designers create innovative solutions but at the same time they need to apply industry standards, which might be at odds with creativity. Respondent A3 questioned how creative designers can be and stated that good design is not very subjective, 20 % of good design is the designer's opinion, while 80 % is focused on following industry standards. Moreover, respondent A3 highlighted that designers should think like developers when they create a prototype to consider both the limitations and the possibilities. This also ensures the designers do not promise something they cannot deliver. Thus, the developers in the company are often involved in the design process. However, respondent A2 emphasized that designers should not focus on the limitations from the beginning to ensure the process is creative rather than restrictive. This requires developers to be open minded, even when the proposed ideas seem to be challenging to develop.

Usually, company A is in charge of developing the solutions until the prototyping phase. Sometimes, it continues the design process until the *evaluation phase*, which lasts few weeks to ensure the prototype and developed solution match end-users expectations. Designers and other employees assess all details such as layout, fonts, and colours. Based on clients' requests, the company can also be involved in further development improvements, which include redesigning parts of the solution, changing functionality and others.

4.1.2. Reflections about ML for the design process

Although ML technology can improve the design process and complement other traditional tools, company A did not embrace this opportunity and provided a fine grained explanation of such choice. It experienced several challenges in the preadoption phase. First, the term Machine Learning (ML) was perceived as a buzzword and a "hype" but in reality, they did not know what ML entails. Indeed, the designers highlighted that they did not know enough about the current state of AI and ML in the design industry due to the lack of design communities to share ideas and tools. However, such concerns decreased in the last years. Second, ML works well only when the information is in English or with a clear handwriting. Thus, its implementation might be difficult in countries that speak other languages. Third, the lack of consistency and predictability of the outputs elaborated by ML raises scepticism especially during the prototyping phase (e.g., when ML is used to create components that need to follow specific styles). Therefore, the company preferred to use a component pack made by a well-known designer. Fourth, although several employees believed ML has potential to facilitate and streamline the process, they were concerned with the time necessary to learn how to use this new technology. Therefore, the company did not introduce ML in the design process as it can result in wasting time respondent A1 explained:

> *"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. It might result in wasting time and might create issues because we're such a small firm. If one or two of us will focus on finding new tools, this would reduce our working capacity."*

ML can be particularly useful for automating repetitive and tedious tasks. However, respondent A3 was concerned with the trend that ML would substitute designers for the creation of wireframes:

> *"The designer's role could be completely removed from the wireframe creation. So, if Machine Learning (ML) creates 10 different designs and then tests them, you (designer) can find the best option. Then my responsibility (as designer) 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 will embrace it. For example, respondent A3 perceived ML as a way to help designers follow universally accepted design conventions and to improve prototype responsiveness. ML could be useful for providing suggestions, but the designers remain in control of the design process. Even if most of the employees were sceptical about the introduction of ML in the design process, respondent A2 hoped it will become part of the design process in the future because it has the potential to make the process easier and faster:

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

4.2. Company B

Company B is a micro-sized design consultancy, but it is not a typical consultancy that works in their customers' offices. Instead, most employees sit together in their own office, collaborate with their customers through web meetings or working as semi-in-house designers for technology companies. The company focuses on designing and creating digital products. Their end users are primarily businesses; thus, it creates solutions for the employees or for the customers of such businesses. 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 near future, company B would like to remain a micro-sized company, but it aims to build a design community.

4.2.1. The design process

The company follows the double diamond iterative framework. The designers divide and explore different ideas before converging to few concepts. Then the solution diverges and converges again during the prototyping phase. The design process has evolved from the times when the employees contacted the client, delivered a proposal, and followed a design process, which consisted 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. 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 designers use post-its and whiteboards to structure the information they collect during the meetings and workshops. Sometimes, they use also Miro is also for the presentations, and drawings, and as a whiteboard. However, respondent B2 mentioned the importance of white paper for sketching the idea without any indications of digital tools. The often had regular meetings to define the problem with the entire team, and the 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. 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."

In the *prototyping phase*, company B feels most confident and empowered because of their vast expertise. The process entails multiple iterations to define the details of the prototypes. According to respondent B1, they usually start with the lowest fidelity paper-based prototypes to remove details because digital tools provide multiple details that might influence the perception of the end-users. 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 necessary. 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 behaviour. Therefore, they follow such standards and update their knowledge on this, which requires resources.

In the *evaluation phase*, the company checks if the final solution meets user requirements and delivers 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. Reflections about ML for the design process

Company B created some products with ML functionalities based on customers' requests and the designers had a basic understanding of ML. However, the company has never intentionally used ML in its design process. According to respondent B2, multiple AI-driven automatic page builders have promised a lot but failed to deliver. Also, Bailey found the same inhibitor, in his podcast he stated that multiple ML tools have not delivered what they promised, such as The Grid a website designing tool. This negatively influenced designers reaction to ML. In addition, ML needs high quality data to provide good results, which is challenging when there is less relevant training data for a Norwegian company. In addition, the designers did not trust much the feedback or suggestions provided by a ML. Due to unpredictable results provided by ML, respondent B1 found it scary to leave too much responsibility to ML. Another concern refers to the perception of losing control during the design phase, which is also linked to the responsibility they feel for the end product, as respondent B1 affirmed:

"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 such concerns, the company is willing to use ML and explore new options. However, it is not a topic often discussed among designers. They are more likely to try tools when they don0t need 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 should provide suggestions, but the designers should be able to override ML decisions.

4.3. Company C

Company C is a micro-sized design agency composed only of designers. Different from the other companies, it creates mainly solutions for consumers. The company focuses on digital product design, service design, and visual identities for both the private and public sectors. 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 along the three design phases. In the *insight phase*, the designers collect information from their customers with a qualitative approach to understand the goal, the domain, and the customers' specific needs. Most of their clients are start-ups. The employees do not have the skills or time to collect and analyse user data to provide the designers. In addition, they do not analyse such qualitative data because this is a task outside designers' scope and more appropriate for developers. 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. Thus, the company customizes customer involvement based on their knowledge. The employees avoid using laptops during customer meetings because they limits the connection between the designers and the customers. Moreover, respondent C1 mentioned that designers prefer to avoid digital tools in this phase because they create 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. Such insights are used to pitch an idea, which is based on the information collected from the end-users, the design principles, and best practices. 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 without spending too much money on the wrong functionality.

The next step is a new iteration of the *prototyping phase*, which requires professional examples of the final solution 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 their 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. However, some customers might lack expertise in the field and good imagination. Therefore, they prefer to show 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 to better understand what to improve.

In the *evaluation phase*, it is important to think about how the user test is framed, as this affects the final 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 often is 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.

4.3.2. Reflections about ML for the design process

The introduction of new technologies in organization C is described as a teamwork. 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[4] 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,[5] which uses ML to create palettes of colour 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 colour 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 that could support designers 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. Bailey suggested that future AI tools should not replace designers but instead collaborate with them. One of the challenges the company experienced is a lack of time, and this is the aspect to which ML can mostly contribute. However, if the tool is too complicated, it is often not worth the time to learn, especially for tools solving a very specific problem.

4.4. Company D

Company D is a design consultancy, which creates digital 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, which 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. The company consists of approximately 95 % designers, which means they do not have employees with degrees in product management and sale, but 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.

4.4.1. The design process

The design process of company D is inspired by the double diamond framework and unfolds along the following phases. The *insight phase* traditionally involves post-its and whiteboards to structure the information collected during meetings and workshops with customers, designers, and end-users. Usually, customers don't have a clear idea of the product or service they would like to have. Sometimes the customer asks for an app, but during the first stage of the double diamond, the designers discover the actual needs of the customer. Moreover, designers build empathy during this phase which plays a pivotal role for the entire project, thus they involve 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 six months later with 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, but they also need to develop a good relationship with the client for a closer collaboration as respondent D1 explained:

> *"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."*

When the end-users of the solutions are companies, designers often visit their clients in their own location because it reveals crucial facts about how the users work and what solution they need. For example,

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

company D had a project with fish farming industry to digitize a process that was previously done using a walkie-talkie, pen, and paper. The customer asked to create an app, but when the designers visited the facility, they noticed that employees had to keep one hand on the rail to avoid falling in the water, and the cold weather conditions often required the employees to use gloves. In such working conditions, it would be difficult to use an app. In addition, the designers conducted interviews with several employees such as facility managers, people that feed the fish to better understand end-users' needs. Often time, the clients have large datasets of data, but they don't know how to analyse and use this information, thus company D helps the clients with data analysis in the insight phase.

In the *prototyping phase,* designers create the overall layout and structure of the solution starting with low fidelity prototype which allows 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. 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.

4.4.2. Reflections about ML for the design process

The company believes 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. The company incentivised its employees to update their knowledge by working 80 % of their time on projects for customers and the remaining time they learn new technologies, techniques, trend, and others, as respondent D3 said,

> *"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 the new technology offer. And also, many of our clients are driven by technology, so I think tech is probably more important now than ever."*

Company D used some ML tools as an experimentation, such to generate new icons, to create synthetic human faces, to digitize sticky notes and other text. ML translated the handwritten text into digital text to help designers to summarize the information collected during the workshops. 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 goal of the tool was "*to help people with idea creation, to help people open conversations*".

Respondent D1 questioned whether there is a need for all ML tools today. When introducing ML, there is a need to translate the designer's knowledge into something that ML can understand. Respondent D3 mentioned ML is still a buzzword and it did not deliver what it promised. Respondent D3 explained 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. The uncertainty towards ML is also related to the black box issue as it is not possible to see which kind of data was used to train ML. Respondent D1 explained they, as designers, lack the knowledge of data quality and ML to build and train models themselves. Another challenge related to data quality is the risk of developing a tool based on human biases, 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."*

The company tried relatively simple ML tools to automate some tasks, but not the entire process (e.g., use ML to reduce the number of input fields for the user). In addition, one of the main qualities of future ML is to make quantitative data understandable, which can create valuable predictions and assumptions. However, the way ML is used should be transparent. Respondent D1 also states that prototyping tools should create output in a format that can be imported into multiple tools. For example, SVG gives the designers more freedom and adds flexibility. Respondent D3 believed ML could help with new ideas generation and as an inspiration tool.

5. Enablers and inhibitors of the diffusion of ML in the design process

The objective of our study is to investigate the enablers and the inhibitors of ML in the design process and to present the reflections that emerged during the diffusion phase of ML along the three design phases. In this section, we provide a greater understanding of the inhibitors that limit the introduction of ML in the design field but also the enablers that can improve the creativity and innovativeness of the designers.

The companies included in our study follow three main design phases with a user-centred approach and multiple iterations until designers and the end users are satisfied with the solutions created. The three phases do not occur sequentially but based on the user satisfaction and the iterations done to define specific aspects of the final solution. The designers start with the insight phase to collect the information necessary to generate innovative and functional ideas, then they can proceed with the prototyping phase to provide a graphical representation of the proposed solution proposed or they can go directly to the evaluation phase. In the evaluation phase, the designers assess the final solution and check if proposed solution matches the standards and the preferences of the end-users. Multiple iterations occur between insight, prototyping and evaluation phases until relevant details are defined (please see Fig. 1). Several technologies are used during these design phases such as Figma, Adobe XD, Google Design Sprint among others. Recently, ML started to attract more and more attention in the design industry however none of the companies introduced it in their design process. We identified several inhibitors and enablers of ML in the diffusion phase for the three design phases as follows.

In the *insight phase*, the companies collect qualitative information through interviews, workshops, and visits in the place where the requested solution will be used. This is particularly important for idea generation and customization of the solution. The way information is collected and analysed plays a pivotal role as it delineates a potential idea for the solution, however designers face several limitations with the use of the current digital tools. For example, they take notes on whiteboards, use sticky notes, make some initial drawings to make sense of the domain knowledge. Then, then they take pictures of the whiteboard multiple times as the board fills up. Next, designers analyse this information and continue with idea generation. These tasks are tedious and time consuming, which could be performed by ML. For example, ML could be useful for transcribing the interviews, or other registrations, for transcribing handwritten annotations from the sticky notes into digital text, or for summarizing other text information to help designers better understand the domain. In addition, ML could be useful for data analysis by creating groups of similar notes and for new patterns identification. Some ML tools available to perform these tasks, however they can be used mainly in English with satisfactory results as they have not been trained also in other languages. In addition, the lack of knowledge about

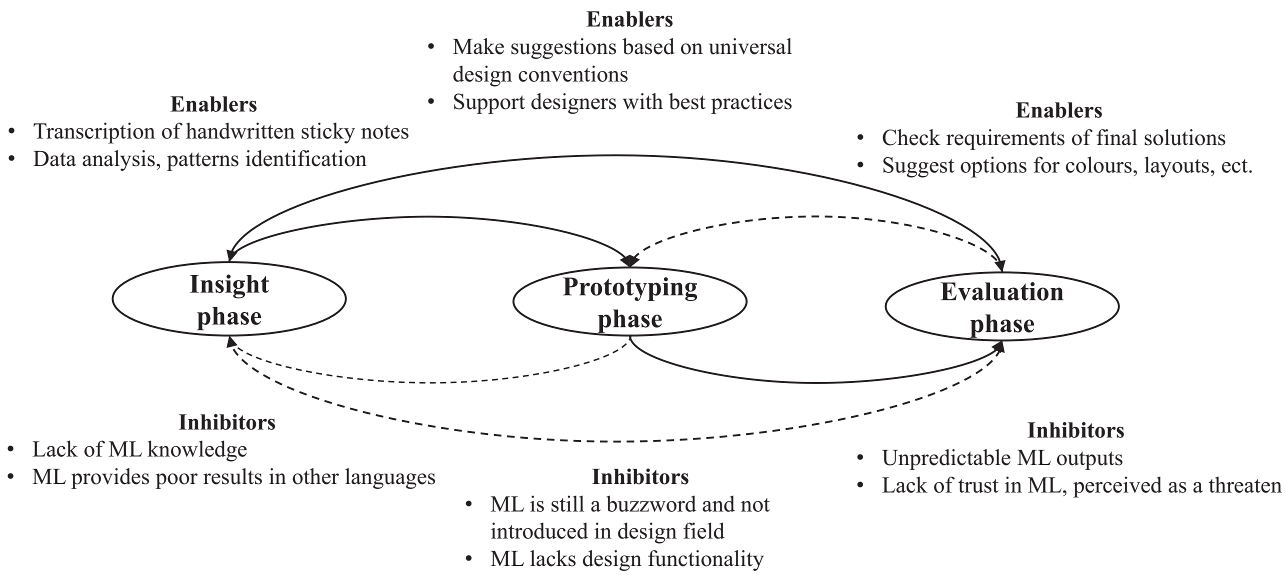

Fig. 1. Enablers and inhibitors of Machine Learning (ML) in the design process. Arrows with full lines represent the first iteration: ⟶. Arrows with dotted lines represent the multiple iterations among the three phases: ⇢.

ML for the design community inhibits the introduction of ML in the design process as designers have limited or no knowledge about how ML works and how it can contribute to their work. Lastly, several designers felt threatened by ML tools as they do not understand this new technology, thus they feel insecure, and are afraid of being substituted and losing their job.

In the *prototyping phase*, designers make a graphical representation of the ideas generated in the insight phase. They create samples of potential solutions in line with universal design conventions, specific rules, and best practices. ML would be useful for creating dynamic prototypes, for exploring different options for each solution, and for making suggestions based on universal design conventions. The application of best practices and universal design conventions is pretty challenging especially when designers make changes to some parts of the prototype. Thus, ML could help designers to create more responsive prototypes without the need of redesigning the different screen sizes. Thus, ML could help designers with the creation of easy and responsive solutions for mobile and desktop by providing suggestions for any other desired size, based on which the designer can customise the solution. Next, ML could be used to generate designs based on rules, specific characteristics inputted by the designers and best practices. Indeed, designers spend considerable time for the research of best practices. This task could be automated by ML, the designers could define the desired characteristics in the tool, and ML could provide several suggestions for design options. In other cases, ML could support designers with automatic notifications when designers change the style of a component, and it actually does not fit in with the rest of the prototype. Moreover, ML could support the transition between physical and digital designs by playing the role of a fictitious end-user. Lastly, ML could be used for matching new components with what is already designed, for improving the navigation in the solution with automatic suggestions for new placements and styles for the navigation components. The different options for navigation could be presented to the designer, such as suggest the switch from a hamburger menu to a menu bar. However, ML is not yet introduced in the design field, indeed it is perceived a buzzword, which did not deliver what it promised to deliver and most of the desired functionality mentioned above are not inscribed in the ML tools.

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 colours slightly different. ML could notify 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. Customers sometimes do not understand that it is important to negotiate developers' and designers' standards and requirements. However, sometimes developers had different opinions on some parts of the solution created compared to designers. Often, developers create their own interpretation of the design and overlook details in the design prototypes. To make this process easier, ML could be used for matching the design with the implemented version, ML could analyse the two solutions, identify their components, and suggest what should be changed to match all requirements. Then, ML could be useful for accessing more complex user patterns based on the operating system. For example, ML could check if Android users signed up to a newsletter more or less 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, colours, and other differences. In other situations, the employees might forget to check that every detail is properly designed. ML could assist designers by checking all requirements, including spell checking and layout. However, several designers were concerned with losing control in the evaluation phase and more in general in the design process if ML will be implemented (Mikalef et al., 2022). 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. Several designers highlighted the importance of transparency of ML because for now it is perceived as a black box tool. 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.

6. Discussion

Our article provides a deeper understanding of what designers think about the diffusion of ML in the design process and discusses the enablers and inhibitors experienced in three main phases that are insight, prototyping, and evaluation. Semi structured interviews were collected in line with Eisenhardt's (1989) guidelines for the research setting and data collection. We analysed four Norwegian design consultancies by following Gioia methodology (2013). We interpreted the rich data from Norwegian designers, developers, and leaders working in the design industry, and we uncovered the key phases designers follow and which technologies are involved in the design process. Conducting a qualitative study has provided a rich insight into the creative industries. Our study contributes to the discourse on AI literature (Collins et al., 2021).

We identified that the diffusion of ML in the design process is still in an early stage, and often times the tools available today do not meet user needs. Although a link between technological knowledge and the willingness to embrace new ML tools emerged, 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 diffusion 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 this technology. This is especially true for tools that can assist the designers and allow for control when working.

6.1. Theoretical implications

Our findings contribute to the literature about Artificial Intelligence (AI) in information systems Collins et al., 2021; Mikalef and Gupta, 2021) and in the design research (Verganti et al., 2020). While several scholars investigated the adoption or the post-adoption phase of AI in organizations and in design research, less is known about the diffusion phase of this new technology. Indeed, AI has great potential to improve the performance of organizations or of workers, but at the same time its application in real cases is still very limited. We contribute to this research by presenting the reflections and the desires of both designers and developers related to AI. Moreover, we present not only the desired features or functionality of AI necessary in the design field, but we also discuss the inhibitors that are limiting the introduction of AI in the design consultancy. Such reflections are fundamental for better understanding the hindrance that restrict the use of advanced technologies. In line with Berente et al. (2021) and Glikson and 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.

Extant literature investigated the design process by focusing on some phases in isolation, limiting current knowledge about how the three main design phases interact with each other and use advanced technologies to accomplish their tasks. Our research contributes to this stream of studies by providing a more complete perspective of the design process along the three design phases, which are insight, prototyping and evaluation and by reflecting on the enablers and the inhibitors of each phase. Previous studies suggested that designers should focus on sense-making and understanding what problems should be addressed, working as problem setters (Verganti et al., 2020). 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. Our study found that ML should be introduced as an assistant to designers' work, thus the future of AI is more related to human-AI hybrid collaboration. Designers continue to lead the design process and rely on ML tools to automate some tasks and to provide some suggestions. Therefore, ML should be used to complement the designer instead of replacing them by simulating human behaviour and acting as the designers' "best friend".

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. We 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, we found that ML tools still have the potential to aid this part of the process such as tools for automating tedious tasks like transcribing notes, gaining domain knowledge, and 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 favourable 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 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.

7. Limitations and future research

Our study has some limitations that can lead to future studies. First, we included companies located in Norway to limit cultural differences among companies we interviewed. However, design consultancies located in other countries might experience difference enablers and inhibitors in the diffusion phase of ML. Therefore, future studies might investigate similar studies in other countries to consider and include also other cultural differences and identify other findings. Second, we conducted an exploratory case study with semi-structured interviews to investigate the enablers and the inhibitors of ML in the design research. However, more sources of data might further enrich our understating of this emerging phenomenon. For example, observation of the way design work along the three phases. Third, we interviewed mainly designers and developers with different backgrounds. Therefore, this influenced the focus on the design field along the three design phases. 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 technologies. Future studies might consider interviewing also professionals with other backgrounds and expertise that work in design consultancies. Forth, we included only ten participants from four companies. 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. Future research might consider conducting more interviews from larger companies to analyse the diffusion phase of ML in design companies. Lastly, none of the companies included in this study used ML tools for every design process, thus future scholars might involve companies that have already introduced ML in their design process.

CRediT authorship contribution statement

Cristina Trocin: Conceptualization, Data curation, Formal analysis, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Åsne Stige:** Conceptualization, Data curation, Formal analysis, Software, Writing – original draft. **Patrick Mikalef:** Conceptualization, Supervision, Resources, Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

References

Anthony, C., 2021. When knowledge work and analytical technologies collide: The practices and consequences of black boxing algorithmic technologies. Adm. Sci. Q. 66 (4), 1173–1212.

Bedingfield, W., 2023. Musicians, Machines, and the AI-Powered Future of Sound. Wired UK. https://www.wired.co.uk/article/generative-ai-music.

Berente, N., Gu, B., Recker, J., Santhanam, R., 2021. Managing artificial intelligence. MIS Q. 45, 1433–1450. https://doi.org/10.25300/MISQ/2021/16274.

Brown, T., 2008. Design thinking. Harv. Bus. Rev. 10.

Brown, T., Katz, B., 2011. Change by design. J. Prod. Innov. Manag. 28 (3), 381–383. https://doi.org/10.1111/j.1540-5885.2011.00806.x.

Chatterjee, S., Mikalef, P., Khorana, S., Kizgin, H., 2022. Assessing the implementation of AI integrated CRM system for B2C relationship management: integrating contingency theory and dynamic capability view theory. Inf. Syst. Front. https://doi.org/10.1007/s10796-022-10261-w.

Collins, C., Dennehy, D., Conboy, K., Mikalef, P., 2021. Artificial intelligence in information systems research: a systematic literature review and research agenda. Int. J. Inf. Manag. 60, 102383. Elsevier.

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. In: 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), pp. 28–33. https://doi.org/10.1109/ICAIS50930.2021.9395994.

Davenport, T.H., Keith, J.D.D.O., 2018. AI will change radiology, but it won't replace radiologists. Harv. Bus. Rev. 27 (https://hbr.org/2018/03/ai-will-change-radiology-but-it-wont-replace-radiologists).

Davenport, T.H., Mittal, N., 2022. How generative AI is changing creative work. Harv. Bus. Rev. (https://hbr.org/2022/11/how-generative-ai-is-changing-creative-work).

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 (accessed March 24, 2022).

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

Eisenhardt, K.M., 1989. Building theories from case study research. Acad. Manag. Rev. 14 (4), 532–550.

Gambatese, J.A., Hallowell, M., 2011. Enabling and measuring innovation in the construction industry. Constr. Manag. Econ. 29 (6), 553–567.

Ginsberg, B., 2023. Artificial Intelligence in Fashion. Forbes (https://www.forbes.com/sites/theyec/2023/02/21/artificial-intelligence-in-fashion/).

Gioia, D.A., Corley, K.G., Hamilton, A.L., 2013. Seeking qualitative rigor in inductive research: notes on the Gioia methodology. Organ. Res. 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. Acad. Manag. Ann. 14 (2), 627–660. https://doi.org/10.5465/annals.2018.0057.

Grierson, J., 2023. Photographer Admits Prize-Winning Image Was AI-Generated. The Guardian (https://www.theguardian.com/technology/2023/apr/17/photographer-admits-prize-winning-image-was-ai-generated).

Hsu, T., Myers, S.L., 2023. Can We No Longer Believe Anything We See? The New York Times (https://www.nytimes.com/2023/04/08/business/media/ai-generated-images.html).

Koch, J., 2017. Design implications for designing with a collaborative AI. In: The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems. Association for the Advancement of Artificial Intelligence.

Lebovitz, S., Levina, N., Lifshitz-Assaf, H., 2021. Is AI ground truth really 'true'? The dangers of training and evaluating AI tools based on experts' know-what. Manag. Inf. Syst. Q. 45 (3b), 1501–1525.

Martin, K., 2019. Ethical implications and accountability of algorithms. J. Bus. 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/10.1016/j.im.2021.103434.

Mikalef, P., Conboy, K., Lundström, J.E., Popovič, A., 2022. Thinking responsibly about responsible AI and 'the dark side' of AI. Eur. J. Inf. Syst. 31 (3), 257–268.

Mustonen-Ollila, E., Lyytinen, K., 2003. Why organizations adopt information system process innovations: a longitudinal study using Diffusion of Innovation theory. Inf. Syst. J. 13 (3), 275–297.

Nguyen, T.A., Csallner, C., 2015. Reverse engineering mobile application user interfaces with REMAUI (T). In: 2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, Lincoln, NE, USA, pp. 248–259. https://doi.org/10.1109/ASE.2015.32.

O'Donovan, P., Agarwala, A., Hertzmann, A., 2015. DesignScape: Design with Interactive Layout Suggestions, CHI'15. Association for Computing Machinery, New York, NY, USA, pp. 1221–1224. https://doi.org/10.1145/2702123.2702149.

Padmanabhan, B., Fang, X., Sahoo, N., Burton-Jones, A., 2022. Machine learning in information systems research. MIS Q. 46 (1), 17.

Pandian, V.P.S., Suleri, S., 2020. BlackBox Toolkit: Intelligent Assistance to UI Design arXiv preprint arXiv:2004.01949.

Porter, W.W., Graham, C.R., Bodily, R.G., Sandberg, D.S., 2016. A qualitative analysis of institutional drivers and barriers to blended learning adoption in higher education. Internet High. Educ. 28, 17–27.

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

Rogers, E., 2003. Diffusion of Innovations, 5th Edition. Simon and Schuster, NY.

Rowe, L., 2023. RadioGPT: Should You Be Worried About AI Radio Hosts? *Radio.Co*. https://radio.co/blog/ai-radio-hosts (accessed May 8, 2023).

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. In: *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, CHIIR'19. Association for Computing Machinery, New York, NY, USA, pp. 225–229. https://doi.org/10.1145/3295750.3298942.

Shaikh, M., Vaast, E., 2022. Algorithmic interactions in open source work. In: Information Systems Research. INFORMS.

Smith, D., 2023. 'Of Course It's Disturbing': Will AI Change Hollywood Forever? The Guardian (https://www.theguardian.com/film/2023/mar/23/ai-change-hollywood-film-industry-concern).

Strich, F., Mayer, A.-S., and 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," J. Assoc. Inf. Syst. (22:2). (doi:10.17705/1jais.00663).

Suleri, S., Sermuga Pandian, V.P., Shishkovets, S., Jarke, M., 2019. Eve: A sketch-based software prototyping workbench. In: *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI EA'19. Association for Computing Machinery, New York, NY, USA, pp. 1–6. https://doi.org/10.1145/3290607.3312994.

Swearngin, A., Li, Y., 2019. Modeling mobile interface tappability using crowdsourcing and deep learning. In: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI'19. Association for Computing Machinery, New York, NY, USA, pp. 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, Lexington, Mass.

Trocin, C., Hovland, I.V., Mikalef, P., Dremel, C., 2021. How artificial intelligence affords digital innovation: a cross-case analysis of Scandinavian companies. Technol. Forecast. Soc. Chang. 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. Acad. Manag. Perspect. 35 (4), 642–659. https://doi.org/10.5465/amp.2019.0062.

Vaast, E., 2022. Future Imperfect: How AI Developers Imagine the Future, p. 18.

Verganti, R., Vendraminelli, L., Iansiti, M., 2020. Innovation and design in the age of artificial intelligence. J. Prod. Innov. Manag. 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: Degen, H., Reinerman-Jones, L. (Eds.), Artificial Intelligence in HCI, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 146–166. https://doi.org/10.1007/978-3-030-50334-5_10.

Watkins, S., 2023. The Impact of AI on the Graphic Design Industry. DevStars. February 4. https://www.devstars.com/blog/the-impact-of-artificial-intelligence-on-graphic-design-industry/ (accessed May 8, 2023).

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.

Yang, Q., 2017. The Role of Design in Creating Machine-Learning-Enhanced User Experience. Association for the Advancement of Artificial Intelligence (https://www.aaai.org/ocs/index.php/SSS/SSS17/paper/view/15363).

Yang, B., Wei, L., Pu, Z., 2020. Measuring and improving user experience through artificial intelligence aided design. Front. Psychol. 11, 3000.

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. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. Association for Computing Machinery, New York, NY, USA, pp. 3346–3355. https://doi.org/10.1145/3394486.3403387.

Cristina Trocin: Cristina Trocin is doing research at the intersection of technology, organisations, and digital innovation. Currently, her research projects include the development of Artificial Intelligence (AI) technology in healthcare organisations, Human Resource Management (HRM) and how this is generating disruptions into organisations. Cristina spent her post-doc at the Norwegian University of Science and Technology (NTNU) and received the PhD in Management with a focus on Information Systems in healthcare from Ca' Foscari University of Venice, Italy. Cristina presented her work in the

leading conferences such as International Conference on Information Systems (ICIS), Academy of Management (AoM), the European Group for Organizational Studies (EGOS), International Research Meeting in Business and Management (IRMBM). Her work was published in journals such as Technological Forecasting and Social Change, Information Systems Frontiers, and books such as Impacts of Information Technology on Patient Care and Empowerment IGI Global, and Digital Transformation in Norwegian Enterprises.

Asne Stige: Asne holds a masters and bachelor's degree in computer science from the Norwegian University of Science and Technology (NTNU). Her research interests focus on the use of AI in the design process.

Patrick Mikalef: Patrick Mikalef is a Professor in Data Science and Information Systems at the Department of Computer Science of NTNU, and a senior research scientist in SINTEF Digital. In the past, he has been a Marie Skłodowska-Curie post-doctoral research fellow working on the research project "Competitive Advantage for the Data-driven Enterprise" (CADENT). He received his B.Sc. in Informatics from the Ionian University, his M.Sc. in Business Informatics for Utrecht University, and his Ph.D. in IT Strategy from the Ionian University. His research interests focus the on strategic use of information systems and IT-business value in turbulent environments. He has published work in international conferences and peer-reviewed journals including the Journal of Business Research, British Journal of Management, Information and Management, Industrial Management & Data Systems, and Information Systems and e-Business Management.