# User Experience Design meets Machine Learning

## Interdisciplinary collaboration in a human-centered design process

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Milena Suter

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First Supervisor: Dr. Marcel B.F. Uhr
Second Supervisor: Hans Kaspar Hugentobler

# MILENA SUTER | WRITTEN THESIS

# ABSTRACT

This project aims to give an understanding of the problems and challenges of interdisciplinary collaborations between user experience (UX) designers and machine learning (ML) engineers during a project process. Research showed that in recent years, the application of ML technology has become part of everyday life. This widely used technology has been applied to a variety of business problems, such as web search, online advertising, product recommendations, and object recognition. Used correctly, these applications offer numerous benefits for companies and users. For companies to take full advantage of ML, UX designers and ML engineers must collaborate.

Thus, the research questions aim to discover what would be required to facilitate an interdisciplinary collaboration between UX designers and ML engineers during a project process and to reveal the added value. Furthermore, this study investigates the influence of a standardized HCD process model in an interdisciplinary collaboration. In this academic work, a survey is conducted to find out the current state of knowledge of UX designers and ML engineers in practice including biases and existing work processes. Additionally, expert interviews with UX designers and ML engineers are conducted.

Five key factors are identified from the literature review, the survey and the expert interviews: Basic knowledge and understanding towards the other expert area, sufficient and qualitative communication, alignment of different methods, functioning group dynamics, and a standardized HCD project model. Based on the findings the written thesis develops guidelines on how the collaboration between UX designers and ML engineers during a project process can be improved. The HCD process model is used to promote an interdisciplinary collaboration between UX designers and ML engineers, guaranteeing the production of a product with an enhanced user experience.

Keywords: machine learning, user experience, interdisciplinary collaboration, human-centered design process, design material

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# AFFIDAVIT

I hereby solemnly declare that I have independently prepared this final-year thesis.

Ideas directly or indirectly taken from outside sources are indicated as such.

The work has not previously been presented to another examination authority nor otherwise published either in the same or in similar form.

DATE: Zug, 31.01.2022

SIGNATURE MILENA SUTER:

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| **A I** | Artificial intelligence |
| **HCD** | Human-centered design |
| **HCI** | Human-computer interaction |
| **ML** | Machine learning |
| **UCD** | User-centered design |
| **UI** | User interface |
| **UX** | User experience |

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# INTRODUCTION

# 01

# 1. INTRODUCTION

Any product is considered good if it solves the problem it is designed to address. However, what separates the best solution from others is how the user feels about the proposed solution. How the user feels about a product can be referred to as user experience (UX). Hence, UX is a key factor for any business (Sumaiya, 2018).
The transformation of various companies to an “experience economy” made UX a priority design goal. To stand out from the competition and gain a competitive advantage, they changed their priorities from merely providing efficient production and distribution to creating a memorable UX (Chromik et al., 2020).
To ensure a positive UX, the experience must be adapted to the user and their behavior. This process requires data collection on user behavior. In the digital, globally connected world, users span a wide range of geographical regions and user needs, which means that users from different time zones can be potential customers of the same company. The user scenario changes continuously, so to generate the greatest added value from the data collected, a framework is needed to adapt to the constantly changing user scenario (Sumaiya, 2018). This is where ML comes into play because ML methods and technology have become part of daily life. To personalized music playlists by recognizing friends in a user’s photos from automatic recommendations on movies, food, or various other products, many modern websites like Facebook, Amazon, and Netflix contain ML algorithms at their cores (Andreas C. Müller & Sarah Guido, 2017). While a user is using such a product, all activities are recorded in the background. Next, the data collected from this process is added to a machine learning algorithm. The algorithm recognizes patterns, thus helping developers notice any unusual behavior to initiate appropriate actions based on this data (Sumaiya, 2018).

To guarantee a good digital product with high UX, it is important that ML engineers and UX designers collaborate. Teams of professionals from different expert fields who share diverse approaches can promote a deeper understanding of the project topic at hand. Interdisciplinary collaboration encourages ideas to be developed that a team of experts would not be able to develop alone (Aboelela et al., 2007).

## 1.1. PROBLEM CONTEXT

Although interdisciplinary teams are related to stronger problem solving abilities or innovations, they can also cause negative effects on group cohesion and team performance, such as conflicts and high financial costs (Jehn et al., 1999). The known problem areas in such endeavors can be divided into five categories: communication difficulties, methodological problems, difficulties in mutually defining project goals, prejudices and false expectations, and group dynamic problems (Aboelela et al., 2007).

The issue map below provides an overview of these five problem areas of nonfunctional interdisciplinary collaboration, its issues, and its possible causes:

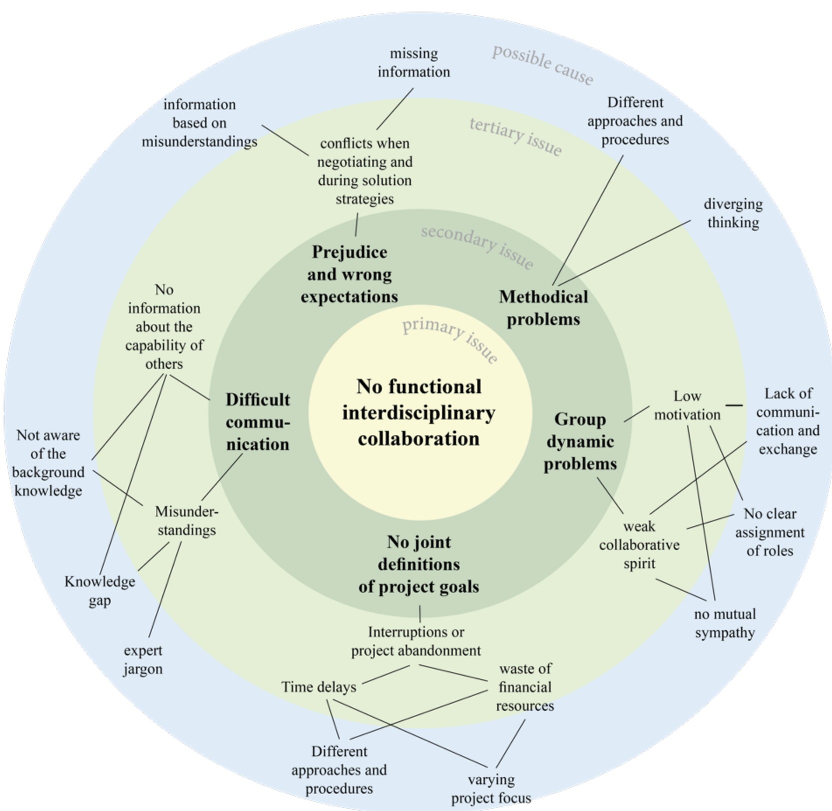



Figure 1: Issue map on the subject of interdisciplinary collaboration, in accordance with Aboelela et al., (2007)

Communication difficulties occur when the use of expressions or certain technical terms lead to misunderstandings. Even though some words are the same, their meanings may differ across disciplines. Although it may be clear to experts that a certain term often stands for a whole concept, a specific assumption, a history, and further information, the same information might not be clear to nonexperts. Additionally, experts may not be fully aware of the knowledge differences between specialists on the same project team. As a result, communication among these experts can become more difficult to the point that some facts and beliefs are challenging to explain. One of the primary causes of conflict in interdisciplinary collaboration is the changing focus due to differing interests and thinking styles (Brandstädter & Sonntag, 2016). Project goals that are incomplete or not mutually elaborated can lead to unnecessary interruptions or even to project abandonment. In turn, this issue can lead to unnecessary delays, ultimately requiring more financial resources than originally calculated. In addition, an interdisciplinary collaboration may fail due to group dynamic problems. If there is a lack of communication and exchange, the team's motivation might be low. Furthermore, these problems can be intensified when experts in the field of study are prejudiced toward those in different fields. Finally, false expectations based on misunderstandings, missing information, and biases can lead to conflicts in negotiations and strategizing.

These cautions also apply to the interdisciplinary collaboration between UX designers and ML engineers. That is, ML is used to exploit user behavior and contextual data to make accurate recommendations, filter out spam, predict traveling times, and log behaviors such as sleeping or walking (Sumaiya, 2018).

ML indirectly benefits users through improved UX. Through ML, UX researcher can more effectively identify and validate user needs (Chromik et al., 2020).

To make ML more useful and user friendly, UX designers are needed to bring a human-centric approach to ML methodologies. Algorithms should be developed to consider human goals, contexts, ethical problems, and work styles (Gillies et al., 2016). Through the UX design approach, UX designers have great potential to identify new ML opportunities. These designers dispose practical experience and work in close collaboration with different audiences, enabling designers to apply diverse ML algorithms to different contexts (Sumaiya, 2018).

However, even though UX designers have great potential and the necessary experience, they have been slow to leverage this increasingly prevalent technology.

For instance, ML is not yet a standard part of UX design practice, either in design patterns, prototyping tools, or education (Yang, 2018).
It is already apparent from many sources that ML will be the primary way to improve the UX and will thus strongly influence the work of a designer in the future (Yang, 2017).
However, if UX designers fail to recognize the potential of ML, it will be impossible for them to create a digital product that meets current users' needs.

The following figure summarizes the area of friction in this project context that leads to various challenges and problems for the people involved:

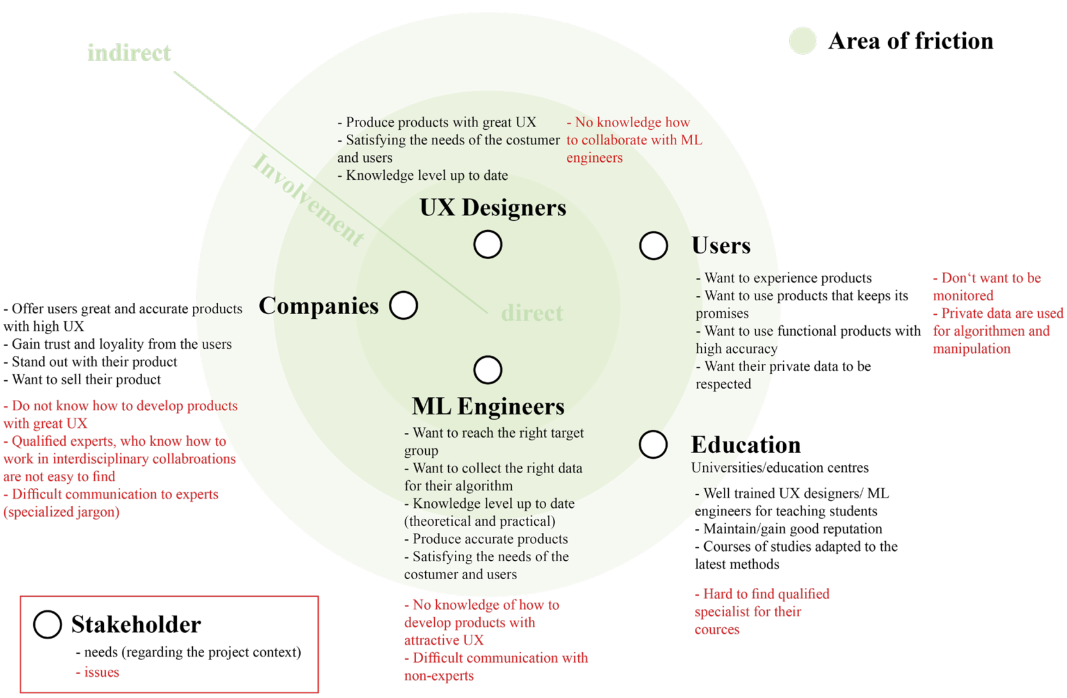



Figure 2: Issue Map, an overview of the parties involved, challenges, and problems related to the area of friction, Suter (2021)

As can be seen from the graphic, UX designers and ML engineers have different expectations of the respective product. UX designers are fully focused on the user and their desires during the development of a product. The goal is to develop a tailored UX that satisfies the needs of the target group. In contrast, ML engineers deal exclusively with the technical factors of the product. Their focus is on the available data sets and how to use them to develop algorithms that can execute the predefined application as accurately as possible (Yang, 2017). No or little knowledge about the other expert's field represents another conflict for a functioning interdisciplinary collaboration.

Since most companies do not have the knowledge internally on how to develop a product with a successful UX, they seek external help from experts to develop their desired products. For a company's product to stand out from the competition and to gain trust as well as the loyalty from users, qualified experts from various research fields are essential. However, only if the experts in the project team know how to work together during the project process the full benefit can be derived from all parties involved and a product with successful UX can be developed. The key factor that determines the success of a product is that it needs to meet the expectations of the users. This requires that the users' data be handled in a trustworthy and ethical manner.

To remain attractive in the job market, it is important for UX designers and ML engineers to keep their knowledge up to date. This includes knowledge of the latest theoretical and practical application models. This requires that UX designers and ML engineers at universities learn how to collaborate with experts from other disciplines over the course of a projects in an interdisciplinary manner and apply the established process models.

To answer the research question, it is first necessary to examine the general problems and challenges of interdisciplinary collaboration.

## 1.2. RESEARCH QUESTION

Since UX has become the focus of businesses, ML has become inevitable. Specifically, with the increasingly pervasive and powerful technology of ML, companies have attempted to create advantages for themselves by implementing this technology in their products and services. Many popular mobile apps already regularly exploit user behavior and contextual data to provide personalized recommendations and thus ensure a more accurate user experience (Yang, 2017).
To develop a digital product with great value to the user, UX designers and ML engineers must work together. However, collaborations involving multiple disciplines often pose challenges. For instance, team members may differ in their academic and professional backgrounds, leading to communicational, cultural, or methodical challenges (Brandstädter & Sonntag, 2016).
On closer inspection, UX designers have been lagging in leveraging this increasing common technology. Various practice-oriented design patterns and academic UI/UX literatures rarely address how to gather the information needed for ML and design possible adaptations. Too few resources are provided in many UX educational programs for tomorrow's UX designers to develop a basic understanding of ML. This lack refers not only to the understanding of technical knowledge but also to the practical thinking required for better collaborations between UX designers and ML engineers (Marcus, 2015).
Another missing component in UX designer and ML engineer education is how to collaborate on interdisciplinary teams. To optimize the UX with ML, there must be a mutual understanding of the subject matter. This is the only way to build bridges between professionals in these areas to promote a functional interdisciplinary collaboration. When these two fields cooperate, design goals become the foundation for ML, and its methods can be applied to solve UX problems (Yang, 2017).
This idea leads to the following research question, the core of this project:

**What are the success factors for a functional interdisciplinary collaboration between UX designers and ML engineers in digital projects?**

This question necessitates the following sub-questions:

- Why does a functional interdisciplinary collaboration between UX designers and ML engineers lead to a digital product with greater value to the user and therefore to an enhanced UX?
- How does an interdisciplinary, human-centered design process encourage better collaboration between UX designers and ML engineers?

# SECONDARY RESEARCH: INSIGHTS FROM THEORY AND PRACTICE

# #02

# 2. SECONDARY RESEARCH: INSIGHTS FROM THEORY AND PRACTICE

This chapter provides a clear view of the current state of the art of interdisciplinary collaboration between UX designers and ML engineers in theory and practice. The goal of the literature research is to gain a deeper insight into the defined research area. On one hand, the purpose is to find out how the collaboration between UX designers and ML engineers in a project works in practice and whether there are methods for a functioning interdisciplinary collaboration. On the other hand, possible theoretical approaches from research are investigated in more detail.

For the research questions to be answered and for the sake of comprehensibility, the following categories are considered in detail: Theoretical context of the research area, interdisciplinary collaboration in general, deeper insight into collaboration between UX designers and ML engineers, and what project processes already exist that promote interdisciplinary collaboration between UX designers and ML engineers. For the reasons mentioned, each subchapter is dedicated to one of the predefined topics and provides an overview of its theory and practice. At the end of this chapter, the interim results of the secondary research are presented.

## 2.1. THEORETICAL CONTEXT

This research project addresses the following areas, which occur in the theoretical context of interdisciplinary collaboration. First, some core terms and their meanings are defined to promote general understanding.

### INTERDISCIPLINARY COLLABORATION

Interdisciplinary collaboration involves a group of specialized experts from disparate disciplines working on a problem together, studying the issue and sharing their findings (Bruhn, 2000). The National Academy of Science defines interdisciplinary collaboration as follows:

> ". . . a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or field of research practice . . ." (National Academiy of Sciences, Nactional Academy of Engineering and Institute of Medicine of the National Academies, 2005).

### USER EXPERIENCE

Countless definitions for UX exist, so this written thesis employs the explanation most appropriate for this research. This definition comes from Don Norman, founder of the Nielsen Norman Group:

> "For the UX to be successful, the customer's needs must be met. However, true UX goes far beyond giving customers what they want in each case. To achieve a high-quality UX, the services of different disciplines, such as technology, marketing, graphic and industrial design, and interface design, must flow seamlessly together" (Don Norman & Jakob Nielson, 2021).



The fact that the definition of UX is not uniform is shown by the 2nd edition of the User Experience Careers Report by the Nielsen Norman Group. The report is based on several research studies and responses from over 700 UX professionals. In this edition, a slight decrease from the first edition in job titles was noticeable. That is, there were 210 different job titles in 2013 but only 134 by 2019. These findings demonstrate that no agreement has been reached on job titles (Rosala & Krause, 2019). Thus, whenever UX designers are mentioned in this research project, all 134 job titles related to UX are included.

### MACHINE LEARNING

ML is subcategory of artificial intelligence (AI). This field focuses on developing algorithms that learn from collected data and improve their accuracy over time without being constantly programmed to do so. To find patterns and features among vast quantities of data and make decisions and predictions based on new data, ML uses “trained” algorithms. The better the algorithm is and the more data it processes, the more accurate the decisions and predictions become. Thus, the experience for the user has been improving (IBM Cloud Education, 2020).

## 2.2. COLLABORATION IN THE DIGITAL AGE

This subchapter presents the relevance of interdisciplinary collaboration and what needs must be considered for such work to be successful.

There are typically many different parties involved when a company wants to develop a new digital product. Usually, the largest challenge in such projects is not the technology but the people, namely the interdisciplinary collaboration of the team members inside and outside the organization. This statement was confirmed 2012 by a survey from Zumstein and Meier. These researchers found that interdisciplinary collaboration was ranked as more challenging than data protection, data integration, lack of resources, and data quality (Meier & Zumstein, 2012). Although interdisciplinary collaboration is already challenging, its level of difficulty continues to increase due to technological developments. According to Portmann (2017), such growth also increases the versatility and complexity of interdisciplinary collaboration in the digital age.

Furthermore, the National Institute of Health (NIH) made interdisciplinarity an explicit priority over a decade ago. This organization involves scientists from a variety of disciplines in diverse research efforts. Additionally, NIH sees the integration of two or more often disparate scientific disciplines as a strength in solving problems. By working together across disciplines, such scientists can overcome traditional gaps in terminology and methodology. Only when these obstacles are mastered can collaboration successfully solve problems (Aboelela et al., 2007).



According to researchers Kahn and Mentzer, a combination of the following factors is needed to ensure successful interdisciplinary or cross-functional collaboration (K. B. Kahn, 1996; K. B. Kahn & Mentzer, 1998):

### 1. EXCHANGE OF INFORMATION

This component focuses on the exchange of information between two independent departments. This endeavor ensures that the departments consult with each other, coordinating planned procedures, project plans, and expected results (Kahn, 1996; Kahn & Mentzer, 1998). For the exchange of information, frequency is a key component of effective collaboration. As soon as the involved areas are easily accessible for an exchange of information, regular communication is guaranteed. In this exchange of information, a distinction is made between formal and informal communication. For instance, written communication is a method of formal exchange, whereas oral and spontaneous communication are forms of informal exchange. Furthermore, quality (accuracy, punctuality, explicitness) represents another important aspect in the information exchange (Gerster, 2018).

### 2. COLLABORATION

There are no explicit prompts or rules for collaboration. What is important is that the departments involved drive the collaboration themselves. Typical success factors for this type of collaboration include sharing of resources, common goals, commitment, mutual appreciation, a good working atmosphere, trustworthy relationships, mutual understanding, a certain degree of involvement of the department in typical tasks of the other departments, reliability, and team spirit (Kahn, 1996; Kahn & Mentzer, 1998). Although no systematic or consistent combination of the sub-aspects of the two components can be identified, this combined approach has gained acceptance in research measuring interdisciplinary collaboration. A project leader can more easily influence behavior by setting appropriate rules and goals, so many researchers focus mainly on the following aspects when conceptualizing (Gerster, 2018):

- sharing of resources,
- degree of involvement of the department in typical tasks of the other department, and
- existence of common goals and visions.

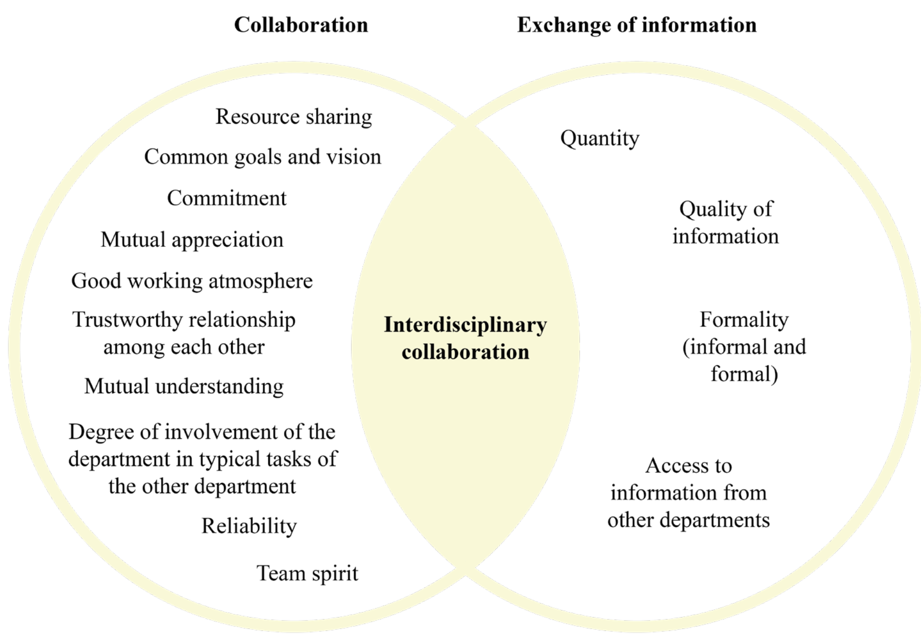



Figure 3: Dimensions of interdisciplinary collaboration, in accordance with Kahn (1996) and Kahn and Mentzer (1998)



Brandstädter and Sonntag conducted three studies to examine competencies for interdisciplinary collaboration that must be fostered. Through use cases, these researchers found that interdisciplinary collaborations lack knowledge regarding the strengths and methods of other disciplines. This issue causes false expectations about possible contributions to project goals. An awareness of one’s own disciplinary dependency helps to bring collaboration to an equal level so that those involved work together effectively and efficiently. Notably, the participants were recruited in a scientific context. Since the majority of the sample comes from an academic context, the tendency toward an outstanding level of competence can be explained (Brandstädter & Sonntag, 2016).

## 2.3. COLLABORATION BETWEEN ML ENGINEERS AND UX DESIGNERS

To more thoroughly explore the topic of collaboration between UX designers and ML engineers, it is necessary to clarify how UX designers and ML engineers currently work together in practice. Additionally, this section examines challenges and benefits that can arise during this process.

According to Yang (2017), intelligent UX (with the support of ML) adapts to three factors: context, user, and time. Specifically, the design possibilities around the temporal dimension are key. For instance, ML's ability to evolve the UX over time opens beneficial design opportunities for interaction and service designers. In addition, using data-driven personalization, long-term customer relationships can be built and maintained. Thus, the goal of creating lifetime value can be targeted (Yang, 2017).

Furthermore, the same study addresses the different expectations and goals of UX designers and ML engineers on a given project. This process begins with the fundamentals; that is, UX designers consider divergent frameworks and solutions to choose the "right" element to design. In contrast, ML engineers focus on data availability and desired learner performance rather than a deliberate vision (Yang, 2017).

Aligning machine learning skills with the right UX problem is critical and challenging. One of the problems in this process is the lack of communication between UX and ML expertise in design processes, ML development, and training. To improve communication, Yang relied on the early use of ML in the project process because planning carefully defined and thoughtful goals is important (Yang et al., 2016).



According to current research, many UX designers are not prepared to effectively use ML methods in practice. Although some UX designers are generally aware of how ML works, they do not understand its potential, capabilities, and limitations in the context of their design projects. In many cases, ML is introduced only toward the end of a project, when the functional and financial decisions have already been created (Yang, 2018).

In combining ML capabilities and UX opportunities, it has become apparent that designers' understanding of ML differs from textbook definitions. Thus, design researchers should focus on providing abstractions, examples, and new tools so that the design potential of ML can be better captured, sketched, and prototyped.

Finally, this process improves collaboration with data scientists. In the same vein, the case study “Investigating How Experienced UX Designers Effectively Work with Machine Learning” by Yang (2018) suggested an alternative view to the widely held assumption that teaching designers how ML works is the most effective way to help them apply it as a design material to improve the UX (Yang, 2018).

In this team’s research, they interviewed 13 designers with years of experience designing the UX of ML-enhanced products and services to discover how these elements functioned.

Contrary to previous assumptions, the participants did not think that more knowledge about ML would make them better designers. Instead, the participants seemed to be most successful when they engaged in ongoing collaborations with data scientists. To accomplish this goal, the participants embraced a data-centric culture (Yang et al., 2018).

Similarly, Zumstein wanted to use his empirical research to discern why interdisciplinary collaboration is often difficult for analytics professionals and business IT specialists. Since the main target group of Zumstein's research is analytics and analytics is also a part of ML, Zumstein's research results are also important for this written thesis. As each situation is different, the research question stated above cannot be answered definitively. In this vein, Zumstein formulated the following eleven hypotheses, which can be seen in the next figure (Zumstein, 2017):

**The area becomes more complex**
Due to the increasing number and complexity of source and information systems, volume, variety, and processing speed of data and business relevance the analytics teams are growing, and so is their interdisciplinarity.

**There is a lack of understanding of the area**
Employees have different levels of education, knowledge in different disciplines and have limited understanding of the field of analytics. In cases where employees do not (want to) understand more about the other field, any interdisciplinary collaboration becomes difficult.

**The area has great influence**
Interdisciplinary collaboration is challenged by the high need for information, communication, clarification, discussion, and action on data. While data and information create transparency, objectivity and rationality, it stands at the same time for power and professional authority.

**Trust is lacking for the area**
As soon as the figures do not meet the expectations of management or other stakeholders, the credibility, validity, quality or relevance of the data is doubted.

**The area has and creates dependency**
While companies depend on data and information to do their business, analyctics teams depend on IT infrastructure and software providers. Wherever there is a strong dependency on software products, services, employees, teams or consulting, problems can arise in interdisciplinary collaboration.

**The area has many interfaces**
To carry out their work, they encounter numerous other divisions and teams (internal and external).

**Teams grow**
Due to the strong growth, new positions are created, and teams are enlarged. The areas such as data science, data analytics, data engineering and data management must first establish their processes.

**Teams are reorganized**
As the number of new employees in this area continues to grow, new teams are being formed and the company's strategy is being adapted. This leads to the need to reorganize, which can put a burden on interdisciplinary collaboration.

**The area is new**
While some companies are reorganizing their analytics departments, others are just creating such positions. In all these cases, interdisciplinary collaboration has yet to become established.

**Divisions have different interests**
Since each division has different ambitions and interests for reaching their annual goals, it often has a negative impact on interdisciplinary collaboration.

**The area lacks resources**
Employees in this area are heavily occupied in many companies. If they are overworked or understaffed, this can lead to delivery shortages, delays, problems and misunderstandings in communication.

Figure 4: Zumstein's eleven hypotheses, Suter (2021)

## EXCURSION: ETHICAL CONSIDERATIONS

Although significant efforts have been made to establish ethical standards and practices through methods and formal codes of ethics, significant gaps remain in ethical guidance in HCI, particularly in relation to new technologies (Chivukula et al., 2020).

A survey by Dove et al. revealed that some of the greatest challenges UX designers experience with ML are the ethical implications of the usage. This issue raises the question of how not to lose focus on the user during a project. Additionally, one must consider who takes the blame when a system makes a mistake that affects the user (2017).

Incorporating ML from the design process into new fields such as clinical medicine, justice, scientific research, and engineering has demonstrated various benefits. Especially in medicine, medical researchers have seen great potential in ML tools for analyzing big data. By using algorithms, images in radiology and anatomical pathology can be examined in clearer detail (Char et al., 2018).

Nevertheless, ethical challenges arise in decision making due to biases in the data used for training. For example, this issue can occur with ML programs designed to assist judges in sentencing. Such programs should predict an offender's risk of recidivism. However, in this process, the algorithms have exhibited a troubling tendency toward racial discrimination. In predicting which defendants would reoffend, the ML algorithm used made mistakes. For instance, this formula incorrectly classified black defendants as future offenders twice as often as it classified white defendants in this way. Additionally, white defendants were more often misclassified as low risk than black defendants. The following quote from the nonprofit newsroom ProPublica highlights the inaccuracy and flawed nature of the ML algorithm, revealing the ethical consequences of this work (Angwin et al., 2016):

> "We ran a statistical test that isolated the effect of race from criminal history and recidivism, as well as from defendants' age and gender. Black defendants were still 77 percent more likely to be pegged as at higher risk of committing a future violent crime and 45 percent more likely to be predicted to commit a future crime of any kind. […] If it's wrong in one direction, a dangerous criminal could go free. If it's wrong in another direction, it could result in someone unfairly receiving a harsher sentence or waiting longer for parole than is appropriate" (Angwin et al., 2016).

Therefore, designers should understand applied ML model, the data it uses, and the algorithm's capabilities and results. By exploring these issues, designers can avoid ethical problems and a biased or unsettling model. Regarding this model, the participating designers said it was important to them to create something ethical and pragmatic (Dove et al., 2017).

## 2.4. MERGING TWO AREAS OF EXPERTISE

This section clarifies whether there is already an established interdisciplinary project process for ML and UX design, what added value is created by this process, and which challenges must still overcome.

> "Many organizations realize that becoming more human-centered is key to dealing with today's innovation challenges. Human-centered design (HCD) has potential to contribute to this goal" (van der Bijl-Brouwer & Dorst, 2017).

In this study, understanding the target group's goals and concerns, aspirations and motives, and their surroundings are key elements of the UX (van der Bijl-Brouwer & Dorst, 2017). For instance, HCD is a method to provide a better UX to stakeholders and to deliver systems and products with high usability for users and stakeholders. In 2010, the ISO9241-210, an ergonomic standard about the HCD, was published. The ISO 9241-210 standard covers many aspects of hardware and software UI design and contains the best, most widely used advice on software ergonomics (Maguire, 2001).



In software development, there are numerous methods of how software products and applications are developed, however they mainly focus on meeting the technical and functional requirements of the software. To achieve the following benefits of the HCD model, user requirements must not be neglected (Maguire, 2001):

#### INCREMENT OF PRODUCTIVITY

Allows the users to operate effectively rather than lose time struggling with a complex system and UI

#### REDUCTION OF USER ERROR

Avoiding ineffective UI with inconsistencies, ambiguities, or other design flaws reduces human error

#### REDUCTION OF TRAINING AND SUPPORT

A well-designed, usable system can reinforce learning behavior by reducing training time and the need for human support.

#### IMPROVED ACCEPTANCE

Users often prefer to use a system that provides information that is easily accessible and simple to use. Improved user acceptance is often an indirect effect of this process.

#### ENHANCED REPUTATION

A well-designed system should encourage a positive response from users. By working to improve customer responses, companies can improve the reputations of their products.



> "Human-centred design (HCD) is concerned with incorporating the user's perspective into the software development process in order to achieve a usable system" (Maguire, 2001).

One of the main problems with high usability products occurs when one applies the HCD process ISO9241-210 to the development process of ML engineers. In the many UX guidelines for development processes that include ML technologies, little information has been provided on how and when to apply those guidelines to the development process (Fukuzumi et al., 2017).

In one study, Maguire emphasized that the HCD approach is not a replacement but a complement to the software development methods. For this approach to be successful, the following four key principles must be guaranteed (Maguire, 2001):

1. The active involvement of users, clear understanding of the user and task requirements;
2. An appropriate allocation of functions between users and the system;
3. The iteration of design solutions; and
4. Multi-disciplinary design teams.

In this vein, Zhibin Zhou et al. developed a project in 2019 to develop a ML process canvas. This tool was designed to help designers consider various factors involving users and the ML system and scenario during the design process. Next, the developed ML process canvas was applied to a design project to observe the contribution of the model to the conceptual phase of the project.

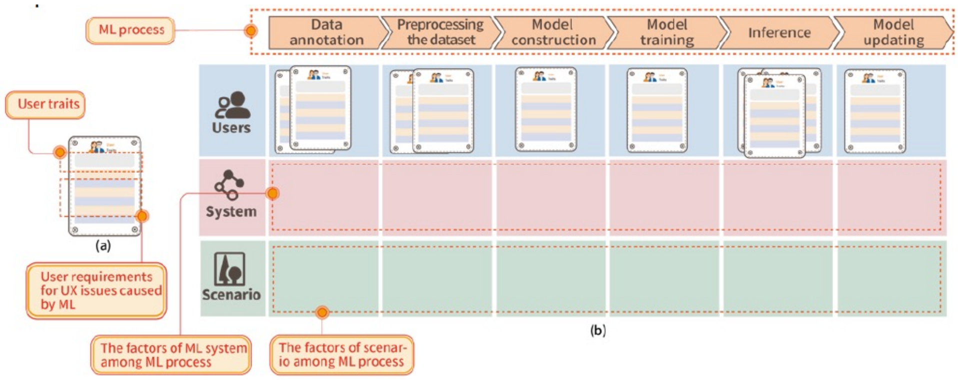



Figure 5: ML process canvas, Zhou et al. (2019)

During this project, it was apparent that the ML process was too abstract for some designers, so they struggled to assign certain steps of the ML process to the appropriate phase of the product life cycle. In summary, the ML process canvas helped the UX designers identify potential innovative opportunities in UX design using specific factors. Additionally, the UX designers asked the right questions and investigated the needed information. Although this project is in an early stage, the tool brings the benefits of ML in UX design much closer (Zhou et al., 2019).

## 2.5. INTERIM RESULT OF THE SECONDARY RESEARCH

The secondary research conducted on the state of the art can be summarized as follows: To keep up with the latest technological innovations in the economic market, companies have been increasingly focused on interdisciplinary collaboration. Because various areas are becoming more complex and versatile, it is difficult to use innovative challenges for one's own benefit. Therefore, many companies see great potential in interdisciplinary collaboration. The two success elements of knowledge sharing and collaboration by K. B. Kahn and Kahn and Mentzer from 1998 serve as an important guide. To unite the two research fields of UX design and ML, the HCD model ISO 9241-210 has been a proven approach. The application of this model ensures that technical requirements are met in projects and brings the user into the center of attention. Additionally, the HCD model ensures that ML technology is considered early in the project process to avoid the difficulties mentioned by Yang in her research (2018).

According to Maguire the HCD model increases productivity and acceptance, reduces user errors and support time, and improves the reputation of the product or company. The four basic principles by Maguire should be considered when applying the model (2001).

In secondary research, the following challenges in the interdisciplinary collaboration between UX designers and ML engineers were identified:

### LACK OF KNOWLEDGE AND UNDERSTANDING

Both areas of expertise are multi-layered and complex. Specifically, UX designers do not understand the full potential of ML and can thus correctly assess the capabilities and limitations of ML. Insufficient knowledge about the influence of ML and UX on users can lead to unexpected consequences, affecting the success of the product.

### CHALLENGING COMMUNICATION

In interdisciplinary collaboration, the frequency and quality of communication is crucial. Since the communication is often project-dependent, there is no reference value for this. Additionally, to avoid misunderstandings, a common language between UX designers and ML engineers must be found.

### GROUP DYNAMIC PROBLEMS

A lack of trust, no team culture, low motivation, and minimal commitment weaken team spirit.

### NO STANDARDIZED HCD PROJECT MODEL

There is no standardized HCD project model that unites the two parties (ML and UX design) in an interdisciplinary collaboration, which has been established in practice.

### METHODICAL PROBLEMS

When parties involved in project have different interests, expectations, and goals, it is difficult to develop a successful product. For this reason, it is important to align these approaches and procedures.

# PRIMARY RESEARCH: EMPIRICAL INVESTIGATION

# #03

# 3. PRIMARY RESEARCH: EMPIRICAL INVESTIGATION

This chapter is divided into two parts. First, the selected research method survey will be discussed in more detail and then the qualitative method of expert interviews.

## 3.1. SURVEY

### 3.1.1. METHODOLOGY SURVEY



The first research method used in this written thesis was a survey. This method was chosen to make a generalized statement using numbers. The survey was selected as a quantitative research method to check what is "objectively true" and displays general validity (Ritschl et al., 2016).

Siegfried Schuman defined the quantitative approach as follows (Schumann, 2019):

> "By 'quantitative' approach is meant that one tries to capture the occurrence of characteristics and, if necessary, their expression by measurement (quantification)" (Schumann, 2019).

Through the established research questions (see Section 1.2.), the following guidelines were developed for the survey:

A) FOR UX DESIGNERS:
If a UX designer has no knowledge of ML, they do not work on interdisciplinary teams with ML engineers and are not interested in collaboration.

B) FOR ML ENGINEERS:
If an ML engineer has no knowledge of UX design, they do not work on interdisciplinary teams with UX designers and are not interested in collaboration.

Because both ML and UX design are relevant to this written thesis, one statement for each expert area was established to be tested by the survey. Before delving further into the type of sample selected for the survey, the representativeness of samples must be mentioned. Although the term "representative sample" has become common, this is not a technical statistical term and is often defined differently in the literature than it is here. In most cases, the representativeness of a sample is associated with how it represents a "reduced image of the population" (Schumann, 2019). However, in this work, the term "representative survey" is used as a synonym for "survey based on a simple random sample."



It would have been too time consuming and difficult to interview all UX designers and ML engineers in Switzerland, so a full survey was not conducted, and a simple random sample was instead chosen. The selection was made randomly in one step from the population (Schumann, 2019). Because the selection of the subjects was chosen according to fixed rules, a deliberate (nonrandom) selection procedure was used for the representative survey. Normally, deliberate selections rarely play a role in survey research. The reason for this negative attitude toward deliberate selections is that no conclusions about the population can be drawn from nonrandom samples (without additional assumptions). That is, such samples can only be considered tools for this purpose. However, as soon as one must attempt to falsify a statement, deliberate sampling can also be used for this purpose (Schumann, 2019).

The prepared quantitative survey was composed of three subsections. In the first one, the questions were designed to reveal the participant's level of knowledge about the other area of expertise in practice. The second subsection was devoted to the motivation and willingness to learn more in the other expert area and the learning method to be used in this process. Lastly, the third subsection focused on interdisciplinary collaboration. The last subsection consisted of questions about the current project process, including the frequency and a detailed description of the collaboration between the two expert divisions.

The aim of the representative survey was to develop a first impression of the current situation in the Swiss labor market through either verification or falsification of the statements made. Thus, this overview is intended to illustrate the relevance of the topic and to provide support for the development of questions for the next research methods, the expert interviews.

### 3.1.2. TARGET GROUP AND DATA COLLECTION



The target audience for the representative survey comprised diverse practitioners from both the UX design and ML research areas. Notably, few experts refer to themselves as ML engineers. For this reason, many participants' job titles may not have designated them as ML engineers, but they were involved with ML or had some experience in the field. Therefore, this group included individuals with the following job titles:

- data scientist,
- software engineer,
- business analyst,
- robotics programmer, or
- backend developer.

The representative survey was sent to various UX companies, software development startups, and technology companies focusing on AI. Switzerland was chosen as the geographic target, including companies located in Switzerland that are internationally active and have various locations abroad. For this reason, the survey was made available in both English and German.

The representative survey was sent to 40 different companies (see Appendix 7.2). In the selection of companies, the author considered whether these businesses involved the topic of interest, indicating companies with a product or services involving UX or AI. The survey was sent to 40 companies with the request to forward it to the respective employees of the expert area concerned. A total of 41 people completed the survey, including 24 people from the UX design area and 17 from the ML area. Notably, of the 17 participants, 9 distinguished themselves as ML engineers. For this reason, answers from people who used or involved ML in their daily work were also accepted, including people with the job titles mentioned before.

Additionally, only in rare cases was feedback received from technical companies. The completion rate from people in the UX design field was significantly higher in percentage terms. To achieve a balance between the two areas of study, the survey was sent primarily to tech companies. However, no explanation can be given for the minimal willingness of people from the technical sector to complete the survey.

### 3.1.3. SURVEY RESULTS

The representative survey found that 70% of respondents had average to little knowledge of ML, and their knowledge of UX design was 50% higher. Additionally, 15 participants distinguished themselves as experts in the field, and two thirds of the respondents wanted to acquire more knowledge in ML area. In the area of UX design, there a total of 30 people who wished to acquire more knowledge. From the five people who answered “No” to this question, it can be concluded from their reasons stated that they are UX designers and already consider themselves experts in this field.

The top ML topics that participants wanted to know more about comprise the following:

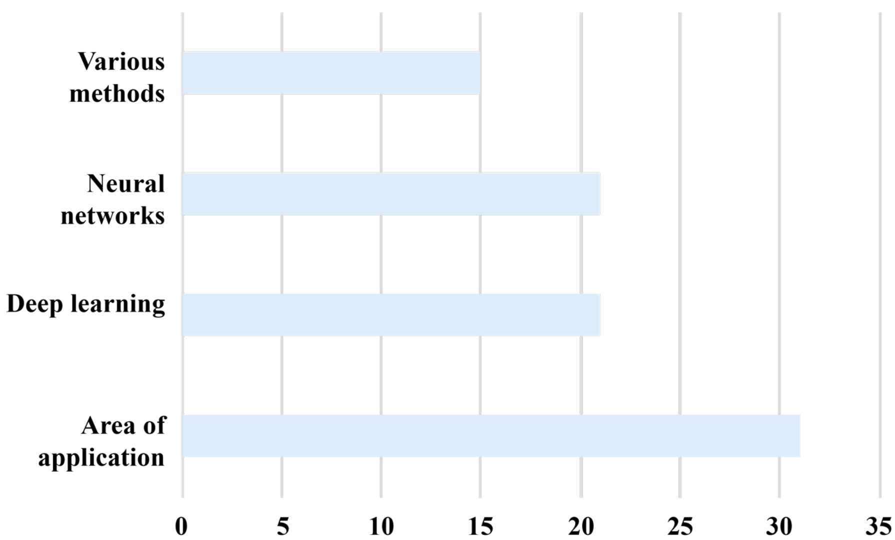



Figure 6: Top ML topics participants want to know more about, Suter (2021)

As seen in the next figure, the most interesting topics in UX design are prototyping, user research, and research methods.

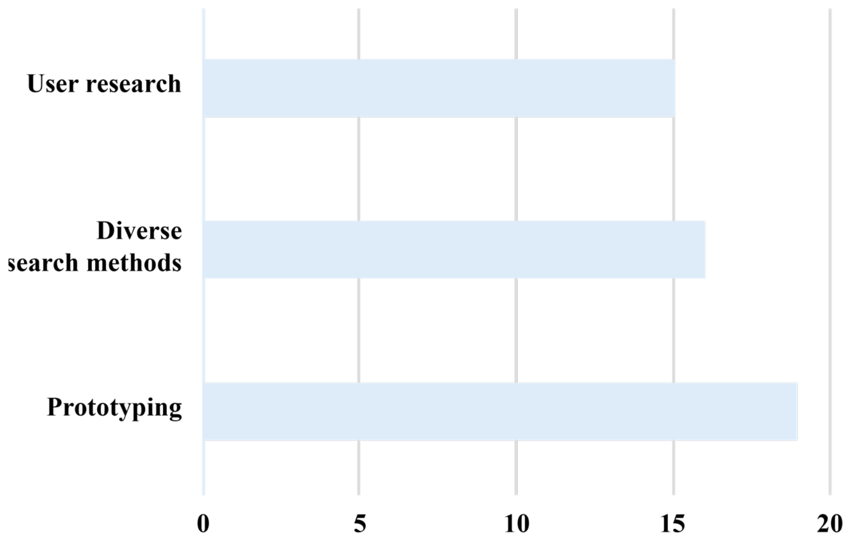



Figure 7: Top UX topics participants want to know more about, Suter (2021)



When participants were asked how they would prefer to acquire this knowledge, they indicated instructional videos as their first choice and workshops as their second. Their third preference was an informative website. In the section on interdisciplinary collaboration, the participants were asked whether UX designers have contact with ML engineers during projects, and 30% of the UX designers answered in the affirmative. Among the ML engineers, more than 75% had contact with UX designers during projects. Eight participants form the technical area abstained from answering this question, and 40% of the participants collaborated in the project phase of prototyping. Additionally, 20% had already contact with UX designers in the previous step, Phase 2, developing specifications for users, and 20% did so in the subsequent phase of evaluation. Beyond this, 8% of the participants had already had an exchange before the project began.

One person indicated that throughout the project process, UX designers and ML engineers were constantly in contact with each other. When asked to describe the exchange between these parties, the participants selected the following responses:

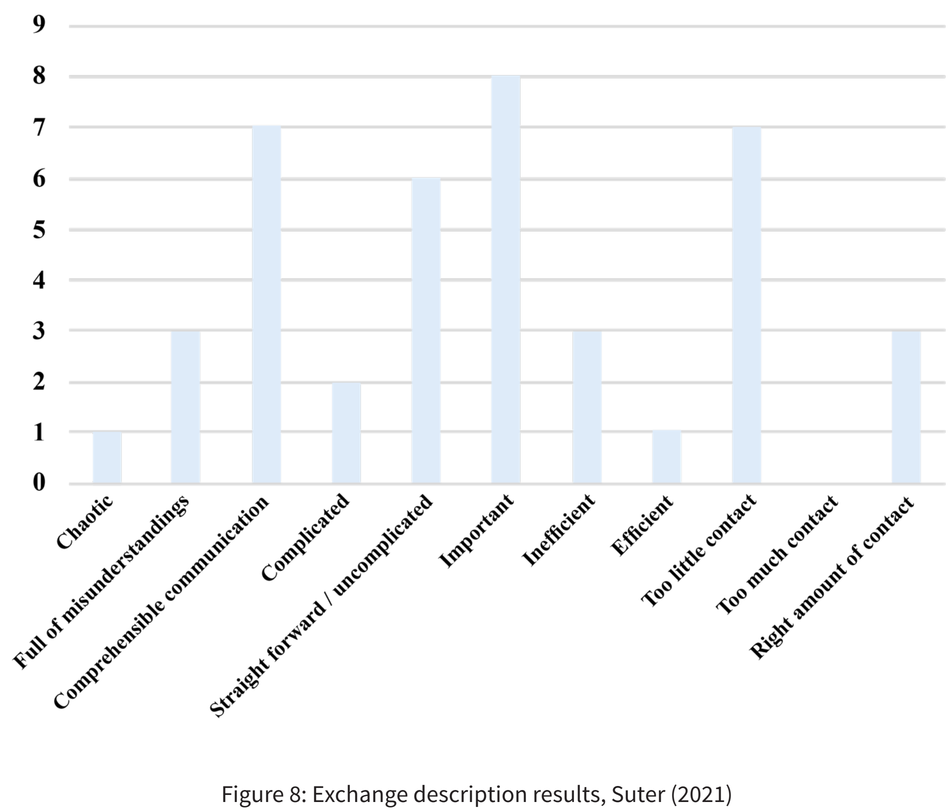



Figure 8: Exchange description results, Suter (2021)

In the last survey question, the participants selected elements requiring optimization so that the two parties, UX designers and ML engineers, could collaborate better. The answers selected appear in the figure below:

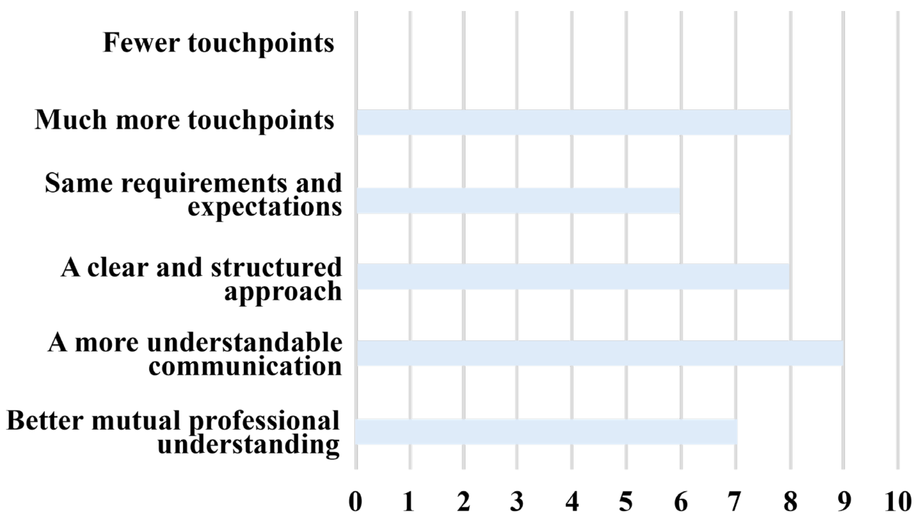



Figure 9: Results of requirement elements selected to optimize the collaboration between UX designers and ML engineers, Suter (2021)

### 3.1.4. INTERPRETATION OF THE SURVEY RESULTS

The evaluation of the survey revealed that there is a significant knowledge gap between UX designers and ML engineers. It can be concluded that involved parties in a project cannot sufficiently assess the potential and possibilities of the other field of experts to be able to create real added value in the project process and therefore for the resulting product. The selected area of interest, which the participants want to know more about, emphasizes the importance of practical application of UX design and ML. This indicates that practical use cases are of more value to the stakeholders then theoretical knowledge. Since in practice very few UX designers work with ML engineers on projects, it can be gathered that the potential of ML for UX has not yet been discovered by many companies. Due to the different answers regarding the frequency of collaboration between the involved parties in a project process, it is concluded that no standardized process model is used in practice, or that no clear structure can be identified. Although the evaluation of interdisciplinary collaboration in a project was not rated as completely negative, it can be concluded that there is still a lot of potential for optimization.

## 3.2. INTERVIEWS WITH EXPERTS

Frist, this chapter justifies the chosen method of expert interviews. Next, it describes the data collection procedure and the criteria used to select the interview experts. After this, the chapter discusses the guidelines of the chosen methods and the interview data preparation. Lastly, the chapter explains how the qualitative content analysis was conducted, presenting the relevant results are presented. The same applies to the interested area in UX design. The practical application is in the foreground.

### 3.2.1. METHODOLOGY EXPERT INTERVIEWS



In this project, the limited literature and the lack of knowledge about the interdisciplinary collaboration between UX designers and ML engineers in an HCD process model led to the choice of a qualitative research method (Mayring, 2015).

The qualitative research method of interviewing experts was chosen because it involves identifying attitudes, images, behavioral motives, barriers, and challenges of participants. Additionally, thus method can generate a variety of insights into the way an interviewee thinks, feels, and acts, which in this written thesis were useful in answering the research questions (Buber, 2007). The goal of the applied research method was to find out what challenges UX designers and ML engineers face when the two parties collaborate on an interdisciplinary project. The different practical experiences of the interviewed experts help to identify important key factors for a successful interdisciplinary collaboration between UX designers and ML engineers. In addition, initial feedback from the interviewed experts on the low fidelity prototype (see Appendix 7.4) of the HCD project model was to be obtained.

Furthermore, expert interviews combine inductive and deductive approaches (Mayring, 2015).

On the one hand, the theoretical research in Chapter 2 lay the foundation for the collection of the empirical data and serves as an assistance in the preparation of the interview questionnaire. From the collected data, conclusions were drawn, and the theses were formulated. Thus, this research methodology is thus based on Mayring's (2015) approach to qualitative questions, as demonstrated in following figure:

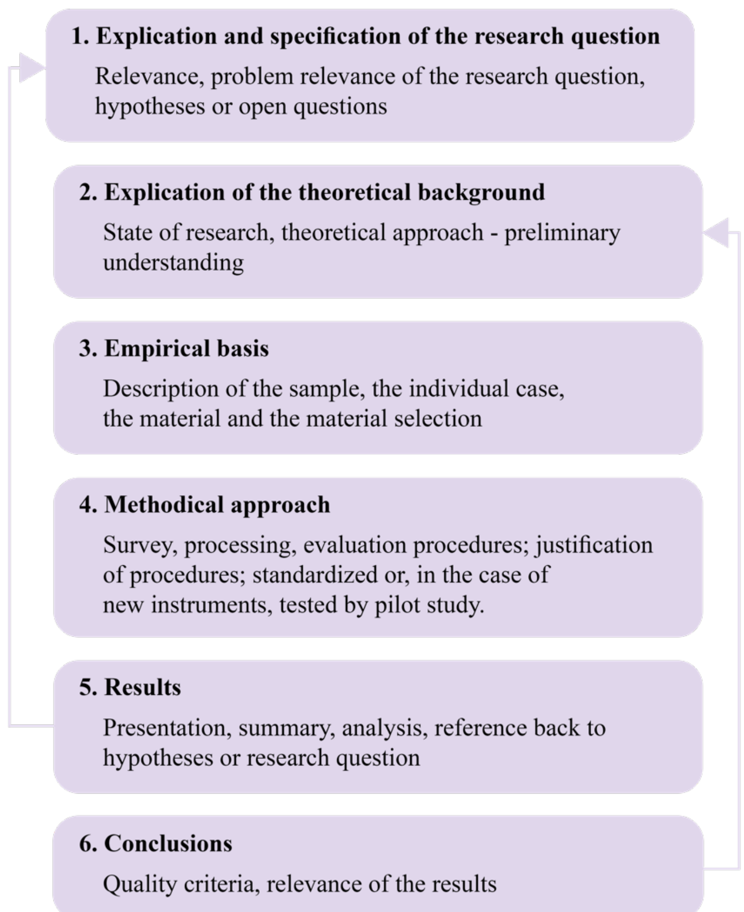



Figure 10: General basic design of qualitative (and quantitative) research, Mayring (2015)

### 3.2.2. DATA COLLECTION AND EXPERT SELECTION

The empirical investigation using qualitative interviews with experts was conducted via video conference (Zoom meetings) or in person. A total of ten expert interviews lasting between 30 minutes and one hour were conducted with people from two different target groups. One of these groups consisted of people with in-depth knowledge in the ML field. The second group included people with UX expertise. Because ML is quite technical and few ML experts call themselves ML engineers, the main criteria for the interview partner selection was on the level of knowledge of ML. In the UX area, the focus was on the different activities of UX designers. For this reason, three UX consultants and two UX designers with different UX roles were invited for an interview. Both target groups were interviewed, facilitating a broad assessment of the topic to be achieved. Furthermore, this research method was conducted to reveal possible opposing attitudes and challenges in interdisciplinary collaboration through various activities and skills. The identification of UX designers and ML engineers was done first by online research of companies working in these areas and then by contacting the people working at the selected companies. Additionally, the social network LinkedIn was searched for people describing themselves as being ML engineers or ML experts. In this written thesis, to be called an expert in UX and ML means having years of experience in a position as a UX designer or an ML engineer or in a similar occupation and having proactively participated in several projects in one's field. Some experts were approached through recommendations by Dr. Marcel B.F. Uhr or previous interviewees. To encourage honest answers, the interviewees were informed that their results, contact details, and companies would be treated anonymously.

Table 1, chronologically sorted by interview date, gives an overview of the interviewees, including their current occupation and roles in the interview.

| Code | Date of interview | Function | Interview role |
|---|---|---|---|
| A | 12.08.2021 | UX consultant | UX designer |
| B | 12.08.2021 | Lead ML engineer | ML engineer |
| C | 12.08.2021 | ML engineer | ML engineer |
| D | 17.08.2021 | Data scientist | ML engineer |
| E | 17.08.2021 | Researcher in ML and particle physicist | ML engineer |
| F | 17.08.2021 | UX expert | UX designer |
| G | 24.08.2021 | UX consultant | UX designer |
| H | 05.10.2021 | Software engineer | ML engineer |
| I | 05.10.2021 | Head of design | UX designer |
| J | 05.10.2021 | UX consultant | UX designer |

Table 1: Interview index, Suter (2021)

### 3.2.3. INTERVIEW GUIDELINES

In preparation for the interviews, two partially standardized interview guidelines were prepared, one for ML engineers (see Appendix 7.4) and one for UX designers (see Appendix 7.3). These guidelines were starting points for thoughts and discussions and were modified spontaneously depending on the interviewees and flow of conversations.

The interview guidelines for the UX designers and ML engineers differed slightly. However, both were based on the topic blocks listed below. The interview blocks were based on the theoretical reference points of Chapter 2 and were designed to cover research gaps and to answer the research questions.

#### VISION OF AN INTERDISCIPLINARY HCD PROJECT PROCESS MODEL

With the low-fi prototype, the first expectations and vision of a functioning interdisciplinary HCD process model that include both parties should be gathered. Accordingly, the expert interviews focused on clarifying the three research questions defined in Section 1.2.

#### CURRENT PROCEDURE IN PROJECT PROCESSES

The detailed explanation of the project process aims to revealed which processes are used and how well they work.

#### CRITERIA AND MOTIVATION FOR A FUNCTIONING INTERDISCIPLINARY COLLABORATION

The correlations between UX and ML are identified with the criteria to be met to ensure a functioning collaboration.

#### KNOWLEDGE OF ML AND UX

First, it should be clarified how great the knowledge about the other field of research is to determine the knowledge gap between the parties involved and possible prejudices.

#### EXPERIENCE IN INTERDISCIPLINARY COLLABORATION BETWEEN UX DESIGNERS AND ML ENGINEERS

This guideline clarifies whether and how these professionals collaborated with experts from different disciplines and how this collaboration is facilitated. The goal of this process is to discover these experts' willingness to collaborate and their motives for collaborating with other experts.

### 3.2.4. INTERVIEW DATA PREPARATION

The data obtained from the interviews were processed as follows. This written thesis focused on the qualitative analysis of the content, so it was essential to record the interview in written form. For this reason, all interviews were transcribed according to their meanings.

During this process, the following rules were followed:

1. The interviews were conducted in the preferable language of the interviewee. Thus, the majority of the expert interviews were conducted in Swiss German and transcribed as well as possible into German.

2. For easier comprehension of the language, repeated words or phonetic expressions such as "ehm" or laughter were not included, as these elements were not relevant to this academic research.

3. All personal details or those relating to the company were treated anonymously. For example, each name was anonymized with a letter (e.g., "X").

4. To structure each interview, the interviewer's questions and statements and those of the experts were always placed in a new section. Next, the interviewer's statements and questions are marked with the letter "M." In this way, the interviewees were each assigned a letter of the alphabet according to the order of the interview dates (e.g., Interviewee 1 = "A," as listed in Table 1).



Next, the following section demonstrates how the transcribed interviews were processed for content analysis.

### 3.2.5. QUALITATIVE CONTENT ANALYSIS

The data analysis of the qualitative expert interviews was conducted using the qualitative content analysis methodology based on Mayring and the Dovetail software. The aim of this methodology was to summarize the findings of the interviews in a structured way (Mayring, 2015).

The basis for the content analysis were the transcripts of the interviews in written form (see Appendix 7.6). Additionally, the focus of the qualitative content analysis according to Mayring was the thematic category formation, in which text passages of the interviewed experts were assigned to the categories and codes (Mayring, 2015).

The categories were formed using the theoretical knowledge acquired in advance (deductively). Next, the transcription and the categorization were done using the online software Dovetail. The text material, the transcripts of the expert interviews, were evaluated and assigned with respect to the categories. If new, relevant text passages emerged that could not be assigned to the existing category system, new categories were inductively formed and added to the existing ones. This process resulted in a coding guide for the entire set of interviews. The final coding guide, including definitions and anchor examples, can be found in Appendix 7.7. After this, the result of the qualitative content analysis was a category system to which the appropriate text passages were assigned (Mayring, 2015). Lastly, the results from the categorization system were included in the prototype interdisciplinary HCD process and were used to answer the research questions.

### 3.2.6. RESULTS FROM THE EXPERT INTERVIEWS

In this subsection, the most important findings from the expert interviews are presented in thematic blocks created using the categorization system (see Appendix 7.7). All quotes were linked to the pseudonyms from Table 1.

#### RELEVANCE OF COLLABORATION BETWEEN ML AND UX DESIGN

> B: "I find UX very exciting. Because it's always the same: You can still make such a good product, but if your UX sucks, nobody cares. I usually also say that you should start with the UX first. Because it does not matter how a problem is solved technically later, first you have to find out what the user needs and how you can implement it so that it helps his work."

The experts interviewed all discovered a close connection between ML and UX design, and ML was seen as another tool to optimize the UX. Generally, the better a product can respond intelligently to the user's needs in the background, the more attractive it will appear to users. In this academic research, all experts agreed that close interdisciplinary collaboration between UX designers and ML engineers leads to an improved UX, thus influencing user satisfaction and trust. Additionally, two of the interviewees mentioned that the enhanced product would not only look nice but would also be intuitive, entertaining, and effective. However, various points must be considered in collaborations. For instance, one interviewee emphasized that to develop a digital product with an optimized UX, interdisciplinary collaboration must not only work but work well so that all involved parties pull in the same direction and can develop a solution that simplifies the user's life. Otherwise, products are produced that do not function well. A UX designer and an ML engineer clarified that the technical side also benefits from functioning digital products with an improved UX. Once the story behind the data is understood, better decisions can be made about the product. In turn, this process means the correct data can be calculated in the model, improving the reliability of the results and improving the UX.

## POTENTIAL AND VALUE OF UX DESIGNER

In this written thesis, one of the most significant potential benefits that the ML engineers saw in UX designers was that the latter could be valuable in communication work. This process included the exchange with the client and communications within the interdisciplinary team, especially when different parties from different professions are involved. In this vein, three ML engineers saw the advantage of working with UX designers because this process helped them better understand users and their problems in context. When these professionals deepened their understanding of users' needs, motivations, and behaviors, they placed users at the center of their work and could thus develop better solutions to problems. On a related note, one ML engineer explained that the potential of a UX designer extended to their visual work:

> D: "On the one hand, for persuasion work or when we want to land follow-up projects. Of course, it is great when we have a visual prototype that works well and delivers in terms of UX. Yes, it helps tremendously. Maybe you do not just say you are doing it, but you make an extra effort and present other ideas that we came up with in the process so that the client, the product, or their business can also benefit from. If you can sell it afterwards, a UX designer is needed."



The visual prototypes developed by UX designers also help ML engineers in their work. For instance, visual screens can save a great deal of time and effort, making it almost unnecessary for ML engineers to consider graphical details. Thus, two ML engineers in this academic research emphasized that efficient work is strongly promoted by a functioning cooperation. Furthermore, through the applied UX principles, digital products have been developed that not only have a visually appealing interface but also are intuitive, providing a high level of user satisfaction.

## POTENTIAL AND VALUE OF ML ENGINEERS

In this written thesis, four out of five UX designers believed that ML influences and optimizes the UX. Through the innovative mindset of ML engineers, several unique end visions can be developed, which can ease the UX. In this vein, one UX designer clarified that when one better understands ML, one can more effectively contextualize the technology involved and consider it during project development. One of the UX designers interviewed in this academic research, still doubts the capability and possibilities of the current ML technology:

> A: "My observation is that the system [ML] must be insanely smart to add value from a usability and UX perspective."

With this statement, this UX designer explained that ML is not appropriate for every digital product.

## KNOWLEDGE LEVEL

When the experts interviewed were asked how they would rate their knowledge in the other research area on a scale of 1 to 10, all ML engineers rated themselves at a 4. On this scale, the number 1 stood for "first heard of the term at matter," and 10 meant "absolute expert." The interviewees agreed that they knew superficially what UX designers do but not exactly how this work was done. Furthermore, they felt they could never accomplish these tasks themselves. All but one of these experts had gained this knowledge themselves over the years through contact with UX designers. However, they had not been taught anything about UX in school in their training to become ML engineers. One of the five ML engineers completed an internship at a web development company as well at a graphics company. During his apprenticeship to become a mediamatician, he encountered UX and studied the field. Among the interviewed UX designers, ML knowledge was a bit more widely dispersed. Three of the interviewees came from more technical educational backgrounds, so they learned some ML in school. Two of these three rated their knowledge at a 4, and the other rated himself at a 3. The other two, who never had anything to do with ML in their educational journeys to become UX designers, rated themselves at a 2 and a 3, respectively.

## INTERESTS

When the experts were asked if they were interested in learning more about the other expert field, everyone agreed. One ML engineer's response captured the general opinion well:

> B: "Of course, I would like to know more about it. But I would also like to know more about many other areas. Realistically, I know enough to understand what the UX designer does and when we need one. I will never get to the level to be able to do the job myself anyway. I understand enough now to be able to do my job properly."

Additionally, all the interviewees were interested in deepening their knowledge in the other subject area, but they either did not feel any urgency to do so or prioritized other topics. When the interviewed experts had to select several topics of interest from the other expert field, the selection was very diverse. For instance, one UX designer wanted to develop a better understanding of how an algorithm is built, whereas another expert was more interested in the use cases and practical examples of ML. Similarly, another UX designer was interested in the capabilities of ML in the abstract, and another wanted to gain more specific knowledge about the data. Beyond this, the ML engineers were very divided in their interests. Two of them wanted to learn more about user testing, as this area had strongly influenced their work. Another ML engineer wanted to be involved in the entire process of how a design workshop is structured, organized, and executed. Furthermore, another ML engineer desired to learn more about the prototyping phase and how to develop a style guide in Figma or Xd.

### CHALLENGES DURING AN INTERDISCIPLINARY COLLABORATION

During the interviews, many difficulties were mentioned that can arise in the interdisciplinary collaboration between UX designers and ML engineers. The majority of experts saw a major challenge in communication during the project process, in both the frequency of exchanges and the language. Three out of ten experts were of the opinion that it is important for the interdisciplinary collaboration to speak a common language. That is, they believed the experts from different departments should find a common language in which no technical jargon occurred so that everyone understood the same thing when using the same word. Speaking from experience, once UX designer said that not only is the right choice of words important, but illustrations can also be used to assist in such cases.

> J: "I sketched out the navigation of the prototype, and countless questions arose as to how it would work afterwards. For me, it was clear, but for the others clearly not. This proves that if I had only spoken with words, a misunderstanding would have arisen."



If communication is not used rightfully, not all people involved will understand the solution they must develop together, so frustration arises. As mentioned above, the frequency of exchange can also become a challenge. If there is infrequent or no contact between these people, many misunderstandings arise or, as one UX designer explained, products may fail. According to one ML engineer, this occurrence originates when project managers do not know when the interdisciplinary team should come together for an exchange. This issue usually leads to another challenge; that is, collaboration happens far too late in the process. However, one ML engineer saw the origin of this problem as occurring before a project's beginning:

B: "Actually, it is our clients who need to understand that software engineers and UX designers need to work together. And not only in the beginning they do these tasks and after that they are gone. [ … ] The clients also need to understand that even though they 'ordered' an AI product, a UX designer needs to be there as well."

However, such an exchange between experts is of no use if no one listens to each other. In this academic research, two ML engineers emphasized that the hype surrounding ML has caused many experts from other fields to lose respect for their work. Due to the copious information available about ML, some team members believed that they were also ML engineers and knew everything better themselves than the ML experts. Such behavior created a barrier that had to be overcome. Furthermore, two experts thought that another challenge involves replacing or adapting old, existing strategies with new, modern models. One UX designer summarized this process as follows:

A: "It [collaboration] is about existing structures: Everyone has their place and their area of responsibility. Working together on something means giving someone in the project space for their work."

Furthermore, several experts addressed the difficulties caused by the collaboration of experts in the two areas discussed here. That is, if one has no understanding or knowledge of the experts in the other area, it is challenging to reconcile the different experts' goals and motivations from UX designers with the ones from ML engineers. Due to the diverse approach between UX designers and ML engineers, the priorities during a project process are set differently. Therefore, there is a high risk that each party would work alone and be trapped in their knowledge. In this academic research, a UX designer and an ML engineer explained that one can get lost in small details and thus not move forward efficiently in a project. According to three experts, there is a high chance that the result of such a process would be a project that does not meet the clients' (the users') needs. Another risk for several UX designers involved the ML technology itself. For instance, for one expert, the quality of the data and thus the result cannot be reliably predicted, whereas another expert saw a major risk in the functionality of ML. Furthermore, two ML engineers agreed that a lack of understanding in the other field would mean that a UX designer would not know when ML could be useful in a project. One of these two experts believed that the two systems, UX and ML, are often incompatible. That is, while the product suggests something to the user, however in reality, the user wants to do something else. In this way, the applied ML algorithm in the product often hinders the user and leads to a bad UX.



## PROPOSED SOLUTION APPROACHES

This section explains the proposed solutions to the challenges described in the previous section that were shared during the interviews. When asked how to develop a common language, most experts agreed that mutual understanding requires extensive communication and a basic knowledge of the opposite expert field. While one ML engineer recommended asking the UX designers numerous questions, another advocated brief daily exchanges between the two expert fields:

> H: "[ … ] if you talk about it [the project] every day, it comes out differently. Most of the time, it does not take much, it can be five-minute stand-ups where everyone briefly gives their stand and asks for feedback."

Other suggestions included having experts in different fields explain their work to each other or taking ML engineers on a design sprint. Through the time-limited design sprint, ML engineers gain knowledge of how to use design methods to reduce risk when launching a new product, service, or feature. However, if those ideas are too time consuming, close collaboration in the same room would suffice. Speaking from experience, one ML engineer said that this strategy also allows one to passively get to know more about the other expert's field, thus promoting the exchange. Additionally, close collaboration can shorten decision-making paths and create a common mindset. Furthermore, four out of ten experts believed that early interdisciplinary collaboration is more target-oriented and more promising than simply coming together in the project process when the other expert field needs to develop a solution. One of these experts emphasized that different parties do not always have to be firmly involved during the entire project, but depending on the project, all should be present at certain milestones. In practice, a UX designer used the following solution approach:

> I: "So there are no two parties in my case. There is only one. But what I strive for is to have a lead designer, a lead developer and then, for example, the project manager. For me, they are a three-person body that has to get along with each other and know which direction to take."



This same expert insisted on an error culture. The error culture addresses a culture that does not see making mistakes as faulty but supports and demands it. This strategy can save a great deal of time in meeting preparations if different ideas do not have to be pixel perfect. Another positive effect of the error culture is that a relaxed atmosphere can be created and can inspire others for innovative solutions. As mentioned above, one UX designer emphasized the advantage of visual tools in communication, also referring to communication with the client. During the interview, several experts explained that many problems can already be prevented proactively if all stakeholders and project members come together at the beginning of the project. That is, by defining project goals together, everyone can understand the basic requirements of that project, and the next steps can be defined. In this way, ML engineers can contribute their knowledge from the beginning of the process and influence the final product. The same is true for UX designers. To this end, two experts stated that while explaining various possible solutions with UX and ML, one must establish limitations and risks. Such behavior ensures the necessary mutual respect and leads to successful interdisciplinary cooperation.

### OPINION ON A STANDARDIZED HCD PROCESS MODEL

After discussing the low fidelity prototype of a standardized HCD process model (see Appendix 7.4), the experts were asked whether they could imagine that a process model for interdisciplinary collaboration between UX designers and ML engineers could be valuable. All but one expert agreed that a standardized HCD process model is helpful as a guideline. However, one expert did not prefer such models in their work. Additionally, one ML engineer said that the process model should not be called a standard but a recommendation.

Beyond this, certain prerequisites must be met for the process model to be helpful. One UX designer emphasized the importance of integrating new and old knowledge in the HCD process model. Furthermore, two experts agreed that this model must be flexible. The reason for their opinion is explained by one of the two experts:



> A: "What the model looks like in a project is different every time. While in one project you focus more on that, in another project you must focus on something else. Maybe you must meet more often during one project than another. It's very project dependent and makes the task very difficult. But models are there to apply them and deviate from them if necessary."

Nevertheless, the interviewees saw various values in a standardized HCD process model. In this vein, three experts believed that a predefined model facilitates collaboration and can save a great deal of time and money. If a team of experts follow a process model, important things are not forgotten, and they retain an overview of the big picture. An additional advantage lies in the communication with the client, as explained by an ML engineer:

> B: "From a high-level perspective, I think it would help—already in the communication with the client. Once it is standardized, and it is clear when the UX designers are involved and how, it is not something that needs to be discussed afterwards when it comes to cost."

# GUIDE PROPOSAL

# #04

# 4. GUIDE PROPOSAL

Through the secondary and primary research, the presentation of the interim results identified various challenges that must be overcome for interdisciplinary collaboration between UX designers and ML engineers to function and be effective (see Section 2.5). Based on these results, the guide discusses the suggested approaches and the aim to be able to master the challenges posed. The guide is intended to serve as an initial overview for companies or team members to support a quick beginning to a collaboration. The following figure provides an overview of the key elements of a functioning interdisciplinary collaboration:

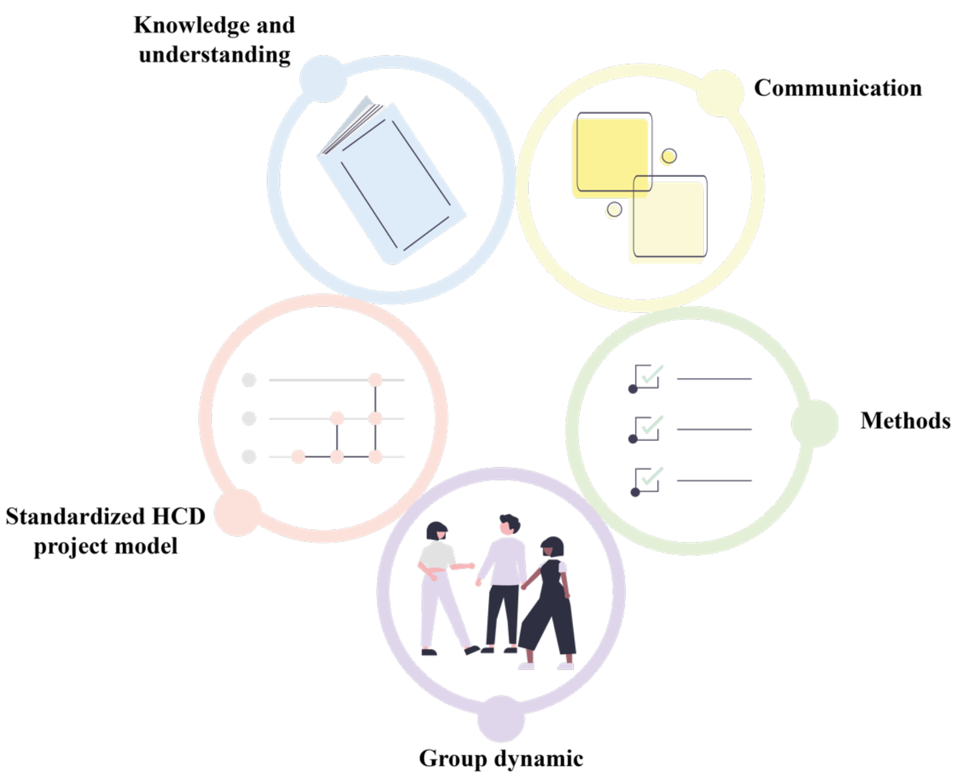



Figure 11: Elements of the proposal guide based on Figure 1, Suter (2021)

In the following section, the key elements for successful interdisciplinary collaboration between UX designers and ML engineers are explained. Because the challenges have already been explained in detail in Section 2.5, to avoid redundancy, the focus of the next sections is on possible solutions to their issues and their goals.

### KNOWLEDGE AND UNDERSTANDING

To overcome the challenges of misunderstandings, UX designers and ML engineers must understand more about the other expert field. Explaining each other's work or taking a ML engineer on a design sprint can help. It is important to ask questions when dealing with complex, difficult topics. Asking the same question several times to different people can lead to explaining a concept's meaning in different ways, strengthening mutual understanding and respect for the other expert's area of expertise. Later in this process, it is easier to decide to what degree the department should be involved in typical tasks of the other department. Additionally, a continuous exchange between all parties involved is helpful. Only in this way can the potential and limits of each field be understood and put into context. However, how often such exchanges occur depends on the project involved.



### COMMUNICATION

For interdisciplinary collaboration to work, communication is a key factor. To be understood by other experts, both frequency and quality of information exchanges are important. Thus, a common language without technical jargon must be found. Working together in the same space can ensure that a mutual understanding and language emerges over time. Beyond this, visual aids can be valuable in overcoming misunderstandings in communication. It is important to discover

## METHODS

To align the different interests, motivations, expectations, and goals of the various expert fields in the project, it is important that all parties involved are present at the beginning of the process. The early implementation of ML and UX in the process helps in setting goals for the project and therefore assists in aligning ML capabilities with the identified UX problem. These efforts can ensure that a product is developed that is ethical and pragmatic. Furthermore, it is crucial that the collaboration of the involved parties takes place in the same place so that a common way of thinking can emerge and develop.

## GROUP DYNAMIC

As previously mentioned, in an interdisciplinary project team non-ML engineers often lacks trust in the ML capabilities and algorithms established. Because this data is often highly dependent on the project understanding of the ML engineers, all stakeholders must understand that no algorithm is 100% error-free. Thus, transparent communication among stakeholders can create an open error culture. Such a culture allows products to be developed that meet the expectations of the stakeholders and builds trust with customers. Additionally, an open error culture has a positive effect on team culture. That is, satisfied team members can develop more innovative solutions in a relaxed working environment and show greater commitment to the project. This process not only ensures targeted, efficient product development but also saves many resources.

### STANDARDIZED HCD PROJECT MODEL

Using an HCD project model that brings together both UX design and ML, the allocation of functions between the user and the system is equally appropriate. All parties know the process and what the next steps are. However, there are certain requirements for the HCD project model that are crucial to its success:

- The model must be adaptable, flexible, and agile.
- There must be a small team of leaders (one from each expert field), that guides the entire team through the whole project process.
- At the beginning of the process and at important milestones, all involved parties are present and allowed to express constructive criticism.

# CONCLUSION

# #05

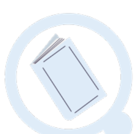
# 5. CONCLUSION

This chapter answers the posed research questions in section 1.2. Furthermore, the research has been critically challenged, and still existing knowledge gaps have been presented. Additionally, the influence the research results have on design practice and theory and which aspects should be addressed in the future are discussed in this chapter.

## 5.1. ANSWERING THE RESEARCH QUESTIONS

To ensure interdisciplinary collaboration between UX designers and ML engineers during a project process, the following key factors are essential: Basic knowledge and understanding of the other expert area, sufficient and qualitative communication, alignment of different methods, functioning group dynamics, and a standardized HCD project model.

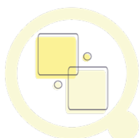




**Knowledge and understanding**

| | |
|---|---|
| **Challenges:** | • Expertise are very multi-layered and complex in their understanding<br>• No understanding of the full potential of the other expert field<br>• No correct assessment of the capabilities and limitations<br>• Unexpected ethical consequences |
| **Proposed solutions:** | • Explaining each other‘s work<br>• Always asking questions<br>• Working in the same space<br>• Constant qualitative exchange |
| **Goal:** | • Understanding more about the other field of expert<br>• Strengthening of mutual understanding, appreciation, and respect for the other area of expertise<br>• Understanding the potential, possibilities and limits of the other field and put into context |

Figure 12: Key element: Knowledge and understanding, Suter (2021)



**Communication**

**Challenges:**
- No sufficient communication
- Low quality of communication
- Misunderstandings

**Proposed solutions:**
- Working together in the same space
- Use of visual aids
- When misunderstandings occur investigate their causes

**Goal:**
- High quality of information exchange
- Established common language
- Avoiding misunderstandings

Figure 13: Key element: Communication, Suter (2021)

**Methods**

**Challenges:**
- Different approaches and procedures
- Different interests, motivation, expectations, and goals

**Proposed solutions:**
- All parties involved are present at the beginning of the project process
- Early implementation of ML and UX in the process
- Carefully defining goals together
- Working in the same space

**Goal:**
- Align the different interests, motivations, expectations, and goals
- Developing of a common mindset
- producing a product that is ethical and pragmatic

Figure 14: Key element: Methods, Suter (2021)

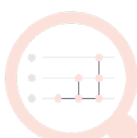
**Group dynamic**

**Challenges:**
- Lack of trust
- No team culture
- Low motivation and commitment
- Weak team spirit

**Proposed solutions:**
- Transparent communication among stakeholders
- Establish a culture of error
- Ensure a relaxed working atmosphere

**Goal:**
- Building trustworthy relationship
- Strenghten the team spirit
- develope products that meets the expecations

Figure 15: Key element: Group dynamic, Suter (2021)



**Standardized HCD project model**

**Challenges:**
- No standardized HCD project model

**Proposed solutions:**

Developing a HCD project model that...
- is daptable, flexible, and agile.
- encourages a small team of leaders for guideance
- actively promotes interdisciplinary exchange with milestones

**Goal:**
- Allocation of functions between the user and the system is equally appropriate
- All parties know the process and what the next steps are

Figure 16: Key element: Standardized HCD project model, Suter (2021)

A functioning interdisciplinary collaboration between UX designers and ML engineers has a positive impact on the project process, the product, and thus the UX and the user. Therefore, the sub-questions must be answered one step at a time.

Different scientific sources have confirmed the advantages of interdisciplinary collaboration. For instance, when several diverse departments work together, they develop a deeper understanding of the subject. By incorporating different perspectives, these experts can place such problems in various contexts, facilitating innovative approaches to deal with these issues. Additionally, the interdisciplinary collaboration of ML and UX design not only ensures that the technical requirements are met but also that those of the user are satisfied. With the help of ML technology, UX designers can better identify and validate user needs. Through close exchange and functioning communication during a project process, UX designers and ML engineers better understand the potential, capabilities, and limitations of the other expert field. The better a problem's context is understood, the better the project decisions that can be made and the more likely the right data will be used for the relevant ML algorithm. Another positive side effect of these two parties' successful collaboration is that ethical issues and biased models tend to be avoided, so a product is developed that is ethical and pragmatic. At the end of the interdisciplinary collaboration, the developed product not only looks visually appealing and performs well but also is intuitive and entertaining. The better a product can respond intelligently to the user's needs, the more attractive it is to users. Through the right interaction of ML and UX design, context, user, and time are influenced in a beneficial way, positively impact usability, user satisfaction, and trust. This process ensures that the goal of many companies is successfully achieved: creating a unique UX with lifetime value to the user.



Through the applied research methods in this written thesis, it was found that an interdisciplinary HCD process promotes collaboration between ML and UX design by providing helpful guidance during a project. Through such a model, all parties are present at each stage of the different project phases (project start, context of use analysis, elaboration of the requirements specification, development of the prototype, evaluation, and finalization.). Each participant knows what is being executed at what time in the project. Naturally, it is assumed that the process model is always adapted to the respective project. Furthermore, by means of the interdisciplinary HCD process model, the involved participants do not lose sight of the big picture, and important tasks are not lost. Additionally, the interdisciplinary HCD process model helps when communicating and budgeting the project with the client. Therefore, the involved UX designers and ML engineers can focus on their project tasks and the interdisciplinary collaboration.

## 5.2. RESEARCH GAPS



When sending out the online survey for this academic research, it was noticed that there is no current list of all ML and UX design companies in Switzerland. Although there are various lists of companies that focus on AI, such as the Swiss Artificial Intelligence Startup Map from Swisscom, all these lists have gaps. The same concept applies to the listing of experts and jobs in this field. For more involved research, this would be an exciting point to continue by creating different lists of ML and UX design companies, existing experts, and jobs in Switzerland so that an up-to-date overview of the research areas can be obtained. This work would go beyond the scope of this research project but could lay the foundation for further research.

Further, it would be interesting to find out why ML engineers were not interested in completing the online survey. With the results it can be found out how to motivate ML engineers to participate in further research studies.

In addition, the small excursion concerning the ethical consequences in Chapter 2.3. presents an important additional layer to this research project. Although this work was not dedicated to the debate between AI and ethics, these aspects had to be included. If UX designers do not incorporate the ethical consequences into their actions, it certainly could have unpleasant consequences for the users. This area of research is something which needs further studies and insights.

## 5.3. PERSONAL REVIEW



Predictably, transcribing the interviews took a great deal of time and effort. Because the experts' opinions on the low fidelity prototype were also asked in addition to the questions during the interviews, it was difficult to understand the constructive feedback later through the audio recordings of these interviews. Next time expert interviews are conducted, a video would be more helpful to better understand the feedback in context.

Additionally, it was difficult to locate the latest information relevant to the topic. The fact that ML is a specific part of AI and that this subject is still a niche did certainly not facilitate this academic research. However, for this written thesis, the digital library of the Association for Computing Machinery was helpful to find relevant scientific sources.

## 5.4. OUTLOOK

The first step involves summarizing the feedback from all interviewed experts on the low fidelity prototype presented (see Appendix 7.4) and uniting them in a medium fidelity prototype. To evaluate the developed HCD process model in practice, a collaboration with a business partner is necessary. With the project team, the prepared HCD process model should be applied to a project process from start to finish. By collaboration with a project team, it can be investigated on how the success factors identified in this academic research would behave in practice in an interdisciplinary collaboration between UX designers and ML engineers during a project process. For instance, the research method of observation could be used to examine which factors are efficient and helpful in an interdisciplinary collaboration during a project process and which are difficult to implement. Theoretical approaches often behave differently in practice, especially when people are involved. Once the medium fidelity prototype has been tested in practice and modified based on the findings, it is recommended to run the prototype through another iteration with another team according to the process model ISO 9241-210. Only after various further iterations can a successful HCD process model for interdisciplinary collaboration between UX designers and ML engineers be guaranteed.

Furthermore, one could work out a strategic way to get other UX and ML companies to strive for interdisciplinary collaboration in their projects. Perhaps, to establish the approach of interdisciplinary collaboration in the minds at an early stage, one would have to start with the universities. Course modules at the universities should show the students benefits of interdisciplinary collaboration and necessary considerations for this collaboration to work. In interdisciplinary project work, students could apply what they have learned from theory directly in practice. Additionally, this experience would be advantageous when students are searching for jobs after graduation.

## 5.5. CONTRIBUTION TO DESIGN PRACTICE AND THEORY

The results of this written thesis provide project teams with clear guidance in project processes when interdisciplinary collaboration is required. The guidelines and proposed solutions should be flexibly adapted depending on the project and the team. With the help of the guidelines, products are developed that not only meet technical expectations, but also ensure user satisfaction and therefore a positiv UX. This leads to products that are sustainable in practice and ethically justifiable.

Further, this written thesis presents profound arguments that offer the mostly unused potential and added value of ML in combination with UX design. The findings from the conducted research serve as a comprehensive basis for further research or as a motivation for companies to promote interdisciplinary collaboration in project processes. As soon as an interdisciplinary project team adheres to the elaborated key factors in combination with the developed HCD project model, an interdisciplinary collaboration during a project process can be successful and a product with an enhanced UX design can be developed.

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# #06

# 6. BIBLIOGRAPHY


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# APPENDIX

# #07

# 7. APPENDIX

## 7.1. ONLINE SURVEY

Online survey in English: https://forms.gle/jCTiEkkFVx3Z4tdL6

Online survey in German: https://forms.gle/RKVjYsqNpwyqueBB8

Results of the online survey in English and German:

https://www.dropbox.com/sh/4qejy16e2om4q3p/AAAGzRl0RN5Z_u6c69w4FFhka?dl=0

## 7.2. ONLINE SURVEY PARTICIPANTS



The companies listed below were sent the online survey with the request that they forward the survey to their respective employees on my behalf:

UX companies:

- Zeix AG
- Soultank
- Unic
- Easy to use
- CKW

Companies in the field of ML, or involved with AI:

- Merkle
- Liip
- Data Art
- Miquido
- Unit8

- Rocketlap
- Telesoftas
- Valdo
- Alpine Institution
- Zurich Data Scientist
- Synthara
- EyeFitU
- FinalSpark
- ARTORG Center for Biomedical Engineering Research
- Pro Cloud
- Simens
- Google
- AXA
- Accounto
- Jaywalker Digital
- AI Crowd
- Recapp
- Magma Learning
- Novigenix
- Retin AI
- Spitch
- Parashift
- Eyeware
- Colendi
- Gamaya
- Pxl vision
- HSLU Research
- Code Excursion
- Studio Llama
- Birdy GmbH

## 7.3. INTERVIEW GUIDELINES FOR EXPERT INTERVIEWS

Insight into the guideline for the expert interview with UX designers:

1. Wie lange arbeiten Sie bereits als UX Consultant?
2. Lernten Sie in Ihrer Ausbildung, bzw auf dem Weg zum UX Consultant Machine Learning (ML) kennen?

   Falls Ja:

   a.) Was lernten Sie kennen und welchem Zusammenhang? (allgemeines Grund wissen, Einsatzgebiet, diverse Methoden, Deep Learning, Regressionsmodell, Neuronale Netze, diverse Algorithmen)

   b.) Fanden Sie es spannend?

   Falls Nein:

   a.) Wieso nicht?

   b.) Hätten Sie gerne mehr darüber gelernt?

3. Wie umfassend würden Sie ihr aktuelles Wissen über ML einstufen (von 1 – 10)?

   a) Wieso dort?

   b.) Können Sie behaupten, dass Sie vom erlernten Wissen über UX in gewissen Situationen davon profitieren konnten?

4. Sehen Sie eine Verbindung zwischen ML und UX für das Produzieren von digitalen Produkten? Welche?
5. Denken Sie, dass eine funktionierende Zusammenarbeit mit ML Engineers ein besseres Benutzererlebnis gewährleisten und somit ein besseres digitales Produkt produziert werden kann?
6. Und Wieso?

7. Haben Sie in Projektprozessen von digitalen Produkten Kontakt zu ML Engineers bzw. arbeiten Sie zusammen?

   Falls Ja:

   a.) An welchen Zeitpunkten im Projektprozess arbeiten Sie mit ML Engineers zusammen und wieso? (eigener Prototyp des HCD-Prozessmodell zeigen und Meinung einholen)

   b.) Wieso an diesen Zeitpunkten?

   c.) Wie würden Sie die Zusammenarbeit beschreiben?

   d.) Wieso würden Sie die Zusammenarbeit so beschreiben?

   Falls Nein:

   a.) Wieso nicht?

   b.) Würden Sie gerne in Projekten mit ML Engineers/UX Designers zusammenar beiten und wieso?

   c.) An welchen Zeitpunkten, denken Sie wäre es sinnvoll mit ML Engineers zusammen zu arbeiten? (eigener Prototyp des HCD-Prozessmodell zeigen und Meinung einholen)

8. Was denken Sie muss gegeben sein, dass die Zusammenarbeit zwischen UX Designers und ML Engineers funktioniert bzw. was kann optimiert werden?

9. Würde ein standardisierter HCD-Projektprozess, welcher genau erklärt, wann und für was ein ML Engineer zugezogen werden muss, helfen als Guideline? (Begründen Sie Ihre Antwort)

10. Würden Sie gerne mehr Wissen über Machine Learning verfügen bzw. erlernen? (Begründen Sie Ihre Antwort)

11. Über welches Thema würden Sie gerne besser Bescheid wissen? (Allgemeines Grundwissen, Einsatzgebiet, diverse Methoden, Deep Learning, Regressionsmodell, Neuronale Netze, diverse Algorithmen)

12. In welcher Form würden Sie gerne mehr Wissen darüber aneignen? (Workshop, Erklär-Videos, externe Weiterbildung, Lehrbücher/Zeitschrift, Online (Webseite))
13. Wie sieht bei Ihnen ein gewöhnlichen Projektprozess eines digitalen Produktes aus? (Bitte Ablauf erläutern)

The guideline for the expert interview with ML engineers can be found here:

https://www.dropbox.com/sh/5mebgxb6odn083u/AACBj9VBC6Ibrk3oTa_M38oRa?dl=0

## 7.4. LOW FIDELITY PROTOTYPE OF HCD PROCESS MODEL

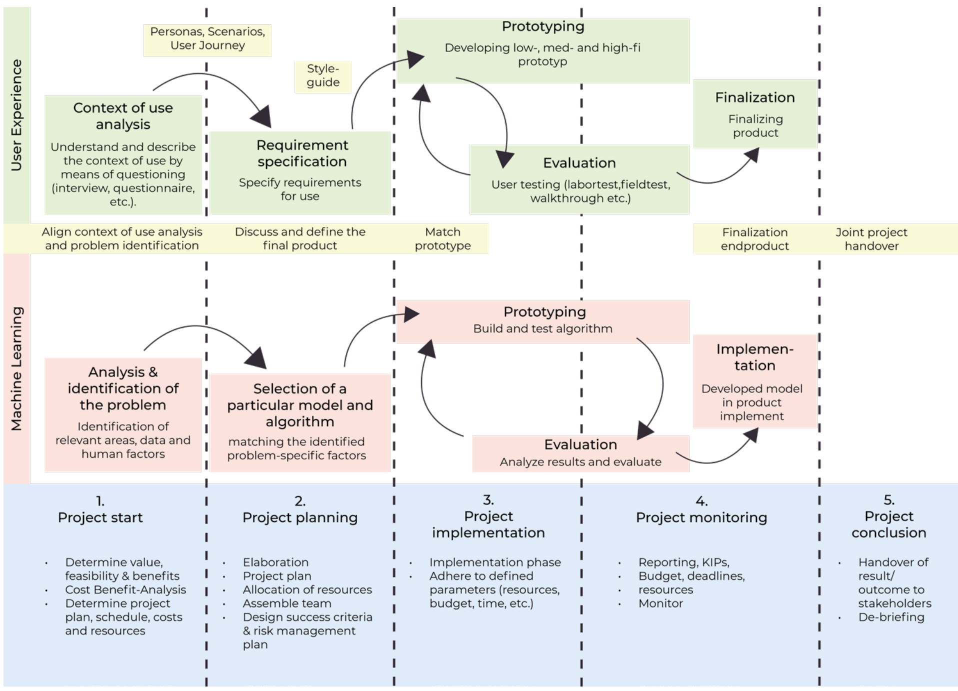


Figure 17: Low fidelity prototype of HCD process model, Suter (2021)

## 7.5. AUDIO FILES OF THE INTERVIEWS

Link to the audio files of the interviews:
https://www.dropbox.com/sh/4m34lsgxoxzetno/AACqjivz-i2QgZ7y_nAnC4cZa?dl=0

## 7.6. TRANSCRIPTION FILES OF THE INTERVIEWS



Link to the transcription files of the interviews:
https://www.dropbox.com/sh/dmmsazxnq97v3v5/AADKOJ6kgfJtl8DMc-_h9C6xa?dl=0

## 7.7. CODING GUIDE

| Category | Definition | Examples | Coding rules |
|---|---|---|---|
| Relevance of collab-oration between ML and UX design | Any statements that indicate the relevance of interdisciplinary collabo-ration | *F: "There are a lot of points to consider ther, and I think it's more the methods and the mindset of the UX designers that fit the problems very well to do meaningful things with machine learning."* | Focus also on the possible connec-tions (good or bad) between the parties involved and added value form the inter-disciplinary collabo-ration |
| Potential and value of UX design | Text passages that high-light the potential of UX design | *F: "What we have learned as user expe-rience designers and do again and again every day is to try to understand people in their context. We have a wide variety of methods for this. Of course, they help a lot to recognize consequences that we might not want."* | Potential and added value of UX desig-ners during a project process and for the resulting product |
| Potential and value of ML | Text passages that high-light the potential of ML | *C: "If we automate processes and five fewer people are needed afterwards, then the ad-ded value is measurable."* | Potential and added value of ML engi-neers during a pro-ject process and for the resulting product |
| Knowledge level | Statements relating to the current level of know-ledge in the other expert field | *B: "I don't think I could design a good UX. But I understand relatively well how the process works and how they [UX designers] proceed in the workshops. I've been through the process a few times already."* | This also includes numbers from 1 to 10 as to how they assess their current knowledge in the other expert field |
| Interest | Any statements that indicate:<br>- interest,<br>- motivation to gain more knowledge, and<br>- topic of interest<br>in the other expert field | *A: "It is certainly an interesting topic, yes. It goes in the direction of AI, however, I find ML better, because I find the other systems rather a bit dull."* | Not only interest relevant, but also the reasons - methods of learning more know-ledge was not taken into account |
| Challenges during an interdi-sciplinary collabora-tion | Any statement that describes a challenge during an interdisciplina-ry collaboration between UX designers and ML engineers | *H: "I think it concerns the prototype phase. That we talk to each other fast enough and do not spend too long working for oursel-ves. Plus I think mutual understanding can also be optimized."* | Detailed description of challenge inclusi-ve context descrip-tion |

| | | | |
|---|---|---|---|
| Possible solution approaches | All text passages that already describe possible solutions or optimization proposals for improved interdisciplinary collaboration between UX deisgners and MI engineers | *A: "The key factor is that at the beginning of the project, all stakeholders are at the same meeting table, and everyone defines the project goal together."* | Detailed description of possible solution approach inclusive context description, and without feasibility inspection |
| Opinion of standardized HCD process model | All statements that promote the value of a standardized HCD process model | *B: "Once you have a standardized process, you can justify why the process works the way it does. I claim that the understanding has become so widespread that a software engineer is needed in the testings and belongs to the process. And not so that costs* | Not only added value relevant, but also the reasons |

Table 2: Coding guide, Suter (2021)

# CONTACT

**MILENA SUTER**
Pilatusstrasse 1
6300 Zug

**TEL: +41 79 270 11 09**

MILI_SUTER@HOTMAIL.COM