Design Intelligence

- Jennifer Moosbrugger -

Design Intelligence

Human-Centered-Design
- principles, processes, methods and tools -
for the development of industrial AI/ML agents

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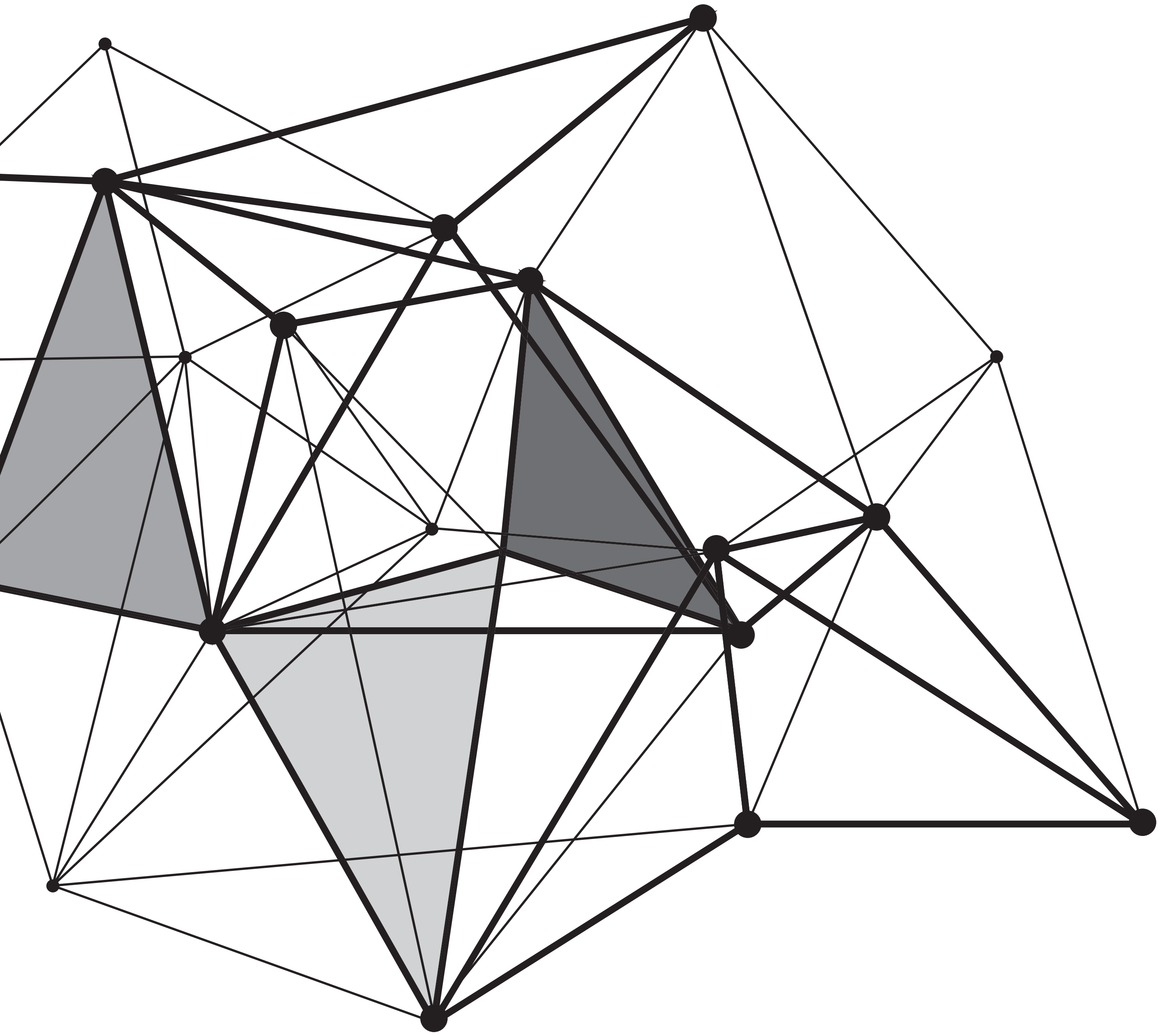
“And nothing the Temple of Design can say or do really impacts what happens with computational products today, because, frankly, the Temple of Tech has sped past it in relevance at Moorean speed.”[1]

1. Maeda, John, "How to speak Machine - Computational thinking for the rest of us", Penguin Random House LLC, p.110, 2019.

John Maeda - is an American technologist, designer, engineer, artist, investor, author, and teacher.



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Abstract (human)

This study deals with design for AI/ML systems, more precisely in the industrial AI context based on case studies from the factory automation field. It therefore touches on core concepts from Human-Centered-Design (HCD), User Experience (UX) and Human Computer Interaction (HCI) on one hand, as well as concepts from Artificial Intelligence (AI), Machine Learning (ML) and the impact of technology on the other. The case studies the research is based on are within the industrial AI domain. However, the final outcomes, the findings, solutions, artifacts and so forth, should be transferable to a wider spectrum of domains. The study's aim is to examine the role of designers in the age of AI and the factors which are relevant, based on the hypothesis that current AI/ML development lacks the human perspective, which means that there are pitfalls and challenges that design can help resolve. The initial literature review revealed that AI/ML are perceived as a new design material that calls for a new design paradigm. Additional research based on qualitative case study research was conducted to gain an overview of the relevant issues and challenges. From this, 17 themes emerged, which together with explorative expert interviews and a structured literature review, were further analyzed to produce the relevant HCD, UX and HCI themes. It became clear that designers need new processes, methods, and tools in the age of AI/ML in combination with not only design, but also data science and business expertise, which is why the proposed solution in this PhD features process modules for design, data science and business collaboration. There are seven process modules and their related activities and dependencies that serve as guidelines for practitioners who want to design intelligence. A unified framework for collecting use case exemplars was created, based on a workshop with different practitioners and researchers from the area of AI/ML to support and enrich the process modules with concrete projects examples.[2]

2. This abstract was written by a human who set out to learn more about machines and their underlying algorithms in order to change the way they are developed.

Abstract (machine)

This study deals with design of AI/ML systems, which is the process of designing systems that learn to respond to users. More precisely, the study investigates design aspects of AI/ML systems in the industrial AI context based on case studies from the factory automation field. It touches on concepts from Human-Centered-Design (HCD), User Experience (UX) and Human Computer Interaction (HCI), Artificial Intelligence (AI), Machine Learning (ML) and the impact of technology in general. The goal is to find areas of convergence between the different schools of thought and look into this domain with a lens of a future-oriented, creative mindset. The case studies the research is based on, are within the industrial AI domain. Although, it expects to apply the findings to a variety of other domains, given that AI development lacks the human perspective; it is hoped that design can add a human nuance to AI development that takes into account the pitfalls and challenges of current design. Thus, the aim of the study is to examine the role of designers in the age of AI. Researchers read studies about AI and ML and realized that AI could change the way we think about design. They decided this would be a good topic for further research. They read previous studies on AI and ML and found that it called for a new design paradigm. They decided they would read the available literature on design and AI, data science, business, and HCI, and they would put their thoughts and ideas together to create a structured argument about how designing for AI differed from designing for other technologies. The researchers reviewed literature on HCD, UX and HCI. They observed designs from the past that worked, designs that did not work, and tried to understand why each one was successful or unsuccessful in response to the human needs or not. They compared traditional methods of research to newer methods. Through this research, they identified themes and areas of opportunity in Human-Centered Design, UX/HCI methods, AI/ML capabilities, and business strategy. They found that AI/ML were a new design material. Designers needed new processes, methods, and tools in the age of AI/ML in combination with not only design, but also data science and business expertise. This PhD thesis presents a methodology that draws on three different methods to teach machines the minds and thinking of the organizations they will serve. The proposed method is based on process modules that design both the data and the AI systems to train it on. The goal is to give machines human-like decision-making skills, so they can adapt to new situations and interact with people in more effective ways. The three processes, design, data science, and business collaboration are each linked by importance and dependencies as shown in the diagram below. First, the design process creates sets of tasks for the data science process to analyze. These tasks reflect organizational problems in the real world and have been developed from previous research and experience. This process also creates sets of training data for the data science process. By defining specific problems, it is limited what AI can do if it gets deployed without oversight. When gathering data, gathering as much use case examples as possible as shown in the table below is necessary. All these examples help machines make more human-like decisions.[3]

3. This abstract was created by a machine - namely GPT3 (OpenAI. Retrieved from https://beta.openai.com/playground. (Accessed on 2022-11-21)) an AI model trained on text - it did not have the same information as the human, just a few prompts (see Appendix III. page 175).

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Part III. Problem Space

Outline of the Thesis

Broadly speaking, this thesis presents research on how AI and ML have impacted design practice, and how design practice can and should have an impact on AI and ML development. The human-centered aspect and perspective play a central role in this context and is the target audience from Design Research, especially interested in paradigms related to and fostered by 'new' technology, or are design practitioners who would like to develop a deeper understanding of AI and ML technology, its influence on design, its concepts and development in practice.

This thesis is divided into five parts and ten chapters. Each part and chapter builds up-on the previous and leads to the next. Nevertheless, it is possible to jump to the Solution Space for readers interested in the results of this research endeavor, while readers whose interest is the case study and research process can start with the Problem Space and its related chapters. A short description of each part and its chapters follows to guide to the reader where to find particular content and information.

Part I. presents the Foundations of the thesis. **Chapter 1. Introduction** contains four subsections. The 1.1 Motivation and Purpose sections explain the basis of the research and the stance adopted by the researcher. This is followed by a list of 1.2 Abbreviations used, later supplemented with a glossary also explaining their meanings, to support the reader throughout the whole manuscript. The 1.3 Definitions and Core Concepts section introduces and defines the relevant terms and concepts used throughout the manuscript, with the stance taken in the related and affiliated areas of design and AI/ML, and the overarching themes, by defining and explaining how the researcher perceives design and related practices. Finally the 1.4 Problem Statement and Starting Point is what guided and informed many of the decisions made. **Chapter 2. Research Scope** contains three subsections. First the 2.1 Research Questions that this thesis explores, and the underlying 2.2 Propositions and Hypothesis are described. The 2.3 Goals and Objectives inform the reader of the aims and outcomes of the thesis.

Chapters 1 and 2 serve as the basis of the whole thesis and subsequent chapters all contain reminders of these guiding principles. These chapters address a wide spectrum of concepts and ideas from design, AI/ML, industrial contexts, as well as case study/best practice sharing, the focus being further narrowed down in subsequent parts and chapters. This broad approach also lays the ground for detecting white spots and research gaps in the current research discourse.

Part II. concerns the notion of Framing. **Chapter 3. State of the Art Research** and **Chapter 4. Research Approach** narrow down the scope of the thesis from two distinct perspectives. Chapter 3 provides an overview (3.1) through a) a map of resources, relevant actors and their contributions, institutions and artifacts in the design and AI/ML space, b) the new design paradigm derived from those sources, and by c) mapping all this to the AI discourse. With this information the 3.6 Research Gaps were identified that the thesis addresses. *A publication is related to this chapter, for further information see (Heier, 2020).* The Research Approach chapter outlines the methodological choice (4.2) of the thesis. While this chapter refers back to the Definitions and Core Concepts section (Chapter 1.3.2), the methodology of this thesis is framed by critical and functional-referential-methodological Pragmatism informed by Dewey's model of inquiry (1938) and Goldkuhl's investigations into knowledge and action (2008, 2011), with the addition of postphenomenological aspects of technological mediation provided by Verbeek (2006, 2011) and Ihde (2012). The 4.5 Methods section is closely related to the choice of methodology and framed primarily by qualitative research, as well as 4.6 Multiple Case Study Research as defined by Yin (2003). The 4.8 Research Tactics and Tools section informs the reader of the data collection, analysis and synthesis approaches.

Part II. of the thesis provides the overall framework of the research, based on the foundations from Part I. The State of the Art chapter identifies the research gaps in design and AI/ML in the industrial AI context and the lack of case studies from this domain. The Research Approach chapter based on these gaps explains the methodological choice suitable for this combination of boundary objects. Both chapters lay the basis for the research described in Part III.

Part III. is related to the Problem Space in the design process. **Chapter 5. Case Study Research** presents three case studies from the industrial AI domain at Siemens, dealing with the development of an AI/ML solution based on time series forecasting, so-called predictive demand planning, at three different factory sites, representing a convergent approach, exploring the case studies to gain an overview of pitfalls and challenges from a broad spectrum of different team roles and professions. 5.2 Case Study 01 (Meta-Sample) is related to a factory in Erlangen and serves as the starting point, while 5.3 Case Studies 02 and 03 (Beta-Samples) from factories in Karlsruhe and Berlin serve as cross case validation sets. 17 themes emerged from that research which can be grouped by their connection to general AI/ML challenges, project specific issues, as well as the design domain (5.4). **Chapter 6. Expert and External Input** takes a divergent approach, to narrow down the design perspective and align the findings to external concerns, though the responses from 6.2 Expert Interviews and a 6.3 Structured Literature Review.

Part III. of the thesis has already contributed to the overall scientific and research community with two publications. *For further information see [Heier, et al. 2020 / Heier, 2021].* The Problem Space opens up to discover relevant themes related to the research within the thematic areas of design and AI/ML in the industrial domain based on real world scenarios, as outlines in part II. This allowed potential action areas be derived from that space to be defined in preparations for the solutions part of this work. It became clear that a system approach providing a holistic view of the issues and challenges found while combining the design, data (science) and business perspective was most promising.

Chapter 7. From Problem to Solution Space connects Parts III and IV with a 7.2 Summary of Challenges for the Design of AI/ML Solutions based on the insights and findings from the Problem Space and introduces Design Science Research as an 7.3 Additional Methodological Angle to the overall methodological components. It lays the ground for the transition to Solution Space.

Part IV concerns the Solution Space in the design process, following the Design science Research and practice paradigm, which comes from the intersection of the design and information science domains. It presents the ideas and concepts underlying the design artifacts the Solution Space ought to create. **Chapter 8. AI Process Modules** has two main areas: Build and evaluate, and theorize and justify. Build and evaluate has subsections 8.2 AI & Design Process Mapping, 8.3 AI & Design Process Modules and 8.4 Overview of AI & Design Tools together presenting a design artifact that encompasses the notion of a process map to support collaboration between design, data (science) and business experts. Theorize and justify is concerned with testing the outcome for an external case (8.5) in order to transfer the solution to a wider spectrum than the industrial AI domain. This part of the Solution Space aims to bridge a selection of the gaps from Chapter 3, Chapter 5, as well as Chapter 6, presenting a convergent approach. *A publication is related to this chapter. For further information see (Moosbrugger, 2023).* **Chapter 9. AI Use Case Framework** is similarly divided into the two main areas of Design Science Research and practice. Aspects dealing with build and evaluate have been derived from organizing a 9.2 Workshop on: 'Use Cases of Designing AI-enabled Interactive Systems' at the HCI International 2021 conference, and the related results. The purpose of this workshop was to include external expert angles and bring together practitioners and researchers from various domains to provide their design and AI/ML use cases to create a unified framework for collecting and documenting them. This represents a more divergent approach, focusing on the research gap concerning best practice sharing in the context

of design & AI/ML. The section theorize and justify took the initial results and mapped them to the provided use cases from the workshop to collect feedback from the relevant practitioners (9.4) and reveal the solution based on this (9.5). *A publication is related to this chapter. For further information see (Moosbrugger/Ntoa, 2022).*

Part IV provides practical solutions and contributes to current research. It relates to the practice-based nature of this PhD, while providing two artifacts. One focuses on the overall development process of AI/ML infused systems, addressing design, data science, business perspectives and ways of supporting their collaboration through seven process modules (8.3). This offers guidance to designers wishing to contribute to the development of AI/ML projects through concrete activities, with their implications and the necessary tools for the different modules. The second artifact is a framework for collecting and documenting use cases supposed to supplement the process modules with concrete example projects (9.5). It responds to a very operational gap - lack of best practice sharing in AI/ML projects. By its nature, it stems from different use cases with various domains and experts involved in the field of AI/ML, which with more information and input, the more useful it could become. Both artifacts provide a starting point, but also make room for further investigations.

Part V. is dedicated to Reflections & Results. While **Chapter 10. Summary and Conclusions** guides the reader through the 10.1 Summary of Results of this work. The 10.2 Main Arguments section summarizes the points made in each chapter which contribute to the 10.3 Conclusion and Discussion section for the implications of this research for its various audiences, which leads to the 10.4 Outlook section that suggests activities for future research and collaboration in the area of design & AI beyond the remit of this thesis.

Part I. Foundations

Chapter 1. Introduction

1.1 Motivation and Purpose

"The term 'industrial designer' originated in the U.S. Patent Office in 1913 as a synonym for the then-current term 'art in industry'. In 1927 Macy's department store in New York City held a well-attended Exposition of Art in Trade, which featured 'modern products', many of them from the 1925 International Exposition of Modern Decorative and Industrial Arts in Paris. Public and manufacturer demand for these new 'Art Deco' styles immediately surged, and a number of design professionals (including architects, package designers and stage designers) began for the first time to focus their creative efforts on mass-produced products. These professionals adopted the title of 'industrial designer'."[4]

4. Industrial Designers Society of America (IDSA) Records. Retrieved from https://library.syr.edu/digital/guides/i/idsa.htm (Accessed on 2022-11-21)

Technology does and has always influenced the work of designers. Industrial design, for example, has its origins in the Industrial Revolution. The change in the way humans made objects, also changed the way they were able to buy and consume products. For the industrial design professional, this meant the change from a small amount of hand-crafted items to a mass-produced product market. This, in turn, influenced the overall design process, methods and tools. At the start of this turn towards machine-made objects, designers primarily dealt with aspects of style and aesthetics, but since in the age of mass production, the physical appearance of an object distinguished it from that of competitors. Later on, collaboration with engineers, ergonomics, safety, ease of use, maintenance and manufacture were taken into consideration, again changing the overall design approach. Names such as Henry Dreyfuss, Dieter Rams, Charles and Ray Eames are notable in that regard for shaping the ideas and best practices of the designers of that era.

Today, in the digital age, products and services disappear in an online world. In the past, the role of an industrial designer shifted from making products and physical objects look nice, to focusing on function and the overall manufacturing process. Nowadays, designers have to take into consideration the whole design experience of their customers and their needs. Service Design, User Interface Design (UI), User Experience (UX) Design, Web Design to mention a few concepts emerged from these new needs related to the internet, mobile technologies and applications to give shape to shapeless objects. *"While interaction design is a wholly new discipline, visual and industrial design are older, pre-existing fields that have been wholly transformed by digital technology."* (Goodwin, 2009, Foreword)[5] Aspects of Human-Computer-Interaction (HCI) and the integration of user-specific needs play a central role in the rise of the new fields of design, which again influences the designers' approaches, processes and tools.

UX design describes the process of defining all aspects of an experience of a user when interacting with a digital product or service. Decisions in UX design are driven by research, data analysis, testing and evaluation. UX design includes aspects, such as usability, usefulness, desirability, performance and overall interaction with a company.

5. Goodwin, Kim, "Designing for the Digital Age: How to Create Human-Centered Products and Services", Wiley Publishing, 2009.

HCI is related to research and design that focuses on the interfaces between humans and computers. HCI practitioners observe humans and how they interact with computers and as a result, design technological solutions that allow humans to interact with computers in intuitive and, at the same time, innovative ways. It is situated at the intersection of computer science, behavioral sciences, design, media studies, and several other fields of research.

The next technology revolution already influencing the design profession is Artificial Intelligence and the sub fields of Machine and Deep Learning. This thesis aims to shed light on the influence of this technology on design and designers - and the other way around, how design can play a key role in the development of AI systems. Do designers have to change their approaches, development processes and tools again? Focus on the field of industrial AI seems promising, because that area is missing a human-centered approach, which implies a lot of potential.[6] This thesis aims to identify challenges and research gaps to define new methods and tools for designers, in the area of industrial AI. To create a foundation for the profession to have an impact in the age of digital transformation. Design needs to prepare for the new challenges ahead and so catch up with the 'Temple of Technology', as John Maeda put it in the preface.

6. Ngoc, Hien Nguyen, et al. "Human-centred design in industry 4.0: case study review and opportunities for future research", Journal of Intelligent Manufacturing, Vol. 33, pp. 35–76, 2022.

1.2 Abbreviations

HCD Human-Centered-Design
UX User eXperience Design
HCI Human-Computer-Interaction
AI Artificial Intelligence
IA Intelligent Augmentation
ANI Artificial Narrow Intelligence
XAI eXplainable AI
HCAI Human-Centered-AI
ML Machine Learning
iML interactive Machine Learning
DL Deep Learning
PoC Proof of Concept
MVP Minimum Viable Product
CRISP DM CRoss-Industry Standard Process for Data Mining

1.3 Definitions and Core Concepts

This part of the thesis deals in detail with the two main features, design and AI. Each already contains important aspects, definitions, meanings and scope for action which need to be described so that for the given research work can be positioned with them. This is the foundation upon which all further observations and conclusions in the following chapters are based on to inform the reader about the core concepts this work builds upon. For design this means looking into origins and development over time to understand what changed and what is relevant for the profession today and in the future, to explain how design is understood and defined in the context of this thesis as well as the concept of the design principles and design processes relevant in the practical part of this PhD. Lastly, the area of Design Research and the implications for the theoretical foundations of the research process. Going on to the area of AI, a short historical overview illustrates the factors that influence the AI profession, then an outline of aspects of Machine and Deep Learning, how they relate to each other, and AI in general, and how terms will be used throughout the thesis. This is followed by a short paragraph on technical input and terminology to provide basic knowledge of ML concepts and methods. Both sections also provide some explanatory side notes to further define certain words or aspects of a topic, namely Critical Theory, artifacts as outcomes, Design Thinking, design process mapping, AI and creativity, AI and (human) intelligence.

1.3.1 Design Theory

1.3.1.1 Origin and history of design

Fundamentally, design means making, actively shaping, creating with a purpose - one could say purposeful creation. As Klaus Krippendorff expressed it *"The etymology of design goes back to the Latin de + signare and means making something, distinguishing it by a sign, giving it significance, designating its relation to other things, owners, users, or gods. Based on this original meaning, one could say: Design is making sense (of things)."* (Krippendorff, 1989, p.9)[7]

The early designers were craftsmen/women; they dealt with form, style and the appearance of objects, back in the days hand made things. That was their core competence. With the rise of the Industrial Revolution this perspective changed. Hand made things became the machine-made things imagined by designers.[8] Still, in the end, the design creation was represented in and related to a physical object, but with different constraints and produced on a larger scale. Designers had to learn the art and process of craftsmanship, but they also had to acquire the skills necessary to understand and address the manufacturing processes. An even bigger development in the design paradigm was the digital age.[9] Whereas *"In the early days of industrial design, the work was primarily focused upon physical products. Today, however, designers work on organizational structure and social problems, on interaction, service, and experience design. Many problems involve complex social and political issues. As a result, designers have become applied behavioral scientists, ..."* (Norman, 2010, p.92)[10] In addition to focusing on solutions other than physical objects, every change in the design profession related mainly to technological advances, meant that parameters of involved stakeholders also increased. In the beginning, designers had to deal mostly with their clients, later on with people involved in the manufacturing process as well, such as engineers, or business people, and today, with an even more complex stakeholder network of legal and compliance, marketing, sales, management to name a few. The skills needed to perform in this environment are equally complex. As Norman continues: *"... we need a new breed of designers. This new breed must know about science and technology, about people and society, about appropriate methods of validation of concepts and proposals."* (ibid., p.95) The core competence of designers is no longer about and focused on physical objects, but on a network of different actors. *"... It is a move toward human-centeredness, the acknowledgment that meaning matters. This is the core of the semantic turn."* (Krippendorff, 2006, p.13)[11] The newly acquired core competence of design is - at least within the scope of action - focuses on people. This implies gaining knowledge and skills in many different areas, but without becoming an expert. This approach is still in its development stage, devising new methods and tools.[12] As Dieter Rams puts it: *"We know how important it is to make devices even more intelligible, even more useful, even more durable, even more human. We know that the opportunities for concrete, user-oriented design are not yet exhausted!"* (Rams, 2021, p.38)[13] Another concern within the remit of designers in the many different areas of expertise in other domains is the challenge of differentiation and making design propositions unique. *"If design does not want to disappear into insignificance, then it must clarify its role/function and formulate it much more radically than before."* (Jonas, 2011, p.10)[14] In the end, design is everything and everything is designed. Is that the end of design as a profession then? This PhD thesis does not set out to answer this question, but to reveal the great potential of design and designers within the ability to adapt to new challenges, especially in the current volatile and unpredictable economic and environmental circumstances.

1.3.1.2 The attempt at a definition

Design is difficult to define. *"People outside of design professions have difficulty drawing the line, and there are so many philosophies and assumptions attached to it that even designers seldom agree on exactly what 'design' is."* (Goodwin, 2009, p.3) Design is innovative, but it's not innovation, design is creative, but it's not creativity. This is an attempt to offer a workable definition of design that works for this PhD thesis. Languages, such as German and English, have different connotations of the word design. In English, design is universal more related to the original meaning given by Klaus Krippendorff, whereas in German, design and designers are perceived as giving shape and form to a physical object - look and feel - or more recently, a digital interface. Besides language and culture, the factors mentioned above also play a role, since by nature, design is fluid, changeable and adaptable to new circumstances, hence the difficulty in finding a definition of design universally accepted and agreed on. As Erik Mattie put it in an interview with Dieter Rams, "*The world changes and our thinking about design changes along with it. ... Good design is definable, but the definition is not static."* (Mattie, 2017, p.80)[15] This is why there are service designers, user experience designers, interface designers, graphic designers, industrial designers... all with a different area of expertise and scope of activities. Is there a common thread, or do all these domains need their own definitions of design? The answer is complex or at least pluralistic and outside the focus of this thesis. However, one common thread that appears to run through all the above professions is the aim to *"...prefigure something that doesn't yet exist. ... seeking about to bring change..."* (Willis, 2019, p.11)[16] Instead of looking for a definition of core competencies, about tasks or necessary skills, why not define design as change itself? As Dieter Rams put it, *"Designers should always have the ambition to change the world for the better; it cannot happen by itself. In those days we had been challenged by the aus-*

7. Krippendorff, Klaus, "On the Essential Contexts of Artifacts or on the Proposition that 'Design is Making Sense (of Things)", Design Issues 5, No. 2, pp. 9–38, 1989.

8. Schneider, Beat, "Design – Eine Einführung. Entwurf im sozialen, kulturellen und wirtschaftlichen Kontext", Birkhäuser (2. Edition), 2008.

9. Bürdek, Bernhard, "Geschichte, Theorie und Praxis der Produktgestaltung", Birkhäuser Verlag (4. Edition), 2015.

10. Norman, Donald, A., "Why Design Education Must Change", form: The Making of Design, pp. 92-95, 2010. Retrieved from https://core77.com/posts/17993/Why-Design-Education-Must-Change. (Accessed on 2022-11-21)

11. Krippendorff, Klaus, "the semantic turn - a new foundation for design", Taylor & Francis Group, 2006.

12. Norman, Donald, A., et al., "Affect and Machine Design Lessons for the Development", IBM Systems Journal Vol. 42, No.1, pp. 38-44, 2003.

13. Rams, Dieter, "Ten Principles for Good Design: Dieter Rams", Edited by Cees W. de Jong, Prestel, (1st published 2017), 2021.

14. Jonas, Wolfgang, "Schwindelgefühle – Design Thinking als General Problem Solver?", EKLAT Symposium, TU Berlin, pp.1-12, 2011.

15. Mattie, Erik, "The Essence of Dieter Rams Legacy", Edited by Cees W. de Jong, Prestel (1st published 2017), 2021.

16. Willis, Anne-Marie, "Design Philosophy Reader", Bloomsbury Publishing Plc., 2019.

17. Within this attempt at a definition of design, Critical Theory (Frankfurt School and Critical Theory. Retrieved from https://iep.utm.edu/critical-theory-frankfurt-school. (Accessed on 2022-11-21)) appears to be a relevant school of thought (social structures and cultural assumptions cause problems rather than individuals) linked to the rise of machines over man. AI and ML have similar effects on humans, so the ideas of the proponents of Critical Theory are crucial and relevant to this research in general. It is not the methodological framework, but the critical attitude and focus on consumerism, capitalism and technology also play a central role in this work.

terity of the post-War years. Today's big challenges are to protect our natural environment and to overcome thoughtless consumerism." (Rams, 2021, p.44) If a definition of design is so hard to find, why not align it to a purpose? Design equals change. This change refers to the design profession, designers changed their practice as new circumstances presented themselves, over time as stated above, but their aim is also to bring change, design the change, embrace the change, be the change. This comes with a lot of responsibilities and also has critical[17] and ethical components attached to it. Dieter Rams already referred to the consumerism designers are linked to when part of a workforce creating more products and services. But this can also be turned around by having a positive impact on the decisions made regarding those products and services. If change is the core competence of designers, they can choose to influence ethical and sustainable goals.

1.3.1.3 Design and technology

When dealing with design it is important to clarify its relationship to technology by looking into the origin of the term. *"The term 'technē' originates from ancient Greek and still shapes the understanding of art, science and technology in Western philosophy. 'Technē' does not distinguish between art and technology, but can be approximately described with the keywords ability, artistry, craftsmanship and practice."* [18]

18. technē – Was Kunst und Technologie verbindet. Retrieved from https://ars.electronica.art/center/de/exhibitions/techne. (Accessed on 2022-11-21)

In their basic origins, both terms were used in tandem - craft and technology - showing their strongly connections with each other. They were even perceived as inferior to science and logic, as Friedrich Rapp suggests it his book about a philosophy of technology: *"In antiquity and the Middle Ages, technology was considered to be a mere craft, neither capable nor worth theoretical study. Compared with the ideal of theoretical arguments, logical deductions and general laws, craft and technical skills, as well as the practical execution of technical actions were regarded rather as an object of inferior rank. Until the beginning of the Industrial Revolution, …."* (Rapp, 1994, Foreword)[19]

19. Rapp, Friedrich, "Die Dynamik der modernen Welt: Eine Einführung in die Technikphilosophie", Junius Verlag, 1994.

The Industrial Revolution changed this relationship between art, craft - including design - and technology. The terms became separated. *"Thus, what in antiquity belonged inseparably together was attempted to be separated as strictly as possible in the following centuries."* [18] Technology had elevated itself to the level of science and logic and so became superior to the arts, craft and therefore design. *"Conventionally, technology is seen as over-arching design - a technology is developed, the designers come along later - to encase it, style it, give it user interfaces and a 'look-and-feel' package, and to promote it. Such a characterisation only holds from the internal perspective of commercial design practice, and even within that circumscribed domain, this is an increasingly outmoded version of what design is becoming. More fundamentally, design and technology cannot be separated; technology is designed, and technology designs."* (Willis, 2019, p.181) Anne-Marie Willis makes an important point here, besides her call for the two streams to reconnect - each influencing the other - she also sees their separation as rooted in an old fashioned view of the competencies and purpose of design which no longer exist. Her statements go further to suggest today's challenges call for a change in the perception of this superior and separate relationship. *"… combined with climate change, species extinction, rampant consumerism, increasing immersion in IT, skills obsolescing at faster rates, the end of job security, the prospect of genetically designed populations, artificial intelligence that might outsmart us or maybe already has, such a list of unsettling current and emergent factors and forces goes on. In attempting to evoke this complexity of what needs to be thought now, there is no correct place to begin and every concern mentioned connects almost every other."* (ibid., p.251) Dieter Rams has a similar view on the detachment from design and technology, he says *"Technological development is always offering new opportunities for innovative design. But innovative design always develops in tandem with innovative technology, and can never be an end in itself."* (Rams, 2021, p.94) The call to reconnect both terms and practices can also be understood as the motivation for the given work on design for AI.

Positioning

Design is influenced by technological advances. Design has evolved from shaping the appearance and meaning of objects, to focusing on digital artifacts and human-focused experiences and implies the emergence of new design practices, which suggest AI technology may again disrupt the design profession. Given the research area of design for AI, a definition of design as a driver for change is a great fit, and therefore serves a basic purpose. The human focus and the exploration of the Problem Space, as well as the definition of the problem, are the overarching, relevant design superpowers (principles).

Artifacts as design outcomes

This thesis refers to artifacts as design outcomes with the fundamental definition of the term arte - by skill - and factum - something made. This definition enables a variety of representations of design practice, ranging from man made things, such as tools (physical objects), to research outcomes (knowledge). This understanding also conveys multiple meanings: symbolic, commercial or otherwise (Latour, 2008)[20]. This lays the foundations for a design outcome that is a perception of design not primarily focused on physical objects, as Klaus Krippendorff puts it: *"Design has to shift gears from shaping the appearance of mechanical products that industry is equipped to manufacture to conceptualizing artifacts, material or social, that have a chance of meaning something to their users, that aid larger communities, and that support a society that is in the process of reconstructing itself in unprecedented ways and at record speed."* (Krippendorff, 2006, Introduction)

20. Latour, Bruno, "Keynote lecture: Networks of Design", Proceedings of the 2008 Annual International Conference of the Design History Society, 2008.

1.3.2 Design Research

This thesis relates to Design Research. Current standards in research oftentimes originate from scientific approaches and paradigms, but Design Research does not equate to scientific research, *"… design as research is not the same as science as research. … , design research and scientific research convergent at times - especially in the research on materials and statistical analyses - but they diverge just often."* (Lunenfeld, 2003, p.13)[21] Aspects of knowledge that use and produce activities, theoretical, as well as practical stances, are not equally supported by scientific frameworks. *"The purely analytical models of science that we have been using will only get us so far: in the face of such an immensely complex area as design, only experimental methods can bring the clarity and understanding we are seeking."* (Dorst, 2008, p.11)[22] Design Research does not fit typical approaches, as *"…, many researchers in the design world have been realising that design practice does indeed have its own strong and appropriate intellectual culture, and that we must avoid swamping our design research with different cultures imported either from the science or the arts."* (Cross, 2001, p.55)[23] While this represents the design perspective of this issue, the scientific perspective is concerned with the validity of the current Design Research approaches, as Luke Feast puts it: *"… the rigor and robustness of practice-based doctorates has become the subject of significant debate and an important topic of major international conferences and publications."* (Feats/Melles, 2010, p.1)[24] Both perspectives show that Design Research is not yet finally established and is a research area still in its identification stage.

21. Lunenfeld, Peter, "Preface - The Design Cluster", in Design Research: Methods and Perspectives / [edited by] Brenda Laurel, The MIT Press Cambridge, pp.10-15, 2003.

22. Dorst, Kees, "Design research: a revolution waiting to happen", Design Studies Vol. 29, pp.4-11, 2008.

23. Cross, Nigel, "Designerly Ways of Knowing: Design Discipline versus Design Science", Design Issues Vol.17, No.3, pp. 49-55, 2001.

24. Feast, Luke, and Melles, Gavin, "Epistemological Positions in Design Research: A Brief Review of the Literature", Connected 2010 - 2nd International Conference on Design Education, pp.1-5, 2010.

1.3.2.1 Different attempts of Design Research

Some attempts have been made to create a basis for Design Research that would be acceptable as scientific approaches. Two are illustrated in more detail: the Science of Design, and the three types of Design Research proposed by Christopher Frayling. The first concept concerns the positioning of design and related research close to the natural sciences, whereas the latter proposes the outcome of the research as the research rationale.

1.3.2.2 Science of Design

Herbert A. Simon and Armand Hatchuel are proponents of the Science of Design. *"In the 1960's and 70's, at the moment that design research was first formulated as a separate and worthwhile pursuit, the aim was to create a true Science of Design that would be on a par with the Natural Sciences. ... Through their (Simon/Hatchuel) logical analyses they were seeking to create a deep, underlying shared body of work that through its coherence would be the bedrock for more 'applied' (practice-oriented) knowledge, and that through its depth and rigour would demand recognition as an equal to the 'hard' academic disciplines."* (Dorst, 2016, p.1)[25]

25. Dorst, Kees, "Design practice and design research: finally together?", Design+Research+Society, 50th Anniversary Conference, pp.1-10, 2016.

Whereas Herbert A. Simon[26] initiated this attempt, strongly relating his Science of Design towards bounded rationality and problem solving, Armand Hatchuel criticized the orientation towards problem solving and advocated expandable rationality. *"Herbert Simon opened the way towards a major improvement in the economic and social sciences. Not only by criticizing perfect choice theory, but also by understanding the necessity to build Design as a Science and a theory. However, he was convinced that Design and creativity was just a special case of problem solving. If there is no doubt that problem solving is part of a design process, yet it is not the whole process."* (Hatchuel, 2001, p.270)[27]

26. Simon, Herbert A., "The Sciences of the Artificial", MIT Press (3rd Edition), 1996.

27. Hatchuel, Armand, "Towards Design Theory and expandable rationality: The unfinished program of Herbert Simon", Journal of Management & Governance 5, pp. 260–273, 2001.

Their activities remained an attempt, never accepted by Design Research practitioners as, in the words of Kees Dorst: *"Perhaps the early idealism in design research to strive for the creation of a 'Science of Design' was more based on the eagerness to fit into the mould of the sciences than based on confidence in the designers and designing disciplines themselves."* (Dorst, 2016, p.9) Another aspect that might have a role within that context was that the other sciences themselves became less static and rigorous related to postmodern influences.

1.3.2.3 Three types of Design Research

Christopher Frayling's 1993 research paper at the Royal College of Arts contributed to the discourse on Design Research and resonated with the research community. He perceives the fundamental meaning of research as searching. He writes: *"... search involves care, and it involves looking for something which is not defined in advance... It isn't about professionalism, or rules and guidelines, or laboratories. It's about searching."* (Frayling, 1993, p.1)[28] He makes the point that current Design Research paradigms are detached from design practice, which, in his view, is problematic. He proposes three different types of Design Research in relation to the research outcome (practice), namely 1.) *"Research into art and design"*: e.g. historical research on figures and their practice, 2.) *"Research through art and design"*: development projects/work, and 3.) *"Research for art and design"*: embodied in the artefact (ibid., p.5).

28. Frayling, Christopher, "Research in Art and Design", Royal College of Art Research Paper, Vol.1, No.1, pp.1-5, 1993.

Whereas 'Research FOR Design' is related to research to enable design: e.g. Action Research proposed by Bruce Archer (1981[29],1995[30]) / Design oriented research proposes by Daniel Fallman (2007[31], 2008[32])

'Research THROUGH Design' is creating knowledge through practice: e.g. Reflection on action proposed by Wolfgang Jonas (2012[33], 2018[34], 2022[35]) / Research through design proposed by John Zimmerman (2008[36])

'Research ABOUT Design' is conducted to understand design and designers: e.g. Design inquiry proposed by Richard Buchanan (2001[37], 2007[38])

29. Archer, Bruce, "A View of the Nature of Design Research", in Design: Science: Method, eds. Robin Jacques and James A. Powell, Guilford: Westbury House, pp. 36-39, 1981.
30. Archer, Bruce, „The Nature of Research", Co-design, pp. 6-13, 1995.
31. Fallman, Daniel, "Why Research-oriented Design Isn't Design-oriented Research: On the Tensions between Design and Research in an Implicit Design Discipline", Journal on Knowledge, Technology and Policy, Special Issue on Design Research, Vol. 20, No. 3, 2007.
32. Fallman, Daniel, "The Interaction Design Research Triangle of Design Practice, Design Studies, and Design Exploration", Design Issues: Vol. 24, No. 3, pp. 4 -18, 2008.
33. Grand, Simon and Jonas, Wolfgang, "Mapping Design Research: Positions and Perspectives", (Board of International Research in Design), Birkhäuser Verlag, 2012.
34. Erlhoff, Michael and Jonas, Wolfgang, "NERD – New Experimental Research in Design: Positions and Perspectives", (Board of International Research in Design), Birkhäuser Verlag, 2018.
35. Christensen, Michelle, et al. "NERD – New Experimental Research in Design: Positions and Perspectives 2", (Board of International Research in Design), Birkhäuser Verlag, 2022.
36. Forlizzi, Jordi, et al., "Crafting a place for interaction design research in HCI (Human-Computer Interaction)", Design Issues Vol. 24, No. 3, pp.19-29, 2008.
37. Buchanan, Richard, "Research Design and New Learning", Design Issues Vol. 17, No. 4, pp. 3-23, 2001.
38. Buchanan, Richard, "Strategies of Design Research: Productive Science and Rhetorical Inquiry.", In: Michel, R. (eds) Design Research Now, (Board of International Research in Design), Birkhäuser Verlag, 2007.

These two examples are part of the continuum of attempts to define and position Design Research in the (scientific) research community. So far, there has been no final answer and agreement on the Design Research position. Currently, Design Research is detached from design practice, the field is in disarray, current attempts seem too focused on scientific paradigms and not on the future.[25] *"Design needs to develop its own experimental methods. They should be simple and quick, looking for large phenomena and conditions that are 'good enough'. But they must still be sensitive to statistical variability and experimental biases. These methods do not exist: we need some sympathetic statisticians to work with designers to develop these new, appropriate methods."* (Norman, 2010, p.93)

Positioning

There are many different ways to carry out Design Research. Current Design Research does not provide a commonly used methodological framework. Fundamentally, *"..., the goal of any 'scholarly or scientific investigation or inquiry' should be to yield more valuable knowledge than you started with."* (Moon, 2003, p.225)[39] The different approaches have in common that they embrace experimentation and exploration. Their intention is not to *"resolve them into a monolithic Science of Design, but advancing the discussion in this dynamically shifting set of relations"* according to Keith Dorst. He continues: *"Design research should be forward-looking, seeking to future-proof tools and practices in a world that is changing so quickly that the value of 'best practices' (as examples of what worked in the past) is actually rather questionable"*. (Dorst, 2016, p.5) To support the current achievements in Design Research, reducing the distance between research and practice is valuable, therefore a research set up that is based on best practice insights and knowledge producing activities, while making it possible to combine analytical as well as practice-based research paradigms is desirable.

39. Moon, Tracy, "Living Proof", in Design Research: Methods and Perspectives / [edited by] Brenda Laurel, The MIT Press Cambridge, pp. 225-233, 2003.

1.3.3 Design Practice

1.3.3.1 Design principles

To be able to transfer the concepts and ideas of design from a theoretical point of view to a practical point of view design principles are a valuable tool. Design principles are a means to an end to guide designers from theoretical concepts towards practical implications. They are the foundation elements that frame design practice. They provide support by being able to evaluate the outcomes of good design practice. The principles of Human-Centered-Design are as follows:

HCD describes an approach for solving problems and providing solutions in process, product, service and system design, management, and engineering. It provides frameworks, design principles and activities that create solutions to problems that come from considering and integrating the human perspective into all the steps of the development process. Human-Centered-Design contains methods and concepts from numerous fields such as engineering, psychology, anthropology and the arts.

"The design is based upon an explicit understanding of users, tasks and environments;
Users are involved throughout design and development;
The design is driven and refined by user-centred evaluation;
The process is iterative;
The design addresses the whole user experience;
The design team includes multidisciplinary skills and perspectives" [40]

40. ISO 9241-210:2019-07 Ergonomics of human-system interaction — Part 210: Human-centred design for interactive systems

Design principles have different levels of detail, orientations and action. The focus above is clearly on users and their impact and involvement in design activities. To address best practice advice for design in the age of AI, design principles can be a valuable artifact, therefore these conceptions are mentioned here.

1.3.3.2 Design processes

Design processes are another way of supporting design practice. Similar to design principles, they offer concrete advice for best practice. The Industrial Revolution was the main driver of the development of design processes, since *"... the development of technology separated the designer from the production process. Production activities were stretched and divided into distinct areas, or processes."* (Design Council, 2007, p.4)[41]

41. Design Council, "Eleven lessons: managing design in eleven global companies", Desk research report, pp.1-18, 2007.

The development of design processes was driven by Bauhaus, together with HfG Ulm, in the early 20th century. *"The exploration of the design process began to be taken seriously in the work of the Bauhaus in the early 20th century, where attitudes to design were radically changed, specifically in industrial design."* (ibid., p.5) The goal was not only to provide guidance for designers, but also to standardize design methods in practice. Bruce Archer was one of the guiding lights in developing the formal parameters of the design process. *"With the emergence of design methods came the mapping of the design process, generating models, formulae and diagrams that aimed to illustrate best practice. In the early days of formalising the design process (the 1960s), it often took on a linear format and featured a series of arrows and boxes,...:"* (ibid., p.5) Sequences relating to the analysis, evaluation and synthesis were incorporated into the process models, that is activities appropriated to the genre of science, which caused debate from both designers and scientists. Furthermore, the linear approach was criticized and new process models with loops and iterations were added. As the field of design expanded further, focus on the human-centered aspects became more relevant and were illustrated in the design process. *"Given that the role of the designer had become more widely acknowledged, it grew and stretched, crossing boundaries of social science, marketing and branding.... One key result of this was the increased awareness of the user,..."* (ibid., p.7) Different Human-Centered-Design processes became available.[42,43]

42. Human-Centered-Design Society. Retrieved from https://human-centered-design.org. (Accessed on 2022-11-21)
43. ISO 9241-220:2019-03 Ergonomics of human-system interaction — Part 220: Processes for enabling, executing and assessing human-centred design within organizations

A final comment concludes this section, that is, the difficulty of standardizing a process that is iterative and not linear by nature, such as the design process. *"In addition, real life, with its changing market conditions and customer preferences, is much more dynamic, chaotic and fuzzy than any standard model can fully accommodate and often, stages of the design process overlap."* (Best, 2006, p.114)[44] Any attempt to create a process model very much depends on the target audience, or a point of view and represents just one possible way of visualizing among many.

44. Best, Kathryn, "Design management: managing design strategy, process and implementation", AVA Publishing SA, 2006.

The Design Council's framework for innovation - the so-called double diamond process model[45] - visually represents a very clear and comprehensive design process model (see Fig.1.1). Since its launch in 2004, it has become world-renowned with millions of references. It was derived from a team at the Design Council who took a series of reviews of recent projects related to science and technology, business, but also social challenges to create a process model that would be applicable in any field of design activity. The team also looked into the works of Herbert Simon, Thomas Marcus, Thomas W. Maver, Bela H. Banathy, Barry Boehm, Paul Souza and Nigel Cross who had already suggested divergent and convergent phases, as well as cycles and iterative structures. In 2019 additional aspects and resources were added to the double diamond. Four design principles and a 'methods bank' now supplement the process model. The cultural aspects of leadership and engagement, provide a framework for the overall design activities, were added.

45. Framework for Innovation. Retrieved from https://designcouncil.org.uk/our-work/skills-learning/tools-frameworks/framework-for-innovation-design-councils-evolved-double-diamond. (Accessed on 2022-11-21)

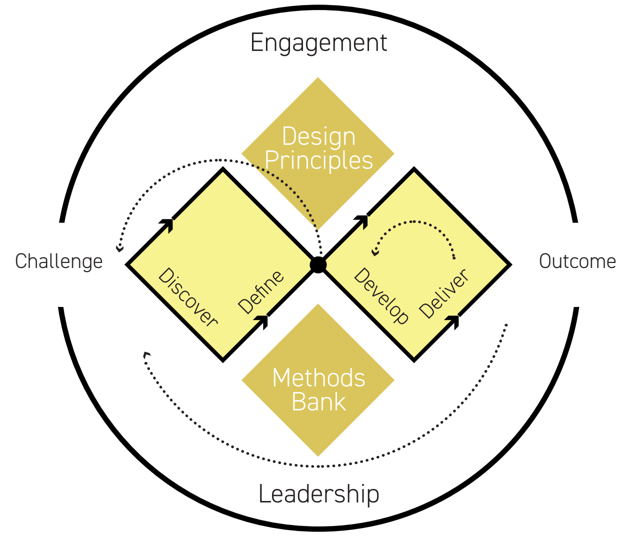

Figure 1.1: Double Diamond process model

Design Thinking

Another recent development in the area of design is Design Thinking. *"Design thinking is a human-centered approach to innovation that draws from the designer's toolkit to integrate the needs of people, the possibilities of technology, and the requirements for business success."* - Tim Brown, Executive Chair of IDEO (2008, p.84)[46] The concept came from Stanford University professor, Larry Leifer, who studied the approaches of engineers and designers to solving problems. He realized that designers spend a lot of time properly examining to understand the problem. When they focused on possible solutions, they generated many different ideas, tested them out with users to come up with a final solution which was often very innovative; engineers, on the other hand found the solutions very quickly and put all their efforts into a single result.

46. Brown, Tim, "Design Thinking", Harvard Business Review, pp. 84–92, 2008.

Human-Centered-Design and Design Thinking process models are different, but contain similar steps, and are both overall iterative. They deal with Problem and Solution Spaces, as well as convergent and divergent phases in similar ways. The main difference between the two approaches is their objectives. The goal of Human-Centered-Design is to ensure high usability and positive user experience of a product. Design Thinking, on the other hand, aims to develop innovative and creative solutions to complex problems to find a solution that satisfies the needs of the user, while being technically feasible and economical.

(Design) Process Mapping

A process map is a visual representation of the process data to guide the observer through the process workflow. It provides an overview of the different steps which are needed to complete a specific task. Process maps have different levels. Each lever represents a higher or deeper level of granularity/detail to answer different questions users of the map might have. In general, *"Process maps are to help them understand design processes in general, and guide them through first design projects. Design process models must be easy to understand and easy to follow for educational purposes, which means they are not all-embracingly valid for any potential case."* (Bobbe et al., 2016, p.1206)[47] Process models are therefore not static; they depend on the perception and interpretation of the observer. Mapping itself is a design tool with design specific notations, an overall support for visualizing thinking styles to foster and support communication. *"This concept is rooted in an understanding of mapping as a design tool. Maps don't merely inform; they propose. They don't offer a neutral representation of reality; they construct reality in a particular way..., when it comes to communication, mapping can play an active role in the presentation of a design. Mapping becomes a device for communication, orchestrating a particular way of presenting a project."* (Paez, 2019, p.9)[48]

47. Bobbe, Tina, et al., "A Comparison Of Design Process Models From Academic Theory And Professional Practice", International Design Conference - Design Processes, pp.1205-1214, 2016.

48. Paez, Roger, "Operative Mapping: Maps as Design Tools", Barcelona School of Design and Engineering, Actar Publishers, 2019.

1.3.4 Artificial Intelligence

1.3.4.1 History and definition of the term AI and related activities

The starting point for scientific research on and with Artificial Intelligence as a newly defined field of work is a conference at the Dartmouth College in Hanover, New Hampshire. John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon organized the 'Dartmouth Summer Research Project on Artificial Intelligence' in 1956.[49] This was actually the first time the term AI was used. They announced seven topics for the conference on Artificial Intelligence, one of which was (No 7) *"Randomness and creativity"* (McCarthy et al.,1955). The founders became the drivers of and contributors to many other projects and research efforts related to the topic. It still needed six decades and a couple of AI summers and winters[50] later, before AI arrived for use in mainstream applications and was no longer primarily and purely a scientific area. The difference today compared to the 1950's is that a huge amount of data is available, partly because of the internet, but also computers now have the power and ability to operate ML algorithms, not a given in 1956. *"Before 1949, computers lacked a key prerequisite for intelligence: they couldn't store commands, only execute them. In other words, computers could be told what to do but couldn't remember what they did. Second, computing was extremely expensive."* (Anyoha, 2017) Herbert Simon, Allen Newell and John Shaw were the creators in 1955-56 of a program called the 'Logic Theorist'[51] designed to simulate the problem-solving skills of a human being by proving mathematical theorems and even proposed new solutions to some of the given 52 listed in 'Principia Mathematica'. They presented their ideas at the 'Dartmouth Summer Research Project on Artificial Intelligence'. From 1957 to 1974, the field of AI research underwent its first hype. 'ELIZA'[52] from Joseph Weizenbaum and the 'General Problem Solver'[53] again from Newell and Simon, were two very promising solutions to demonstrate algorithms capable of problem-solving and natural language processing (NLP). The scientific community was very optimistic about creating a machine able to mimic general intelligence comparable with human intelligence. This raised high expectations. The computers at that time could not process and store the information needed to perform such complex algorithms - the main reason why the expectations couldn't be met. Funding decreased as did activities for the next ten years. AI begin to flourish again in the 1980s after Edward Feigenbaums' 'expert systems'[54], John Hopfield' 'Hopfield network'[55] and Geoffrey Hinton along with colleagues David Rumelhart and Ronald Williams's introduction of 'Deep Learning' back propagation training algorithms.[56] These activities were again accompanied by renewed efforts to improve computer performance. But the field still was unable to keep the promises made and funding and public attention again dwindled. However, the scientific community kept on going. In the 1990s and 2000s the greatest achievements were made without further public attention. In 1997, IBM's Deep Blue[57], a chess playing computer program, defeated the human world champion, Gary Kasparov. Chinese Go champion, Ke Jie, lost to Google's AlphaGo[58] in 2016. The disappearance of the limiting factor of computer storage and the availability of data made these more recent achievements possible.

49. McCarthy, John, et al., "A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence", 1955. Retrieved from https://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html. (Accessed on 2022-11-21)

50. Anyoha, Rockwell, "The History of Artificial Intelligence", Science in the News, Harvard University, Special Edition: Artificial Intelligence, 2017. Retrieved from https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence. (Accessed on 2022-11-21)

51. Newell, Allen, and Herbert, A., "The Logic Theory Machine - A Complex Information Processing System", The RAND Corporation Santa Monica, 1956.

52. Weizenbaum, Joseph, "ELIZA - a computer program for the study of natural language communication between man and machine", Communications of the ACM, Vol. 9, Issue 1, pp. 36–45, 1966.

53. Newell, Allen, et al., "Report on a general problem-solving program" Proceedings of the International Conference on Information Processing, pp. 256–264, 1959.

54. Feigenbaum, Edward, A., "Expert Systems in the 1980s", 1980. Retrieved from https://stacks.stanford.edu/file/druid:vf069sz9374/vf069sz9374.pdf. (Accessed on 2022-11-21)

55. Hopfield, John, J., "Neural networks and physical systems with emergent collective computational abilities, Proceedings of the National Academy of Sciences, Vol. 79, No. 8, pp. 2554-2558, 1982.

56. Chui, Michael, et al., "Notes from the AI Frontier", McKinsey Global Institute, discussion paper, 2018. Retrieved from https://mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning. (Accessed on 2022-11-21)

57. Deep Blue. Retrieved from https://ibm.com/ibm/history/ibm100/us/en/icons/deepblue. (Accessed on 2022-11-21)

58. AlphaGo. Retrieved from https://deepmind.com/alphago-korea. (Accessed on 2022-11-21)

AI and creativity

Creativity was one of the topics of the Dartmouth conference back in 1956, showing that the scientific community related to AI research's interest in the attempts to develop creative machines. AI and creativity often foster the discussion of whether a machine can be creative at all, mainly due to the perception that creativity is a human trait and a core competence of artists, designers and the like. Margaret Boden wrote 1998: *"It is grounded in everyday capacities such as the association of ideas, reminding, perception, analogical thinking, searching a structured problem-space, and reflective self-criticism. It involves not only a cognitive dimension (the generation of new ideas) but also motivation and emotion, and is closely linked to cultural context and personality factors. Current AI models of creativity focus primarily on the cognitive dimension."* (Boden, 1998, p.347)[59] While her observations might still be valid today, in the meantime, 'Edmond de Belamy'[60] an AI generated portrait was sold for USD 432,000 at Christie's auction house in 2018 and just recently, in 2022, an AI generated picture won an art prize. The algorithms might not have had the intention of creating pieces of art, but in the eye of the observer, they did. Associating these developments with creativity is an even further stretch, but it is not the intention of this thesis to finally assess the ability of AI systems. However, the objective it to raise awareness of the recent achievements of AI and ML based systems, even in the domain of creativity.

59. Boden, Margaret, A., "Creativity and artificial intelligence", Artificial Intelligence Vol. 103, Issues 1-2, pp. 347-356, 1998.

60. Portrait of Edmond Belamy. Retrieved from https://christies.com/features/A-collaboration-between-two-artists-one-human-one-a-machine-9332-1.aspx. (Accessed 2022-11-21)

1.3.4.2 An attempt at a definition

John McCarthy, who invented the term Artificial Intelligence in 1955, defines it as follows: *"It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable."* (McCarthy, 2007, p.2)[61] McCarthy's statement implies, machines, as well as computer programs do relate to human intelligence, but are not like human intelligence. This definition indirectly implies an agreed perception of human-like intelligence is necessary, to compare the two directions referred to. There are many different definitions of intelligence, each accompanied by different views of how humans learn. Definition of Artificial Intelligence based on levels of intelligence is multiple and depend on who is asked, making it very hard to judge whether a machine or a computer program can be defined as intelligent. This means the term AI can be used in ways that create high and incorrect expectations of it, that misrepresent current achievements, and also unfulfilled promises. Machines or computer programs that use methods from computer science, mathematics and statistics and that learn to solve data-based problem(s) or specific task(s) which frame Artificial Intelligence in a way that avoids making links to intelligence are more suitable. Furthermore, the field of AI can be divided into three types of AI, contributing to the understanding of the levels of its problem-solving abilities, which also helps to define the term and related classes better.

61. McCarthy, John, "What is Artificial Intelligence?", pp.1-15, 2007. Retrieved from http://jmc.stanford.edu/articles/whatisai/whatisai.pdf. (Accessed on 2022-11-21)

Weak AI - also called Narrow AI or Artificial Narrow Intelligence (ANI) - is AI trained and focused to perform specific tasks. Subfields of weak AI frequently mentioned in conjunction with this type of AI are Machine Learning and Deep Learning.

Strong AI - Artificial general intelligence (AGI), or general AI, is a theoretical form of AI where a machine would have an intelligence equal to humans; it would have a self-aware consciousness with the ability to solve problems, learn, and plan for the future.

Artificial Super Intelligence (ASI) - also known as super intelligence - would surpass the intelligence and ability of the human brain.

AI and (human) intelligence

A Machine Learning algorithm can learn from data to solve problems and achieve goals in a specific context in an accurate and consistent manner, but is not intelligent, even if the definition of intelligence implies the ability to learn and perform suitable techniques to solve problems and achieve goals in an appropriate manner based on a specific context which can later be transferred to a new context. The intelligence implicit in this definition always makes reference to human intelligence, either as equal, superior or inferior.[62] There are some interesting aspects and debates related to this notion. One relates to the human embodiment and the possibility of experiencing life in all its senses; human intelligence can therefore never be perceived as pure cognition. Any attempt to create an intelligent computer program in human terms of intelligence is therefore beyond reach. Second, from a philosophical point of view *"..., human intelligence is in itself always artificial, as it engenders novel dimensions of cognition. Conversely, the design of artificial intelligence is still a product of the human intellect and therefore a form of its augmentation."* (Pasquinelli, 2015, p.11)[63] The area of AI and the goal of machine intelligence needs a completely new definition of intelligence, one we can currently not even

62. McCarthy, John, and Hayes, Patrick, "Some Philosophical Problems from the Standpoint of Artificial Intelligence", Machine Intelligence 4, Edinburgh University Press, pp. 463-502, 1969.

63. Pasquinelli, Matteo, "Introduction - Alleys of Your Mind: Augmented Intelligence and Its Traumas", edited by Matteo Pasquinelli, meson press, pp. 7-17, 2015.

imagine. *"..., we would do better to allow that in our universe 'thinking' is much more diverse, even alien, than our own particular case. The real philosophical lessons of AI will have less to do with humans teaching machines how to think than with machines teaching humans a fuller and truer range of what thinking can be."* (Bratton, 2015, p.72)[64]

64. Bratton, Benjamin, H., "Outing Artificial Intelligence: Reckoning with Turing Tests", in Alleys of Your Mind: Augmented Intelligence and Its Traumas, edited by Matteo Pasquinelli, meson press, pp. 69–80, 2015.

1.3.5 Machine Learning and Deep Learning

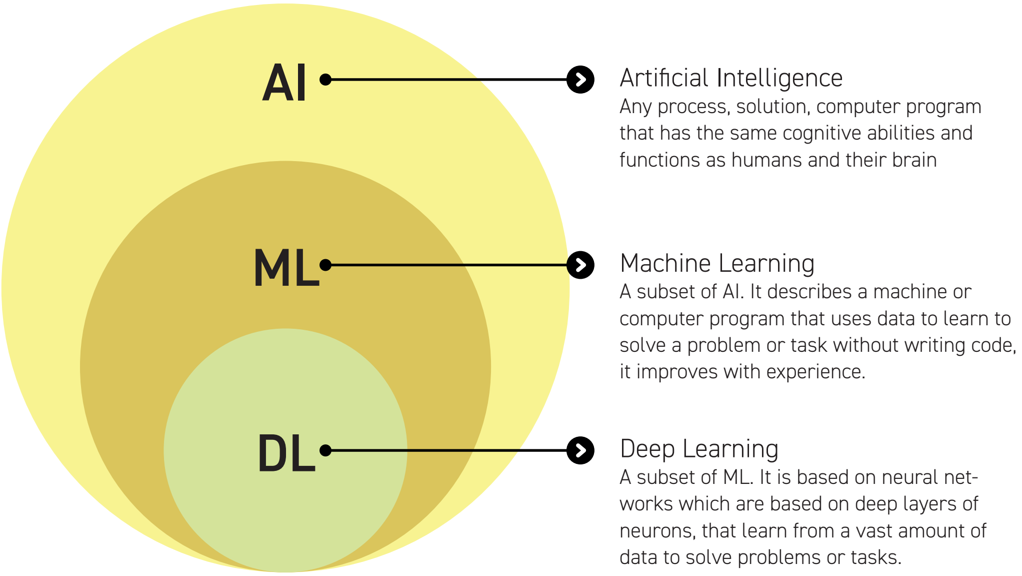

Figure 1.2: Overview of the relationship between AI, ML and DL

The field of Artificial Narrow Intelligence is currently driven by the achievements of Machine Learning. Machine Learning algorithms allow the computer to learn from data without the need to program every single step. The models are based on mathematical logic, statistical methods and artificial neural networks. *"Machine learning (ML) is a particular approach to the design of intelligent systems in which the system adapts its behavior based on data. It is the success of machine learning algorithms in particular that have led to recent growth in the commercialization of artificial intelligence."* (Riedl, 2019, p.1)[65]

Artificial neural networks are models that mimic the structure and/or function of biological neural networks. They use layers of interconnected units to learn and derive weights based on observed data. As data input changes, neural networks are able to adjust and learn new weights, suitable for unstructured and unlabeled data. There are hundreds of algorithms and variations for all types of problems.

65. Riedl, Mark, "Human-Centered Artificial Intelligence and Machine Learning", Human Behavior and Emerging Technologies, Vol. 1, pp. 1-8, 2019.

Machine Learning and Deep Learning are often used interchangeably, so the nuances between the two are worth noting. As illustrated above (see Fig.1.2), both Deep Learning and Machine Learning are subfields of Artificial Intelligence, with DL actually a sub-field of ML. Algorithms related to DL are based on 'deep' artificial neural networks which simulate the cooperation of neurons similar to the operations of the human brain. Input and output processing on many different layers and with a large number of neurons partially replacing manual data preparation, supporting the use of large unstructured data sets, which makes Deep Learning[66] so successful.

An algorithm can be defined as a precise step by step guide for a system to identify which problem to solve. ML algorithms differ from regular heuristic-based algorithms since the data itself creates the model. Much of the system's final behavior, the actual way to solve the problem, emerges through learning from data and experience over time. The choice of algorithm depends primarily on the type of problem and type of input data, and second, on the choice of accuracy and performance levels.

In this thesis the term AI, always refers to Artificial Narrow Intelligence. Machine Learning can be perceived as the method chosen to solve ANI based problems and tasks, therefore both terms - AI and ML - will be used in combination making this relationship and positioning clear.

66. Goodfellow, Ian, J., et al., "Generative Adversarial Networks", NeurIPS Proceedings - Advances in Neural Information Processing Systems 27, pp.1-9, 2014.

1.3.5.1 Types of learning and their related outcomes

As mentioned above there are 'rival theories' as Pedro Domingos puts it in his book 'The Master Algorithm' when it comes to ideas and concepts about how humans learn. Domingos writes: *"Symbolists view learning as the inverse of deduction and take ideas from philosophy, psychology, and logic. Connectionists reverse engineer the brain and are inspired by neuroscience and physics. Evolutionaries simulate evolution on the computer and draw on genetics and evolutionary biology. Bayesians believe learning is a form of probabilistic inference and have their roots in statistics. Analogizers learn by extrapolation from similarity judgments and are influenced by psychology and mathematical optimization."* (Domingos, 2016, Prologue)[67] The result of these scattered views of learning is that each school of thought constructs their own methods and algorithms in the age of AI and that each solves one specific problem or task very well, but none of them provide a general solution to every problem. However, in Machine and Deep Learning, three learning categories can be distinguished.

67. Domingos, Pedro, "The Master Algorithm - How the Quest for the Ultimate Learning Machine will Remake our World", Penguin Science/Tech, 2015.

Supervised Learning:

The training data used for Supervised Learning (see Fig. 1.3) algorithms is either labeled data, such as cat or dog, or data that implies a concrete result, such as a product price at a given time. The model is trained on this data and learns to make correct predictions based on the labels or results. It is corrected when the output is wrong. This process of training takes as many iterations as necessary to derive a certain accuracy level compared to the general training data set. Example problems are classification (fraud/anomaly detection, image classification, medical diagnostics) and regression (market forecasting).

When a Machine Learning model identifies an object it performs a classification. The simplest classification is binary, meaning 'black' or 'white'. Multiple classification algorithms are able to sort input into one of several groups. Classification refers to a class of algorithms, but also to a group of problems and related outcomes.
Regression algorithms model relationships between data points that are iteratively refined using a measure of error within the predictions made by the model. Predicting future values based on historic values is one useful application of regression analysis. Regression methods are used for statistical analysis and have been co-opted by Machine Learning. Regression refers to a class of algorithms, but also to a group of problems and related outcomes.

Unsupervised Learning:

The data used for Unsupervised Learning (see Fig. 1.4) is not labeled, nor does it necessarily imply a concrete result. The model derives structures and relations that can be found in the data on its own. Example problems are clustering / ranking (recommender systems), dimensional reduction (feature elicitation) and association rule learning.

Clustering refers to a technique where the algorithm interprets the parameters of the data, objects with similar parameters and features are grouped in a cluster. All methods are concerned with using the structures inherent in the data, which is not labeled, to best organize the data into groups with the most features in common. Clustering refers to a class of algorithms, but also to a group of problems and related outcomes.
Dimensional reduction is a method that discovers and exploits the features inherent in data. With this it is possible to simplify and reduce a large dataset and eliminate irrelevant data points.
Association rule learning methods extract rules from large multidimensional datasets. These rules observe the relationships between variables in data and discover important associations.

Semi-Supervised Learning:

The input data for Semi-Supervised Learning (see Fig. 1.5) is a mixture of labeled and unlabeled data. The model has to derive its own structure for organizing data and learn the categories to make the right predictions. Semi-Supervised Learning is a common method, when the labeled data set is too small for an algorithm to learn from. The labeled data set in Semi-Supervised Learning is enriched with unlabeled data.

Reinforcement and Transfer Learning:

The input data for Reinforcement Learning (see Fig. 1.6) is not labeled, nor does it imply a concrete result. The model learns its own strategy to solve a problem or task, based on the input data, which is related to a reward function. This type of learning comes very close to how humans learn and is used for Robot Navigation and Gaming. Transfer Learning relates to a model trained on data input A, which is then able to also work with data input B. This method is commonly used for autonomous driving, where an initial model is trained on cars, and that model can be transferred to utility vehicles.

A reward function's goal is to reinforce a certain learning behavior of an algorithm by specifying a desirable result. A reward function provides a numerical score to represent the desired state.

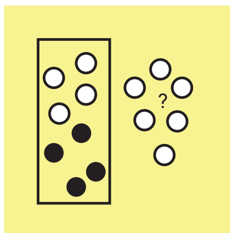

Figure 1.3:
Supervised Learning

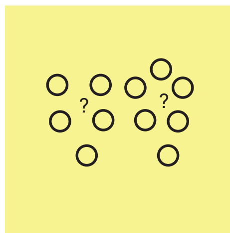

Figure 1.4:
Unsupervised Learning

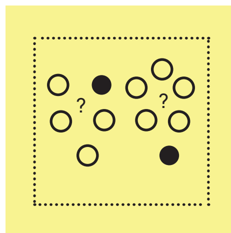

Figure 1.5:
Semi-Supervised Learning

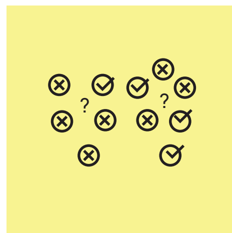

Figure 1.6:
Reinforcement Learning

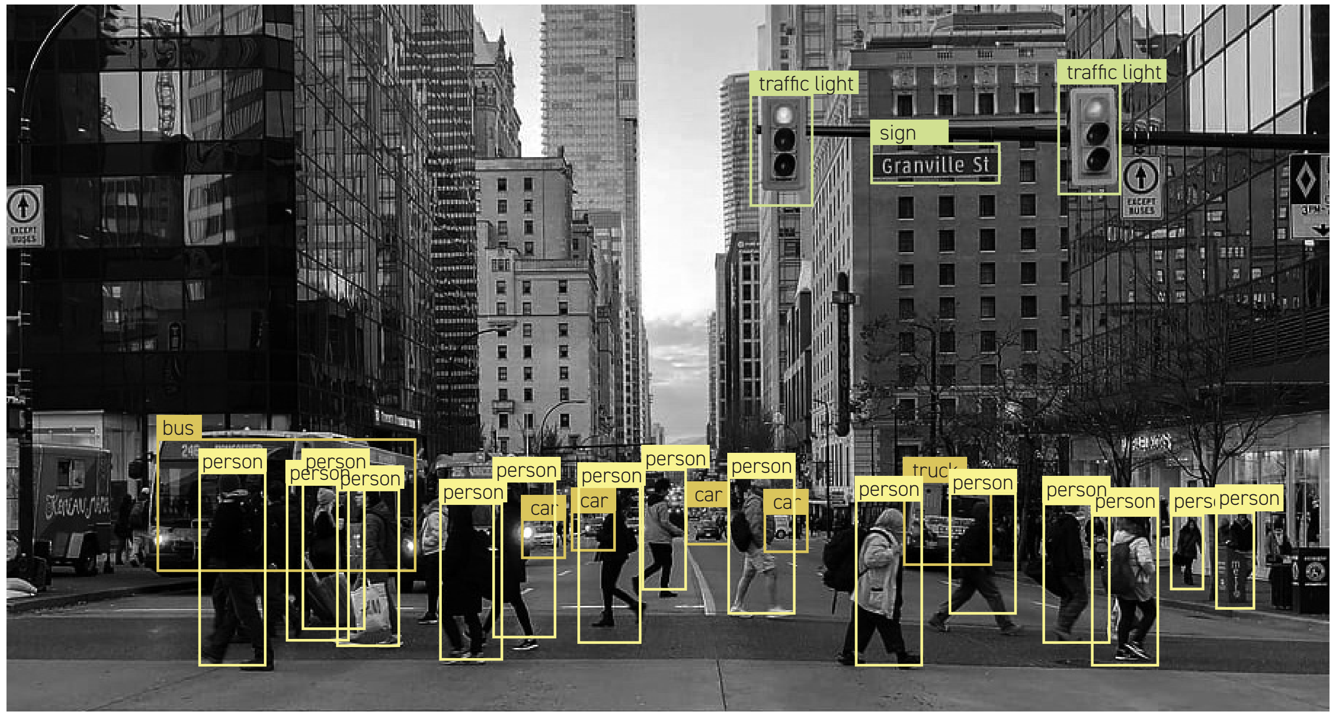

Figure 1.7: How a computer vision system uses object recognition to classify traffic lights, signs, persons, cars, trucks, busses

Machine Learning and Deep Learning solutions can be related to Computer Vision, Natural Language Processing (text and speech) and an area related to other purposes. Each group implies different applications and the combination of different ML/DL methods and models (see Fig. 1.7).

The area of Computer Vision relates to the ability to 'see'. The problems to be addressed are image classification and/or object recognition. Within these areas are face recognition, object detection, image segmentation, object tracking, autonomous driving and medical diagnosis.

Natural Language Processing (NLP), implies the ability to 'speak' and 'hear'. This area can be divided into problems related to text classification implying sentiment recognition, and information retrieval and speech recognition transforming speech to text (STT) and trigger word/wake word detection. Within the area of text classification, web search, name entity recognition, machine translation and chat bots are located. Speech recognition is used for voice assistants, speaker ID, speech synthesis and text to speech (TTS).

Other ML solutions relate to forecasting / time series predictions, recommender systems to personalize and customize content, as well as anomaly / outlier / fraud detection.

1.3.6 Knowledge Discovery and Data Mining Processes

As Artificial Intelligence made its way out of the research laboratory into real world scenarios, the transfer from theory into practice was necessary. A couple of process models focussing on data handling aspects come from this transfer. Knowledge Discovery Databases (KDD) Process Model[68], The SEMMA Process Model (Sample, Explore, Modify, Model, and Access)[69] and CRISP-DM Process Model[70,71] to name a few.

The CRISP DM (CRoss-Industry Standard Process for Data Mining) is currently the most used process model. It is not derived from theoretical and technical principles, but from real-world data mining practice, which might be the reason for its success. In 1996, increased interest in data mining activities in industry called for an open source, unified and standardized process model (see Fig. 1.8) to ensure quality levels and support launching data mining projects. *"CRISP-DM was conceived in late 1996 by four leaders of the nascent data mining market: Daimler-Benz (now Daimler Chrysler), Integral Solutions Ltd. (ISL), NCR, and OHRA. [...] Developed by industry leaders with input from more than 200 data mining users and data mining tool and service providers, CRISP-DM is an industry-, tool-, and application-neutral model."* (Shearer, 2000, p.13) CRISP DM organizes the data mining process into six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

68. Fayyad, Usama, et al., "From Data Mining to Knowledge Discovery in Databases", AI Magazine, American Association for Artificial Intelligence, Vol. 17, No.3, pp.37-54, 1996.

69. Shafique, Umair and Qaiser, Haseeb, "A Comparative Study of Data Mining Process Models (KDD, CRISP-DM and SEMMA)", International Journal of Innovation and Scientific Research, Vol.12, No.1, pp. 217-222, 2014.

70. Shearer, Colin, "The CRISP-DM Model: The New Blueprint for Data Mining", Journal of Data Warehousing, Vol. 5, No. 4, pp. 13-22, 2000.
71. Wirth, Rüdiger, and Hipp, Jochen, "CRISP-DM: Towards a Standard Process Model for Data Mining", Proceedings of the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining, 2000.

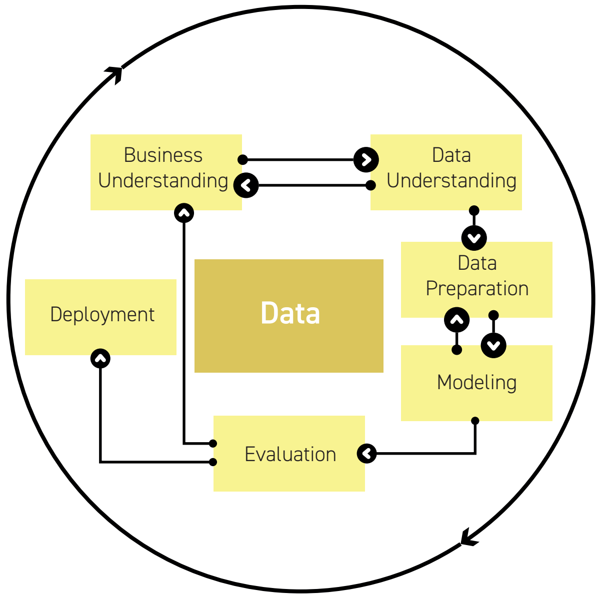

Figure 1.8: CRISP-DM process model

Phase One - Business Understanding: In this phase, business objectives and based on this, data mining goals are determined by assessing the current situation. The outcome of this phase is a project plan.

Phase Two - Data Understanding: This phase deals with the initial data input for the project, which means collecting the initial data, describing the data, exploring the data, and finally verifying the quality of the data.

Phase Three - Data Preparation: This phase refers to the steps necessary to prepare the data for the ML model - selecting the necessary data, cleaning it and if applicable, constructing new data before finally integrating the data, and providing a consistent data format.

Phase Four - Modeling: This phase is about selecting the modeling technique, setting up the data and algorithm pipeline, building the model, and finally assessing the model's accuracy and performance.

Phase Five - Evaluation: The fifth phase is devoted to evaluation - the results of the modeling process, and a review of the overall process, which enables the team to determine the next steps.

Phase Six - Deployment: This phase refers to a plan for the deployment, as well as a plan for monitoring and maintaining of the modeling output. It is also about documenting the process, producing a final report, as well as a final review of the project.

1.4 Problem Statement and Starting Point

(AI) Technology as the solution to every problem

72. Noyes, Jan, "Expectations and their forgotten role in HCI", Encyclopedia of Human Computer Interaction, pp. 205-210, 2005.

Some humans tend to think that technology can solve all their problems.[72] This results in two challenging assumptions: the expectation that the machine is perfect, which is hard to deliver, and the application of technology advances that is the right thing to do or not. This often results in the development of a solution based on technological feasibility alone, missing the multiple perspectives and complex needs of the different stakeholders involved. By contrast, the mindset of the human-centered approach does not start with an idea, but with an identified problem or (market) need, develops several prototypes on the way to finding the best solution to the given problem and eventually, not using technology at all. This approach is based on research and needfinding, to obtain the best possible result for all the stakeholders involved. This approach helps to support the final implementation and facilitate acceptance by users and other stakeholders, such as management. Another important aspect addressed by this approach is the systematic approach. Taking into account business viability, technological feasibility combined with human desirability (see Fig. 1.9), it is the intersection where innovation and sustainable products and services are created.

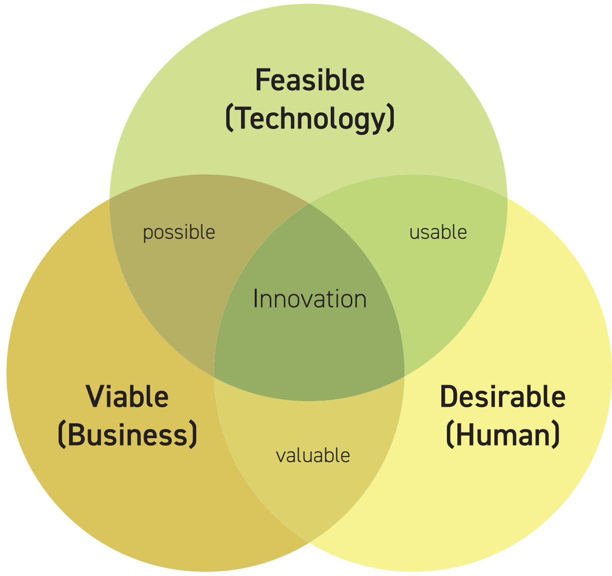

Figure 1.9: Diagram combining people, technology and business for innovation

The mentioned above mindset is not only valid for AI applications as a technological solution. The impact of this technology goes deeper than most other digital products and services that humans have dealt with so far. It suggests and supports decision-making processes like, criminal sentencing or even autonomous behavior like, self-driving cars: it intersects and even overlaps with formerly human traits and responsibilities. Current efforts in science and research are driven by technological feasibility. Attempts to shed light on AI products and applications, especially with a human-centered focus, are rare and efforts in that direction just beginning. However, the current development of intelligent agents lacks a broad perspective, referring mostly to white male workers, so reinforcing a narrow idea of the 'normal' person[73], calling for more input from other experts and professions. Therefore this research will evaluate the development of intelligent agents, from a human-centered perspective in order to make a contribution by evaluating the influence of AI and ML based systems on the design profession, and identifying and proposing new methods and tools for design in the age of AI. More precisely, it aims to find and locate drivers of design investigation, if applicable. This exploratory investigation is based on concrete case studies in the industrial AI context of Siemens AG digital industries division.

73. West, Sarah, M., et al., "Discriminating Systems: Gender, Race and Power in AI", AI Now Institute, 2019. Retrieved from https://ainowinstitute.org/discriminatingsystems.pdf. (Accessed on 2022-11-21)

Chapter 2. Research Scope

2.1 Research Questions

The starting point for this research endeavor was very generic, coming from working as an UX designer in industry. A shift in demand for more projects related to the development of AI/ML based systems became apparent. This led to the following questions:

I. In what ways do current achievements in AI and ML impact on design practice?

II. What do designers need to know to contribute effectively in the age of AI/ML?

From this initial, very broad range, the research focus was narrowed down to the area of design for AI, specifically the development of AI/ML agents in the domain of industrial AI. The general research questions in this study are:

III. How can design/designers add value to the development of AI agents in the industrial AI context?

IV. Which new processes, methods and tools are relevant?

The related sub-questions are:

Case Study Research Meta-Sample & Beta Samples:

What are the general problems and challenges for those who develop AI agents in the industrial domain?

How can designers positively influence the development of AI technology in the industrial domain?

Expert & External Input:

What are the design problems and challenges for developing AI agents in the industrial domain?

What would be different for designers developing AI solutions compared to current practice?

What role do designers currently play in the development of AI agents?

Are the current processes, methods & tools suited to new roles for designers?

2.2 Propositions and Hypothesis

The underlying assumption that guides this section is that designers can add value to the development of AI agents in the industrial AI context, based on the core competencies of design (as stated in Chapter 1.3.1), that design in the age of AI is valuable due to its focus on people, their needs and expectations, not forgetting technological feasibility and business viability, along with the human dimension. Designers explore the Problem Space to understand the complexity of a situation and define a proper starting point based on research before jumping into Solution Space too soon. AI/ML developments can benefit from this approach (see Fig. 2.1, p.18).

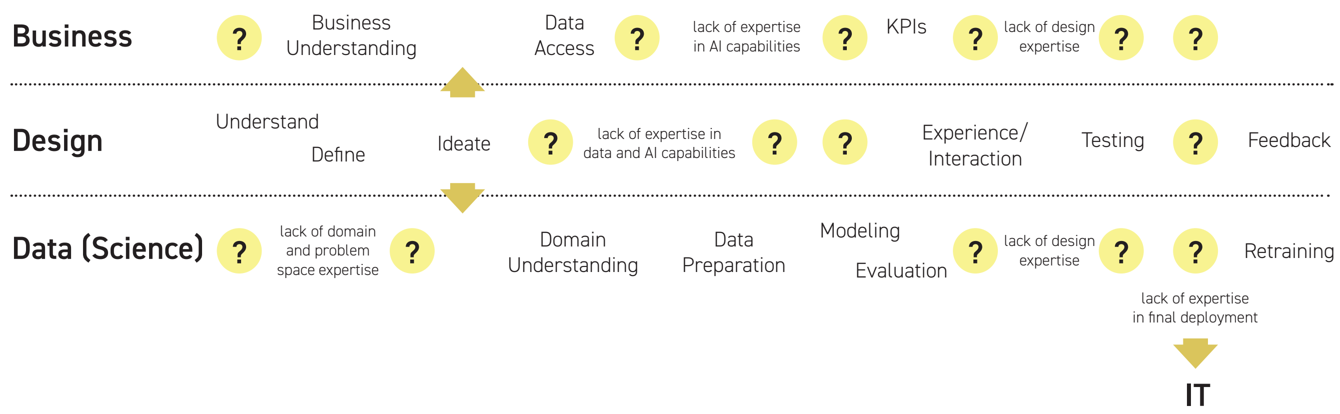

Figure 2.1: Comparison of design, data (science) and business approaches with related gaps

As a consequence there are two directions from which to evaluate those assumptions: design activities should play a fundamental role in AI/ML development; current designers' skills and tools are not adequately prepared to answer the challenges and need to adapt to AI/ML tools to be part of new developments. The following hypothesis can be formed from these views:

Human-Centered-Design is an overall important factor for AI development.

Although the trend in current AI development is to embrace the Human-Centered-Design perspective, real world scenarios and research show that it is not applicable for every AI/ML systems development, which will be shown in Chapter 5.3.4 and Chapter 6.3.2. Some of its key principles of HCD are still neglected, namely users are not involved throughout design and development of the systems and multidisciplinary skills and perspectives are not part of development team skills since the focus is on data-centered approaches rather than human-centered concepts. The absence of the HCD perspective leads to an overall lack of effectiveness and efficiency, without accessibility and sustainability, and does not improve human well-being, as well as user satisfaction. This becomes noticeable through:

» Focus on data and not user problems with a lack of the definition of a meaningful business problem
» Not conforming to user expectations
» Low usability (low levels of effectiveness, efficiency and satisfaction)
» Negative user experience
» Lack of trust in the output
» Low user acceptance
» Grasping at solutions before exploring the problem

New challenges that have not been addressed either by the current development methods of AI-infused solutions, nor by current HCD principles so far are also emerging, such as decisions on the appropriate handling of data, including the origin of the data, its usability and intended use, data protection and data security, as well as guidelines that support dynamic user interactions and lastly the design of the processes for operating and further maintaining and retraining the AI-based systems. This makes new or modified development processes necessary and therefore strengthens the mentioned hypothesis. This leads to an additional hypothesis for the industrial AI domain.

The Human-Centered-Design perspective is currently not perceived as a critical factor in the industrial AI domain and therefore might be more challenging to be implemented.

The use of AI and ML in consumer facing applications (Business-to-Consumer: B2C) is targeted towards customization, whereas the industrial AI domain (Business-to-Business: B2B) focuses on optimization. This has an overall counter-productive effect on aims for a human-centered focus and suggests there could be more difficulties implementing Human-Centered-Design within that context. In addition, development projects in the industrial environment are characterized by very high levels of complexity, partly due to a high number of different stakeholders, so conducting research and needfinding activities use up a lot of time and resources.

Integration Human-Centered-Design approaches into the development processes suggests the need for new methods and tools for designers.

AI/ML based solutions are complex systems, heavily dependent on huge amounts of data points. The data sets are based on statistics and probability, implying a level of uncertainty and therefore the models trained on using that data make mistakes. Such systems learn over time as they are exposed to new data inputs, hence being more dynamic than static. Current methods and tools do not support this kind of behavior. AI and ML therefore imply new challenges for designers. The initial concepts and ideas for addressing this:

Situations with multiple possible outcomes are probabilistic. Each outcome has a varying degree of certainty of it happening.

» Teaching/educational material
» Collecting exemplars/use cases/abstractions
» Collaboration between designers and data scientists
» Development of design principles

2.3 Goals and Objectives

This thesis aims to identify how AI and ML development can benefit by using methods and tools from a Human-Centered-Design perspective, by recognizing the current challenges and pitfalls when developing AI/ML systems. To the hypothesis that integrating Human-Centered-Design approaches in AI and ML development make new methods and tools in the area of design necessary, an additional objective is the naming and defining of new approaches, such as guidelines and principles. This research purpose is to create an outcome that supports and guides designers in the age of AI.

The whole research basis is developed from insights and findings from the industrial AI domain. Although this is a very narrow field with a very concrete area of application, it is hoped results with the potential to be transferable may be generated. By comparing the insights and findings from the industrial sector with input from other domains, as well as expert knowledge, external and secondary sources transferability should be possible. The aim is to create an outcome with application in different domains while focusing on the design community.

Part II. Framing

Chapter 3. State of the Art Research

3.1 Introduction

This chapter provides an overview of the available literature on the status of design and AI/ML with an attempt to locate it in the context of industrial applications. It contains three main parts taking a look at the design community, relevant actors, institutions and artifacts relevant in that space to spot the issues mentioned and discussed there. This is also the initial starting point for this research journey. When the idea for this Ph.D. was born in about 2017, the design community had just started to embrace the topic of AI relatively frequently (see for example[74,75]). Josh Clark, a UX designer and founder of Big Medium, a design agency specializing in Artificial Intelligence, wrote a key article and therefore had a huge impact on this work, outlining the scale of potential changes in the design approach. Several sources are blog posts or online articles; later on, scientific publications also became available. From the initial overview, it has become clear that AI/ML call for a new design paradigm. The second subsection maps the issues identified to the AI and ML discourse looking at the different issues that are relevant for research scholars and other practitioners in the field of AI, from humans being perceived as machines and the attempt to bring explainability, to returning the human focus to the technological domain. This research was pursued through an extensive literature review, and taking part in international conferences, such as the IJCAI 2018 in Stockholm[76]. From theses searches and exchanges, issues and topics that touch on the design involvement in AI have unfolded to show where these domains intersect. In this way, it has been possible to recognize white spots, research gaps and missing parts in the sum of endeavors outlined in the final section. Gaps such as the current focus on technological feasibility, the lack of practice-based use cases and missing insights into industrial AI development, amongst others, justify this research endeavor.

74. Hebron, Patrick, "Machine Learning for Designers", O'Reilly Media, 2016. Retrieved from https://oreilly.com/library/view/machine-learning-for/9781491971444. (Accessed on 2022-11-21)
75. Clark, Josh, "Design in the Era of the Algorithm", 2017. Retrieved from https://bigmedium.com/speaking/design-in-the-era-of-the-algorithm.html. (Accessed on 2022-11-21)

76. International Joint Conference on Artificial Intelligence Stockholm, Sweden. Retrieved from https://ijcai-18.org. (Accessed on 2022-11-21)

3.2 Design and the AI Perspective

"Human-centered design has expanded from the design of objects (industrial design) to the design of experiences (adding interaction design, visual design, and the design of spaces) and the next step will be the design of system behavior: the design of the algorithms that determine the behavior of automated or intelligent systems" Harry West (frog), 2016[77]

77. Brownlee, John, "5 Design Jobs That Won't Exist In The Future", 2016. Retrieved from https://fastcompany.com/3063318/5-design-jobs-that-wont-exist-in-the-future. (Accessed on 2022-11-21)

The quote above represents an opinion about design and its development over the last couple of years that fits with the view of this research, as stated in Chapter 1.3.1. Different technological developments, such as the internet, for example, have influenced the design profession and generated new opportunities for designers in User Interface (UI) and Interaction Design, as will AI and the domain of Machine Learning. This State of the Art chapter suggests the opportunities and challenges related to the technological development of AI/ML. John Brownlee's interviewed design aware leaders of big corporations such as Harry West from frog, among others, about their views on the impact of AI/ML on the design profession and serves as the guiding reference for this chapter.

Intelligent Augmentation is an alternative conceptualization of Artificial Intelligence. It focuses on the assistive and supportive roles of AI with emphasis on the fact that it is supposed to enhance and augment humans rather than replace them.

3.2.1 General overview of design and AI and different manifestations of it

The design community is increasingly engaging with AI systems in many different areas, mainly in consumer facing domains such as mobile phone applications, voice assistants. Big design firms, such as IDEO and frog, realized that the hype about AI and ML demanded positioning design in that area and had already coined the term 'Augmented Intelligence'[78,79] with blogs featuring articles related to AI topics - the human-centered approach plays a fundamental role - and individual designers join and foster the discourse around the

78. IDEO on AI. Retrieved from https://ideo.com/question/how-can-we-use-ai-to-make-things-better-for-humans. (Accessed on 2022-11-21)
79. frog on AI. Retrieved from https://frogdesign.com/designmind/the-ai-playbook. (Accessed on 2022-11-21)

80. Bodegraven van, Joël, and Duffey, Chris, "AI driven Design", brainfood Vol. 4, Chapter I, 2019. Retrieved from https://awwwards.com/AI-driven-design. (Accessed on 2022-11-21)
81. Taschdjian, Zac, "UX design in the age of machine learning", 2018. Retrieved from https://uxdesign.cc/ux-design-in-the-age-of-machine-learning-2fcd8b538d67. (Accessed on 2022-11-21)

technology (see for example[80,81]). Online blog and article sources dominate the discussion, supplemented with a few scientific publications. In general, the discussion can be divided in two main areas: AI for design about how AI and ML solutions interfere with design practice; design for AI which is related to how designers could be included in the development process of smart systems, while different embodiments and overlaps are possible. Relevant themes that are come from those sources are a) the recognition and acknowledgment that AI and ML are a new design material influencing the way designers work and therefore has an impact on the future of the profession, b) the challenges and downside of the technology mainly related to a missing human focus, c) the new opportunities and roles emerging from this, and d) proposals of design principles for AI. All these points are covered in more detail in this first section, each topic going deeper into the current status of the design dialogue around AI.

3.2.2 AI for design

There are voices and opinions in the design area that perceive the current hype about AI and ML systems as overrating their importance. These discussions are mostly related to AI for design, whose supporters question the capabilities of ML algorithms and therefore deny any human-like, possible creative future achievements by machines. *"... machine learning systems can not do much more than look back in time. The data that is used to train them is always from the past, and the systems age quite quickly if they are not properly and constantly maintained."* (Anger, 2020, p.66)[82], so attributing creativity primarily to designers and artists and focusing on the negative effects of the technology, and ignoring the great advantages improved intelligent systems have to offer design practitioners.[83] Although this research focus is more on the design for AI aspect, the State of the Art Research map (outlined below) includes the AI for design aspects and related artifacts because they are part of the overall discussion.

82. Anger, Gerhard, "Drop That Intelligence and Get on with It!", Proceedings of the First Conference on Designing with Artificial Intelligence dai digital, p.64-68, 2020.

83. Engenhart, Marc and Loewe, Sebastian, "Machine Learning as a Wicked Design Material: Questions, Topics, and Challenges for ML-Driven User-Centered Design. An Introduction to the dai digital Proceedings", Proceedings of the First Conference on Designing with Artificial Intelligence dai digital, pp. 6-13, 2020.

3.2.3 Design for AI

The call to action for designers, HCI and UX practitioners is mentioned by different experts in the field. *"Ongoing advances in AI technologies will generate a stream of challenges and opportunities for the HCI community. ... AI-infused systems can violate established usability guidelines of traditional user interface design"* says Saleema Amershi from Microsoft (Amershi, et al., 2019, p.2)[84]. She is one of a few design practitioners trying to shape the debate on Human-AI-Interaction. The scope of focus is not only on the output of the algorithms, but taking care of the input, meaning data collection and preparation. *"As designers, we need to pay attention not only to the output of these algorithms, but their input, too."* (Clark, 2017) Algorithms depend on their data input, so bias in data is a huge concern since feeding algorithms with 'bad' data predetermines a 'bad' outcome, which in turn, affects the people using the solutions. Overall, the human focus is missing in many technology driven endeavors. In order to ensure that outcomes benefit human beings, designers can determine precisely the needs and requirements of users and other stakeholders. *"As machine learning moves out of the research lab and into more real-world systems, the question of how to ensure that these systems are usable and useful for people becomes increasingly urgent."* (Fiebrink/Gillies, 2018, p.7)[85] Practitioners working in the art and design domains ran a workshop at the IIS in 2018 to raise awareness of that issue in a very technologically focused audience.

84. Amershi, Saleema, et al., "Guidelines-for-Human-AI-Interaction", CHI Proceedings, pp.1-13, 2019.

85. Fiebrink, Rebecca, and Gillies, Marco, "Introduction on the special issue of human centered machine learning", ACM Transactions on Interactive Intelligent Systems, Vol. 8, Issue 2, No. 7, pp. 1–7, 2018.

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88. Audrey, Sofian, "Art in the age of Machine Learning", MIT Press, 2021.

89. AutoDraw. Retrieved from https://autodraw.com. (Accessed on 2022-11-21)

90. Bailey, Mark: Design for AI podcast. Retrieved from http://designforai.com/podcast. (Accessed on 2022-11-21)

91. Brandolisio, Alessandro, et al., "The AI Toolbook. Mit Künstlicher Intelligenz die Zukunft sichern: Das unverzichtbare Arbeitsbuch für Macher, Entscheider und Innovatoren", Murmann Publishers (1. Edition), 2021.

92. Carney, Michelle, & Callaghan, Emily, "Designing Machine Learning: A Multidisciplinary Approach", 2019. Retrieved from https://dschool.stanford.edu/classes/designing-machine-learning. (Accessed on 2022-11-21)

93. Carney, Michelle: MLUX meetup. Retrieved from https://meetup.com/de-DE/MLUXmeetup. (Accessed on 2022-11-21)

94. Civic AI: Augmented Collective Intelligence. Retrieved from https://civic-ai.org. (Accessed on 2022-11-21)

95. Clark, Josh, "Designing for Touch", A Book Apart, 2016.

96. DAIR: Distributed AI Research Institute. Retrieved from https://dair-institute.org. (Accessed on 2022-11-21)

97. Designs.ai: Create logos, videos, banners, mockups with AI. Retrieved from https://designs.ai. (Accessed on 2022-11-21)

98. Feminist AI. Retrieved from https://feminist.ai. (Accessed on 2022-11-21)

99. GitHub: Where the world builds software. Retrieved from https://github.com. (Accessed on 2022-11-21)

100. Google Cloud: AI Platform - BERT. Retrieved from https://cloud.google.com/ai-platform/training/docs/algorithms/bert-start. (Accessed on 2022-11-21)

101. HAI Stanford University: Human-Centered Artificial Intelligence. Retrieved from https://hai.stanford.edu. (Accessed on 2022-11-21)

102. Klingemann, Mario: Memories of Passersby. Retrieved from https://underdestruction.com/2018/12/29/memories-of-passersby-i. (Accessed on 2022-11-21)

103. Landing AI. Retrieved from https://landing.ai. (Accessed on 2022-11-21)

104. Midjourney. Retrieved from https://midjourney.com/home. (Accessed on 2022-11-21)

105. ODI: Open Data Institute. Retrieved from https://theodi.org. (Accessed on 2022-11-21)

106. OpenAI: DallE2. Retrieved from https://openai.com/dall-e-2. (Accessed on 2022-11-21)

107. Pearl, Cathy, "Designing Voice User Interfaces", O'Reilly Media, 2016.

108. School for Poetic Computation. Received from https://sfpc.study. (Accessed on 2022-11-21)

109. School of Machines. Retrieved from https://schoolofma.org. (Accessed on 2022-11-21)

110. Sinders, Caroline, "What does sustainable, collaborative data collection look like?", 2018. Retrieved from https://fastcompany.com/90168266/the-designer-fighting-back-against-bad-data-with-feminism. (Accessed on 2022-11-21)

111. Sketch2Code. Retrieved from https://sketch2code.azurewebsites.net. (Accessed on 2022-11-21)

112. Stability.Ai: stable diffusion. Retrieved from https://stability.ai (Accessed on 2022-11-21)

113. Sudowrite. Retrieved from https://sudowrite.com. (Accessed on 2022-11-21)

114. Wärnestål, Pontus, "Designing AI-powered services", Studentlitteratur, 2022.

3.2.4 Map of resources, names of relevant actors and their related work, institutions and artifacts

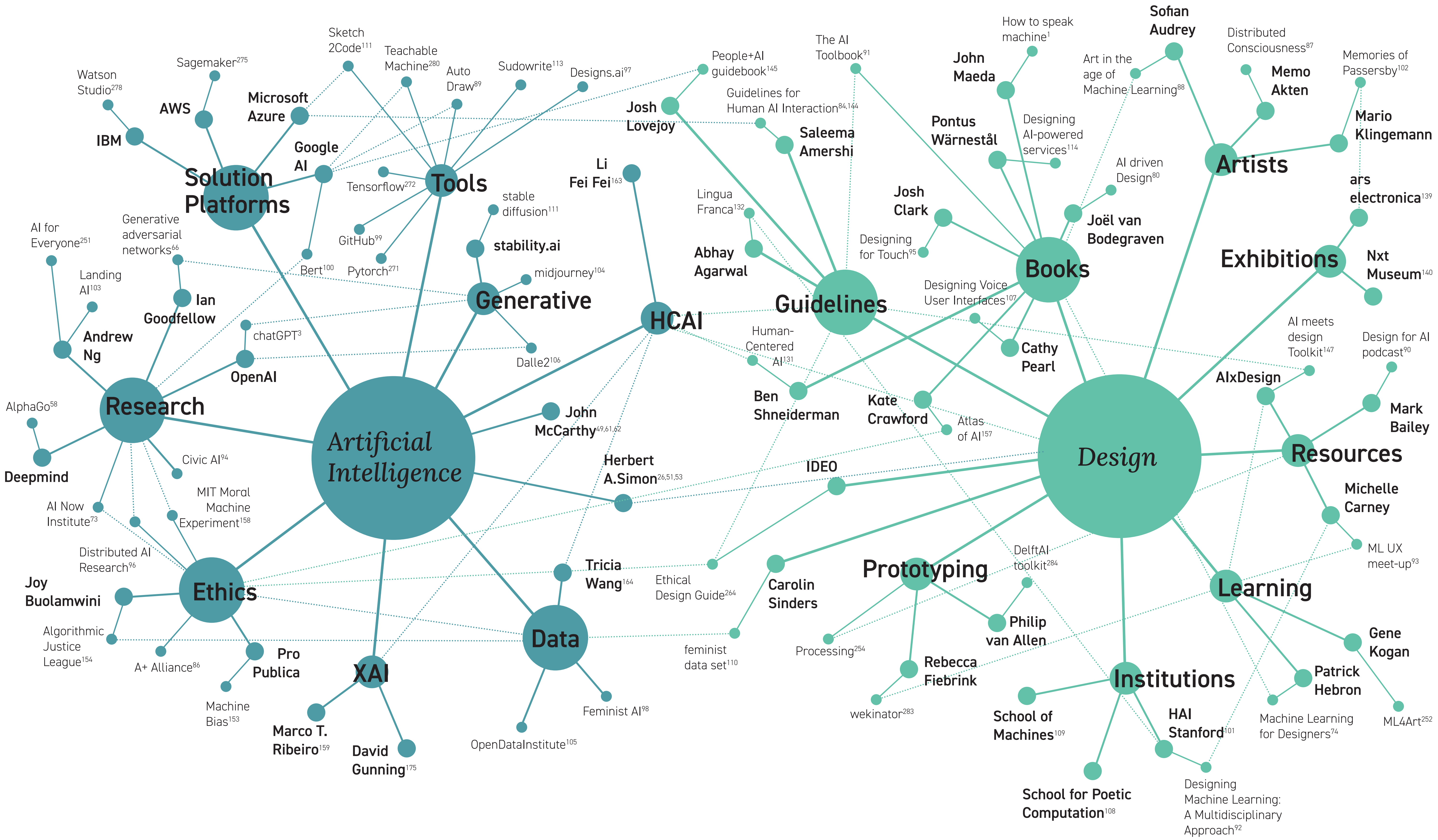


Figure 3.1: Design and AI map of major topics with relevant actors and artifacts

3.3 A new Design Paradigm

Evaluating the statements and current scientific discourse around the topic of AI/ML and design represented in the map it illustrates the AI and ML call for a new design paradigm, resonating with the initial hypothesis for this research scope from Chapter 2. The following section sheds light on the reasons behind this, what the implications are that accompany this, the opportunities for this new design material, and initial ideas about how to establish and support new design practice.

3.3.1 AI/ML as a new design material

This new 'design material' is reshaping and redefining how designers work. Dove et al.'s 2017[115] publication is a work of major importance cited by most of the later publications on Human-Computer-Interaction and UX/HCD. Together with a number of publications from Yang (2017[116], 2018[117], et al. 2018[118], et al. 2020[119]) Dove and Young were among the first to evaluate why and how design and UX practitioners from different fields and domains have a hard time working successfully in the field of Machine Learning. More publications on the same topic became available later[120,121]. The technology touches on so many different aspects of the design process, it *"reconstructs every link from user research to design, user testing and evaluation, etc., forms a new demand for intelligence from macro to micro aspects, facilitates the emergence of new theories, new models, new methods, new products, new formats, and ultimately, leads to a revolution in design paradigm."* (Wu/Zhang, 2020, p.167)[122] More detailed information about the claims of these publications can be found in Chapter 6.3.2.

Within that context two major topic areas emerge as the rationale for AI/ML as a new design material calling for a paradigm shift related to the complexity of the systems and their ability to learn over time[123,124] and their probabilistic nature and dynamic behavior[125,126]. AI/ML systems are based on statistics and probability, which implies a certain level of uncertainty. Their learning abilities over time illustrate their dynamic character, representing new challenges for designing these kinds of systems, since designers' current tools, especially in the area of prototyping and interface design, represent rather static approaches[127-129] Dealing with complexity is supposed to be a design competency[130], however regarding AI and ML activities, this is a somewhat new area and scenarios for handling it are just being explored.

115. Dove, Graham, et al., "UX design innovation: Challenges for Working with Machine Learning as a Design Material", CHI Proceedings, pp.278-288, 2017.

116. Yang, Qian, "The Role of Design in Creating Machine-Learning-Enhanced User Experience", The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems, pp. 406-411, 2017.
117. Yang, Qian, "MachineLearning as a UX design material: how can we imagine beyond automation, recommenders, and reminders?", The 2018 AAAI Spring Symposium Series, pp. 467-472, 2018.
118. Yang, Qian, et al., "Investigating how experienced UX designers effectively work with machine learning". Conference on Designing Interactive Systems, pp. 585–596, 2018.
119. Yang, Qian, et al., "Re-examining Whether, Why, and How Human-AI Interaction Is Uniquely Difficult to Design", CHI Proceedings on Human Factors in Computing Systems, pp. 1–13, 2020.

120. Bergström, Emil, and Wärnestål, Pontus, "Exploring the Design Context of AI-Powered Services: A Qualitative Investigation of Designers' Experiences with Machine Learning", HCII 2022, LNAI 13336, pp. 3–21, 2022.
121. Wallach, Dieter, et al., "Beyond the Buzzwords: On the Perspective of AI in UX and Vice Versa", HCII 2020, LNCS 12217, pp. 146–166, 2020.

122. Wu, Quing, and Zhang, Cun Jun, "A Paradigm Shift in Design Driven by AI", HCII 2020, LNCS 12217, pp.167–176, 2020.

123. Zdanowska, Sabah, and Taylor, Alex S., "A study of UX practitioners roles in designing real-world, enterprise ML systems", in CHI Proceedings on Human Factors in Computing Systems, pp.1-15, 2022.
124. Yildirim, Nur, et al., "How Experienced Designers of Enterprise Applications Engage AI as a Design Material", CHI '22: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, pp.1-13, 2022.

125. Kun, Peter, et al., "design enquiry through data: appropriating a data science workflow for the design process", in Proceedings of British HCI, pp.1-12, 2018.
126. Kun, Peter, et al., "Creative Data Work in the Design Process", C&C '19: Proceedings of the 2019 on Creativity and Cognition, pp. 346–358, 2019.

127. Fiebrink, Rebecca, "Machine learning education for artists, musicians, and other creative practitioners", ACM Transactions on Computer Education, Vol. 19, Issue 4, pp.1–32, 2019.
128. van Allen, Philip, "Prototyping: Ways Of Prototyping", interactions, Vol. 25, No. 6, pp. 46-51, 2018.
129. Horvitz, Eric, "Principles of mixed-initiative user interfaces", CHI Proceedings of the SIGCHI conference on Human Factors in Computing Systems, pp.159–166, 1999.

130. Norman, Donald, A., "Living with Complexity", The MIT Press, 2010.

3.3.2 The missing focus on human needs

The implications that come with this new design material seem to be that designers are currently not involved in the development of AI systems, and so most AI projects are data and technology first focused, targeted towards whatever data is available using algorithms that pretend to be state of the art for the problem at hand. Technological feasibility is the main driver[131], completely ignoring human need as the starting point. *"Despite all the talk of transformation, anything built with AI is secretly a mess. Under the hood, you'll find a cacophony of noisy data, opaque algorithms, and false signals leading to all sorts of awkward and unintended results."* (Agarwal/Regalado, 2020)[132] This has a number of negative implications. The data is mostly collected in a laboratory setting, without any authentic data from real world scenarios, offering a solution that nobody really asked for implemented in a chaotic human setting, thus not able to create value for the user, or user trust and in the end, failing during implementation. This calls for a mindset shift, from data first, to people first, and not just human, but a diverse set of human input to *"...ensure ML and AI are built in inclusive ways."* (Lovejoy/Holbrook, 2017)[133]

131. Shneiderman, Ben, "Human-Centered AI", Oxford University Press, 2022.

132. Agarwal, Abhay and Regalado, Marcy, "Lingua Franca: A Design Language for Human-Centered AI", 2019. Retrieved from https://linguafranca.polytopal.ai. (Accessed on 2022-11-21)

133. Lovejoy, Josh, and Holbrook, Jess, "Human-Centered Machine Learning", 2017. Retrieved from https://medium.com/google-design/human-centered-machine-learning-a770d10562cd. (Accessed on 2022-11-21)

3.3.3 New roles and opportunities for designers

The findings above suggest the involvement of designers in the age of AI and ML is relevant. The challenges referred to also imply new opportunities. There are different ideas and perspectives on the new role for designers and how they can ideally shape AI/ML development, and on the other hand, use AI/ML in their practice. These findings relate to two main strands: the shift in roles from creator to curator, and co-creation and collaboration with data scientists. *"Formerly working as pure creators, this approach is shifting to co-creation with machines and data scientists. Shaping those new job profiles and inventing more tasks to be done by artists and designers is an exciting new area."* (Heier, 2020, p.19)[134]

134. Some of the mentioned aspects have already been published in the Introduction for the Proceedings of the 1st conference of Designing for AI dai 2020 (Heier, Jennifer, "Intro - State of the Art and Design for AI", Proceedings of the First Conference on Designing with Artificial Intelligence dai digital, pp. 16-26, 2020.).

From creator to curator

In the age of AI, algorithms actively create things. In the design domain they can partly take over the work of creating - algorithms don't get tired of coming up with variation after variation. Although these changes might be of minor origin, they can potentially outperform the ability of any human designer to imagine new forms and versions. However, they lack the ability to judge whether a design is aesthetically appealing, and suitable to fulfill the brief. Judging can be the human designers' new task, as well as changing the input parameters to reach the desired model outcome. *"So what will it be like when computers can generate insights on their own and make creative leaps like humans do? It's going to fundamentally change a designer's role in the creative process. In the future, designers will be more like mentors for computers by providing their guidance and experience."* (Kowalski, 2016)[135] Or will designers even become obsolete in the age of AI? A few publications and articles touch on this issue[136,137]. However, even if a couple of design tasks can be replaced by machines, the overall design approach is still a human trait. Therefore talking about human enablement is a more fertile concept.

135. Kowalski, Jeff, "What does the evolution of AI and machine learning look like?", 2016. Retrieved from https://autodesk.com/redshift/machine-learning. (Accessed on 2022-11-21)

136. Chen, Yifei, "Will Artificial Intelligence Remove Designers from the Design Process?", Towards Data Science, 2017, Retrieved from https://towardsdatascience.com/will-artificial-intelligence-remove-designers-from-the-design-process-5e6661430055. (Accessed on 2022-11-21)
137. Rädeker, Jochen, "Future of Design: Macht die KI bald alles?", Page, 2020. Retrieved from https://page-online.de/branche-karriere/future-of-design-macht-die-ki-bald-alles. (Accessed on 2022-11-21)

Another aspect of this discussion about new role for designers is co-creation with the machine, using the model's input as a potential source of inspiration and aspects that the human designer would be unable to imagine, like questioning the status quo of, for example, visual expressions or functional configurations. *"Here, the artist has three roles: to select the data sets used for training the system, to adjust the parameters of the system, and to finally act as a curator who selects the most compelling pieces in a vast space of generated works."* (Pošćić/Kreković, 2020, p.288)[138] These new possibilities for designers and artists open up new ground for collaborative human-machine projects in art, music and film making and areas like ars electronica[139], digitally focused exhibitions[140] and conferences[141] are showcases for the potential of this work. So far there is no 'aesthetic machine' meanings that appeal and aesthetics are still a human quality that can be augmented by machine output in best case scenarios. At least, this is a new perspective for designers concerned with

138. Pošćić, Antonio, and Kreković, Gordan, "Unboxing the Machine: Artificial Agents in Music", Proceedings of xCoAx.org, pp.285-298, 2020.

139. ars.electronica. Retrieved from https://ars.electronica.art/newdigitaldeal/de/you-and-ai. (Accessed on 2022-11-21)

140. Nxt Museum. Retrieved from https://nxt-museum.com. (Accessed on 2022-11-21)

141. Conference on Computation, Communication, Aesthetics & X. Retrieved from https://xcoax.org. (Accessed on 2022-11-21)

formal design, layout and object related design creations, who might be less interested in the development of smart algorithms, more in using technology to enhance their design process.

Co-creation and collaboration with data scientists

Close co-creation and collaboration with data scientists and Machine Learning engineers at the earliest stage of project conception and development is a great way to combine the strength of technological know-how with the human-centered approach represented by designers. *"This can't be the exclusive domain of data scientists or developers, because the stakes go far beyond the underlying data model. ... and this is where we especially need some design and UX skills."* (Clark, 2017) However, this collaboration is not a given. Girardin and Lathia wrote about this issue. *"For that multidisciplinary practice to evolve, we believe that designers and data scientists must immerse themselves in the other's approaches to build a common rhythm."* (Girardin/Lathia, 2017, p.380)[142] They came to the conclusion that there are many differences and distinct practices when it comes to working modes, world views and the approaches of each profession. *"... designers transform a context into a form of experience. Data scientists transform a context with data and models into knowledge."* (Girardin, 2021)[143] Designers try to create an experience, data scientists try to create knowledge. Each uses different technical terms and follows different objectives. *"... as with all multidisciplinary endeavors, we have noticed that the partnership between designers and data scientists must overcome a lack of shared understanding of each other's practice and objectives."* (Girardin/Lathia, 2017, p.379) They don't share a common understanding of data. *"Often, none of these insights will be fundamentally encoded into the statistical models that are used in machine learning to deliver value to one of these users."* (ibid., p.380) This leads to problems with trying to translate user needs from qualitative user research into Machine Learning models, as well as with different development processes and workflows, currently not aligned. Nevertheless, both perspectives definitely benefit from immersing in each other's point of view. So far, there has been no shared process model or set of methods and tools to support the collaboration. *"Some designers also found it challenging to effectively collaborate with AI engineers, because they lacked a shared workflow, boundary objects, or a common language for scaffolding the collaboration."* (Yang et al, 2020, p.3)

142. Girardin, Fabien, and Lathia, Neal, "When User Experience Designers Partner with Data Scientists", The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems, pp. 376-381, 2017.

143. Girardin, Fabien, "Experience Design in the Machine Learning Era", 2016. Retrieved from https://girardin.medium.com/experience-design-in-the-machine-learning-era-e16c87f4f2e2. (Accessed on 2022-11-21)

3.3.4 Establishment of 'new' methods and tools for design practice

In order to take up these new roles and opportunities it is necessary for designers to alter their practice. The new design paradigm also implies the establishment and need for new ways of working. One set of attempts to answer those challenges is the creation of (human-centered) design principles[132,144-147] for the development of AI/ML systems.

In relation to the current principles of Human-Centered-Design proposed by ISO 9241[148] the design of AI-infused systems is currently missing some of the concepts mentioned there, such as controllability, conformity with user expectations, self-descriptiveness and use error robustness. This is where 'new' design principles can make a contribution by adding new steps and activities to the overall design process. They are a great starting point to become familiar with these issues and a first step towards new methods and tools for design in the age of AI. Most of principles refer to similar aspects, such as initial problem definition, managing expectations to the system's abilities, taking care of the data input, the issue of fast and low fidelity prototyping, problems with the transparency and coherence of systems, their failures and the importance of collecting feedback, which can contribute to creating and maintaining trust. A selection of these areas further discussed in Solution Space, Chapter 8. and only touched on here.

144. Guidelines for Human-AI Interaction. Retrieved from https://microsoft.com/en-us/research/project/guidelines-for-human-ai-interaction. (Accessed on 2022-11-21)
145. People+AI Guidebook. Retrieved from https://pair.withgoogle.com/guidebook. (Accessed on 2022-11-21)
146. IBM Design for AI. Retrieved from https://ibm.com/design/ai. (Accessed on 2022-11-21)
147. Toolkit: aimeets.design. Retrieved from http://aimeets.design/toolkit. (Accessed on 2022-11-21)

148. ISO 9241-210:2019-07, Ergonomics of human-system interaction - Part 210: Human-centred design for interactive systems (ISO 13407:1999-06).

3.4 AI and ML Perspective

3.4.1 General overview of relevant AI/ML topics

Due to greater hardware power and the availability of and access to huge amounts of data, AI is facing another 'AI summer'[149]. This development comes with challenges[150,151] as well as some great achievements (see Chui et al., 2018[56]). The implementation of AI in a lot of daily products and services contains some pitfalls, for instance AI and ML can affect jobs[152], the quality and amount of data[153,154] is a consideration as are the output and failures of the systems[155], energy consumption[156,157] during development and runtime, and general ethical[158,159] concerns.

149. Ransbotham, Sam, et al., "Artificial Intelligence in Business Gets Real - Pioneering Companies Aim for AI at Scale", Findings from the 2018 Artificial Intelligence Global Executive Study and Research Project, MIT Sloan Management Review, 2018.

150. Boston, Nick, Superintelligence: Paths, Dangers, Strategies, Oxford University Press, 2014.
151. Hessen Schei, Tonje, "iHuman - documentary", Norway, 2019.

152. World Economic Forum: The Future of Jobs Report, pp. 7-17, 2018. Retrieved from https://weforum.org/reports/the-future-of-jobs-report-2018. (Accessed on 2022-11-21)

153. Angwin, Julia, et al., "Machine Bias", 2016. Retrieved from https://propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing. (Accessed on 2022-11-21)
154. Algorithmic Justice League. Retrieved from https://ajl.org/about. (Accessed on 2022-11-21)

155. Miller, Tim, et al., "Explainable AI: Beware of Inmates Running the Asylum", IJCAI, Workshop on Explainable Artificial Intelligence (XAI), 2017.

156. Crawford, Kate and Joler, Vladan, "Anatomy of an AI System: The Amazon Echo As An Anatomical Map of Human Labor, Data and Planetary Resources," AI Now Institute and Share Lab, 2018. Retrieved from https://anatomyof.ai. (Accessed on 2022-11-21)
157. Crawford, Kate, "Atlas of AI", Yale University Press, 2021.

158. Awad, Edmond, et al., "The Moral Machine Experiment", Nature Volume 563, pp.59–64, 2018. Retrieved from http://moralmachine.mit.edu. (Accessed on 2022-11-21)
159. Bostrom, Nick, and Yudkowsky, Eliezer, "The Ethics of Artificial Intelligence", Cambridge University Press, 2011.

3.4.2 Human machines, humans as machines

Many of the issues in the area of AI and ML mentioned briefly above relate to human factors. *"Machine learning is at the core of many recent advances in science and technology. Unfortunately, the important role of humans is an often-overlooked aspect in the field."* (Ribeiro et al., 2016, p.1135)[159] Artificial Intelligence is supposed to be human-like (Bostrom, 2014) at least to reach a level of intelligence that is human-like. Humans are chaotic, irrational, emotional, trust their instincts and gut feelings rather than facts and figures, making it really hard to create machines that are like and behave like humans. This implies a mismatch between humans and machines, suggesting a possible attempt to turn things round and try to make humans behave like machines. As Genevieve Bell, a well-known user researcher, amongst others (Wendland, 2021)[160] put it in an interview about human-computer interactions compared to relations *"B.F. Skinner… if that is the value set of AI… if you want to teach a machine to be human… if you want to build a machine… oh we have somebody who theorizes humans as a machine; happiness all around."* (Bell, 2017)[161] This is a fundamental aspect that guides a lot of the decisions in the area of AI and ML[162], especially important when talking about human-centeredness within that context.

159. Ribeiro, Marco Tulio, et al., "Why Should I Trust You Explaining the Predictions of Any Classifier", in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1135–1144, 2016.

160. Wendland, Karsten, "Menschenbild ohne Menschen- Subjektkonstitution im Spiegel synthetischer Konkurrenz", in: Wer bist du, Mensch?: Transformationen menschlicher Selbstverständnisse im wissenschaftlich-technischen Fortschritt. Hrsg.: A. Grunwald, Herder Verlag, pp. 240-259, 2021.
161. Bell, Genevieve, "moving from human-computer interactions to human-computer relationships", The O'Reilly Radar Podcast: AI on the hype curve, imagining nurturing technology, and gaps in the AI conversation, 2017. Retrieved from https://oreilly.com/content/genevieve-bell-on-moving-from-human-computer-interactions-to-human-computer-relationships. (Accessed on 2022-11-21)

162. Sharples, Mike, et al., "Computers and Thought: A Practical Introduction to Artificial Intelligence", The MIT press, 1989.

3.5 A new AI Paradigm

Besides the already mentioned issues of a lack of human-centeredness in the AI domain[163, 164], which is directly related to the Human-Centered-Design perspective, other issues in that area also call for new approaches to the AI paradigm.

163. Li, Fei Fei, "Put Humans at the Center of AI", MIT Technology Review, Vol. 120, No. 6, p.26, 2017.
164. Wang, Tricia, "People are your data", 2018. Retrieved from https://dscout.com/people-nerds/people-are-your-data-tricia-wang. (Accessed on 2022-11-21)

3.5.1 Missing examples relevant for best practice

It is very difficult to find best practice use cases examples in the current scientific and expert AI and ML discourse and community. Ones that contain and explain how to use Human-Centered-Design methods and tools have been - up to now - rare to non-existent, particularly the field of B2B and industrial projects is a white spot. This lack of example projects is covered by a small number of experts in the field. *"Much of current machine learning (ML) research has lost its connection to problems of import to the larger world of science and society. From this perspective, there exist glaring limitations in the data sets we investigate, the metrics we employ for evaluation, and the degree to which results are communicated back to their originating domains."* (Wagstaff, 2012, p.529)[165] Most of the approaches and activities mentioned are concerned with a theoretical knowledge of AI systems. They are based on scientific research without real world scenarios. There is clearly a gap for real world examples and concrete use cases. *"Either they evaluate a model's performance using metrics that don't translate to real-world impact, or they choose the wrong target altogether."* (Kerner, 2020)[166]

165. Wagstaff, Kiri, "Machine Learning that Matters", Proceedings of the 29th International Conference on Machine Learning, pp. 529-536, 2012.

166. Kerner, Hannah, "Too many AI researchers think real-world problems are not relevant", 2020. Retrieved from https://technologyreview-com.cdn.ampproject.org/c/s/www.technologyreview.com/2020/08/18/1007196/ai-research-machine-learning-applications-problems-opinion/amp. (Accessed on 2022-11-21)

3.5.2 Focus on model performance and lack of business impact

The current focus of development in the AI research community is on issues such as improving algorithm performance and optimization without any real relevance to business applications, as raised by the topics and focus of respective AI and ML conferences (see e.g. AAAI[167], IJCAI[168]). *"... this hyperfocus on novel methods leads to a scourge of papers that report marginal or incremental improvements on benchmark data sets and exhibit flawed scholarship. ... many papers that describe new applications present both novel concepts and high-impact results. But even a hint of the word 'application' seems to spoil the paper for reviewers. As a result, such research is marginalized at major conferences."* (Kerner, 2020) As a consequence AI is currently not really fulfilling the expectations that were promised[169,170], and missing out on the real advantages it could have. *"Because of the field's misguided priorities, people who are trying to solve the world's biggest challenges are not benefiting as much as they could from AI's very real promise."* (ibid.)

167. AAAI Conference Tutorials. Retrieved from https://aaai.org/Conferences/AAAI-19/aaai-19tutorials. (Accessed on 2022-11-21)
168. International Joint Conference on Artificial Intelligence Program. Retrieved from https://static.ijcai.org/2019-Glance.html. (Accessed on 2022-11-21)

169. Crevier, Daniel, "AI: The Tumultuous History Of The Search For Artificial Intelligence", Basic Books, 1993.
170. Lighthill, James, "Artificial Intelligence: A General Survey", Lighthill Report: Artificial Intelligence: a paper symposium, 1973.

Developing AI systems is currently a very complex, lengthy and costly process with a lot of iterations. One reason is because data scientists with little domain knowledge develop, train and validate algorithms. *"In the past, researchers and developers focused on building AI algorithms and systems, stressing machine autonomy, measuring algorithm performance, and celebrating what AI systems could do."* (Shneiderman, 2020, p.112)[171] This output is then implemented from a lab setting into a real world scenario and is not accepted by the users, or fails for other reasons. *"... in the case of contemporary smart, automated systems, arguably one of the main culprits (along with the logic imposed by venture capital) is the mixture of overconfidence, monocultural biases, and technocentrism afflicting their designers. ... they usually fail to consider that any new automated product will be embedded within larger and increasingly complex socio-technical systems."* (Hernández, 2020, p.203)[172] Development under the controlled parameters in a laboratory setting without any focus on human needs, again highlights the importance of real problem with a human focus as the starting point for any AI-infused systems and is the key to successful implementation.

171. Shneiderman, Ben, "Human-Centered Artificial Intelligence: Three Fresh Ideas", AIS Transactions on Human-Computer Interaction, Vol. 12, Issue 3, pp. 109-124, 2020.

172. Hernández-Ramírez, Rodrigo, "A Sketch of Some Principles for Good Design in The Age Of Smart Automation", Proceedings 2020.xCoAx.org Graz, Austria, pp.202-214, 2020.

Kerner also argues that the impact of development without any real world focus goes a step further. The AI models and algorithms then used in real world applications and the problems which then occur are not solved by the people who would be in charge or able to do so, because they never see the results.

"When studies on real-world applications of machine learning are excluded from the mainstream, it's difficult for researchers to see the impact of their biased models, making it far less likely that they will work to solve these problems." (Kerner, 2020) This is a dead end and a vicious circle for the development of new algorithms with beneficial uses in a business context, since there is no loop that connects algorithm error output from business uses to the data scientists that could possibly improve them, or at least adapt the model(s) to the problem setting of the business context.

The reason for this disconnection and the missing real world examples might be that the data and requirements are very different from case to case, making it hard to match certain models and algorithms to a variety of use cases, which is easier to do with a fixed set of parameters in a lab setting. *"But in the real world, these categories are constantly changing over time or according to geographic and cultural context. Unfortunately, the response has not been to develop new methods that address the difficulties of real-world data..."* (ibid.) These arguments suggest that research which is situated and depending on use cases could add a lot of value to the current scientific discourse and perhaps overall AI development and progress.

3.5.3 Establishment of 'new' approaches and their different manifestations

Evaluating these statements and current scientific discourse in the area of AI and ML reveals that new methods and approaches are needed for the advancement and the development of AI systems in this context. *"...we argue that UX design approaches have great potential in identifying new ML opportunities. Designers can situate ML algorithms in different contexts and for different audiences."* (Yang, 2017, p.408) This call is represented in the field by different approaches, such as interactive Machine Learning (iML), eXplaniable AI (XAI) and Human-Centered-AI (HCAI).

iML refers to the development of ML models in collaboration with a human, incorporating their feedback during the model training process. The aim is to derive more efficient and accurate ML models that also improve the interaction between humans and machines.

The purpose of XAI is to provide a set of ML techniques that foster transparency and explanation of AI and ML models and their behavior and outcomes for humans to understand AI output and build trust, improve model performance on the one hand, but also support humans in effectively developing reliable and equitable ML solutions.

HCAI is an emerging discipline with the purpose of creating and developing AI and ML systems that foster Human-AI collaboration and co-creation. It includes aspects and methods from HCD, while also responding to the new challenges the technology implies, such as preserving human control, aligning with human needs, operating transparently, delivering ethical outcomes, and respecting data privacy.

iML implies that end users are involved in the process of data preparation like data labeling, or users are enabled to fine tune the parameters of the models to meet their needs[173,174]. Another attempt in that regard is the so called explainable Artificial Intelligence (XAI)[175,176] activities. The idea is to explain in detail the reasoning of the algorithms, in order to allow the user to decide whether to trust the system output, trying to overcome the issue of the black box. A key publication is by Marco Ribeiro, 2016, who illustrated with an example from an image classifier of dogs and wolves how an ML model made its decisions.

173. Amershi, Saleema, et al., "Power To The People: The Role of Humans in Interactive Machine Learning", AI Magazine AI Magazine, Association for the Advancement of Artificial Intelligence, Vol. 35, No. 4, pp.105-120, 2014.
174. Bernardo, Francisco, et al., "Interactive Machine Learning for End-User Innovation", The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems, pp. 369-375, 2017.

175. Gunning, David, "Explainable Artificial Intelligence (XAI)", DARPA-BAA-16-53, 2016. Retrieved from https://darpa.mil/program/explainable-artificial-intelligence. (Accessed on 2022-11-21)
176. Miller, Tim, "Explanation in Artificial Intelligence: Insights from the Social Sciences", AI Magazine, Vol. 267, pp.1-38, 2019.

Finally, the Human-Centered-AI (HCAI)[171,177] movement is where design and AI meet, where design can add value to the development of AI and ML systems, where the biggest similarities in approaches can be observed. However, activities are in their early stages, still with plenty of room for further investigations and new methods and tools, and lacking joint teams of design and computer science practitioners, making it hard for either group to fully embrace the principles developed from the other standpoint.

177. HAI: Workshop on Humanizing AI, 2018. Retrieved from https://humanizing-ai.com/hai-18.html. (Accessed on 2022-11-21)

3.6 Research Gaps

3.6.1 Missing links for the input of Human-Centered-AI

Current advances in AI are mainly driven by technological feasibility, but lacking business viability and human desirability, represented by products and services that often fail when implemented and then rejected by users due to a lack of trust, or output which is error prone, even dangerous due to bad data or development in a laboratory-like setting. The missing link is human needs, ways of thinking, working and seeing the world, with expectations of machines that cannot be fulfilled or feelings of being overwhelmed by technological advancement. A human-centered approach is one possible way to respond to those issues. *"Human-centered AI is an emerging space that requires much-valued input from practitioners, researchers, and creatives of all stripes and disciplines."* (Agarwal/Regalado, 2020) Not only can designers have a say in that domain, the input from a variety of professions is crucial, too. However, designers are a good fit for this approach, since they already embrace this mindset. Using the knowledge and experience from working in that area could therefore be very productive to coming up with new methods and tools that can also answer the challenges imposed by AI-infused systems. *"... the complexity and opacity of artificial intelligence makes human-centered principles more urgent than ever."* (ibid.)

Practitioners in the field of computer science perceive that the involvement of design, HCI and UX is missing in the current development of AI-infused systems. *"We suspect that one reason we might see less design innovation with ML than with previous technology is that ML is a more difficult design material to work with."* (Dove et al., 2017, p.279) They see similar issues to those mentioned in the design part of this literature review as the root cause, like missing knowledge and training in the capabilities of the technology, *"...user experience (UX) practitioners are lagging behind in leveraging this increasing common technology. ML is not yet a standard part of UX design practice, in either design patterns, prototyping tools, or education."* (Yang, 2017, p.406) and without the methods and tools to align with computer science activities and processes *"ML is not part of a typical user-centered design process; wireframing tools or patterns do not yet support the UIs that change over time or personalize to users."* (Yang, 2018, p.469) and without best practice that deals with the complex nature and adaptable behavior of those systems (Fiebrink, 2019).

3.6.2 Missing industrial AI applications

The scientific and computer science discourse has slowly picked up on the use of Human-Centered-Design approaches, but so far it has not been clear about how to best integrate it into the development process. Most examples follow experimental use cases which do not represent a general approach. Moreover, it is notable that the small number of use cases which do represent the use of Human-Centered-AI are primarily located in the B2C market. Hardly any publications are related to industrial AI applications[178]. With these gaps identified this research focuses on examining real world scenarios located in the industrial AI domain to identify the kind of topics, issues and challenges relevant in this context.

178. Passalacqua, Mario, et al., "Human-Centered AI in the Age of Industry 5.0: A Systematic Review Protocol", HCII 2022, LNCS 13518, pp. 483-492, 2022.

Therefore the context and physical location of this thesis is within the Siemens AG digital industries unit dealing with factory automation issues, projects and the manufacturing hardware sector. In industrial AI, the optimization of processes is the main driver for AI and ML driven projects, in contrast to B2C applications where customization and personalized products and services are the main lever[179]. This already represents a fundamentally different perspective of end users, namely that the output of industrial AI/ML algorithms is in complete contrast to a human-centered approach. However, the solutions implemented and output generated need to be used by humans and are affected by algorithms as within the B2C domain. The surveyed case studies show that the late involvement of end users caused pitfalls and challenges for the overall success of the AI/ML driven solutions. Scaling from one factory to another is equally not easily done, due to a lack of trust in the output of the system and a lack of understanding of the technological capabilities, ending in unrealistic expectations of the technology. This work assumes that the example of Siemens is largely similar to the experience of other industrial AI companies[180].

179. Dunning, Ted, and Friedman, Ellen, "AI and Analytics in Production", O'Reilly Media, 2018.

180. Kureishy, Atif, et al., "Achieving Real Business Outcomes from Artificial Intelligence", O'Reilly Media, 2019.

3.6.3 Missing design specific material and notational forms

Current AI/ML is primarily driven by computer science and technology researchers as stated above. Much of the available material, information and resources is created for this audience, to be used and understood by experts but is inaccessible for non-experts and people outside the AI domain. The field lacks diversity in many different areas. Solutions that also address design and business practitioners are rare, showing the need to explore notational formats and artifacts that suit design requirements or in the best case scenario, are also suitable for application in a range of different professions.

3.7 Conclusion

Analyzing the current research shows that AI development, especially in the industrial domain, lacks a human-centered perspective. Ideas and concepts as well as from design, namely design principles for AI, and from the area of computer science, namely the call for Human-Centered-AI already exist to address this issue, but in each case the approaches are very generic, without a contextual perspective, so it is hard to implement these concepts and guidelines discussed in practice. Additionally, most concepts originated in the B2C domain and are not easily transferable to the industrial AI context, but they can serve as a general understanding of the current issues and challenges for the development of AI systems, therefore create a starting point for further investigations.

In general, more research needs to be done to implement the concepts of a Human-Centered-AI approach in the overall area of the very technologically driven AI development. For this purpose, the overall development process needs to be taken into consideration. Only measures that support the whole value chain are able to generate a positive impact. The introduction of distinct Human-Centered-Design methods and tools in different phases of the process can add the missing human perspective. Exploring where the biggest impact can be created is an important part of this research work. The choice of where to include design approaches depends on where they can have the biggest impact, not primarily focused on for the output of an AI system, so defining the initial problem and data preparation must be part of this journey. Bringing together these aspects and characterizing key points of influence is the intention of this work.

Furthermore, the need for practice based research has been identified, whereby use cases from Siemens AG Digital Industries can serve as a basis for research investigations. In the given unit, a team with different skill sets work together to provide beneficial conditions for the exploration and transfer of Human-Centered-AI systems, as well as to understand, analyze and validate how designers, data scientists and business experts can work together. Supplementing this with additional use cases from other sources can support the design and UX community to have a beneficial impact on AI-infused projects.

Chapter 4. Research Approach

4.1 Introduction

This chapter covers the methodology and framework for the research rationale and its boundaries, derived from the research gaps found in Chapter 3.6: a) Human-Centered-Design and the research specialties that come with this, such as flexibility of methods and combining knowledge in use, as well as producing activities (see Chapter 1.3.2); b) technology and more specifically, recent developments and rise in AI/ML approaches; c) input from real world industrial AI use cases. These three areas underpin the setting-up of an open, novel and critical pathway of exploration that reflects them in the overall methodological approach of this thesis (see Fig. 4.1). This section provides the philosophical background covering the boundaries, methods, tactics and tools supporting the research. The three key topics are introduced incrementally to outline the methodology, methods and tools framework. Part IV. Problem Space Chapter 5. and 6. explain the use in practice.

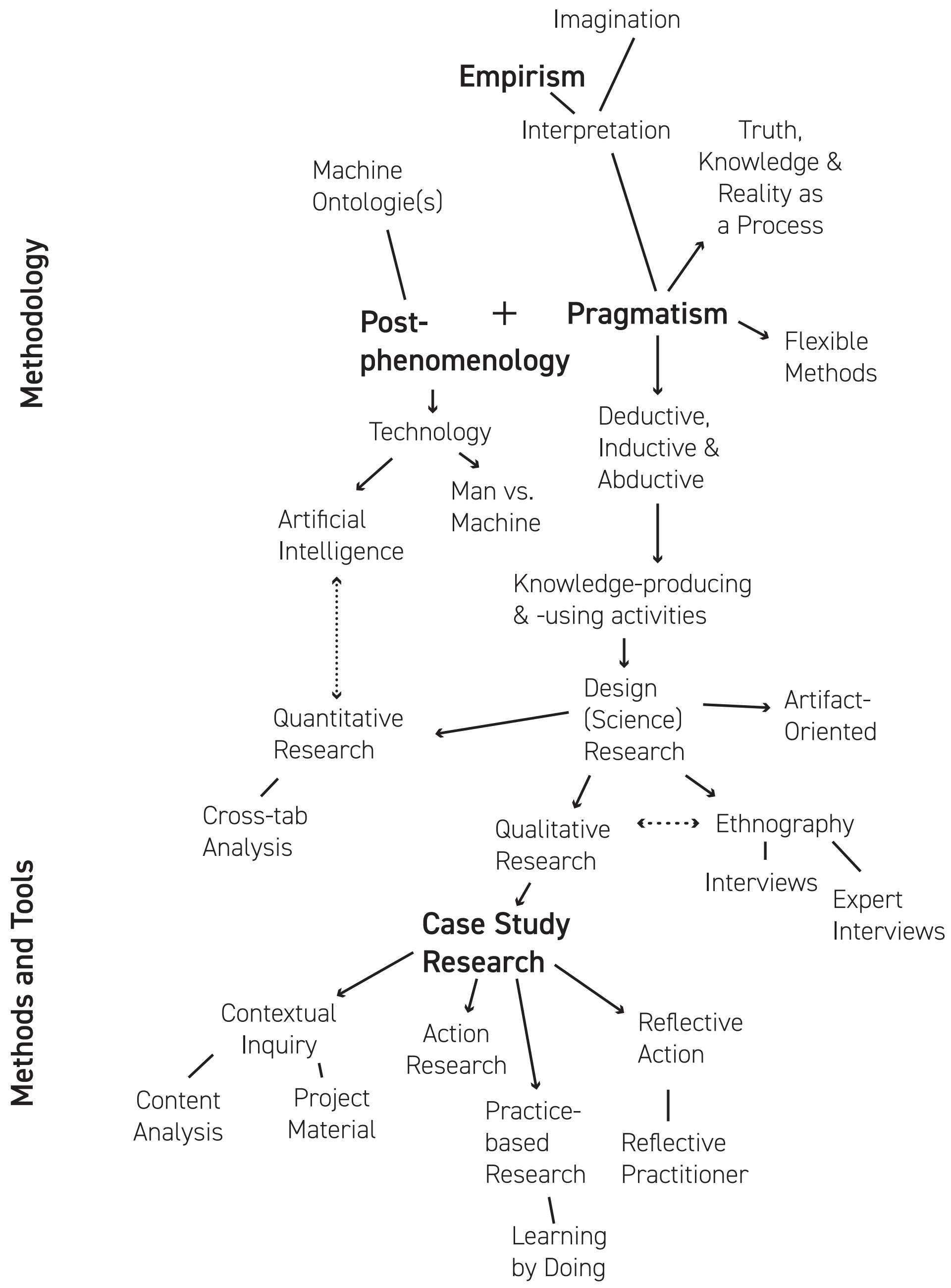


Figure 4.1: Research approach mind map

4.1.1 Setting the stage

This work is partly theoretical and partly practical, representing knowledge-producing and knowledge-using activities. Therefore no single methodology or method fits all the parts of the overall process and research approach. A mixed, hybrid set of methodologies is necessary to fit the different phases and research participants, a dynamic, not static, distribution of paradigms and functional methodologies.

This methods section describes these multiple stand-points with their social, natural, as well as artificial paradigms. This work is based on three areas: the social context (human society and relationships); the natural (physical world) science; design (artifacts) science. The social aspects are related to the context of the research - questions about the lack of Human-Centered-Design methods and tools as well as the role of designers in the age of AI - in the Problem Space section (Chapters 5 and 6), which outlines the natural and artificial research approaches with a central role in the development of technology and systems in the context of AI technology and the practical part of the Solution Space of this work (Chapters 8 and 9) seeking to develop new artifacts (processes, methods and tools) within the context of design and industrial AI. This setting is the basis for choosing a philosophical stance, itself a design assignment. *"As information and data about everything explode in a frenzy of rhizomatic connectivity, the very search for what to research becomes its own research issue. The research model becomes a design problem that can also function as its own solution."* (Lunenfeld, 2003, p.13) In this work, the research is not intended to function as its own design solution, but the framework needs to reflect the multiple facets of this endeavor. Making clear that no one single method will work as the only source of orientation and positioning means *"... it is not a matter of starting from certain theoretical or methodological problems: it is a matter of starting from what we want to do, and then seeing which methods and theories will help us to achieve these ends."* (Eagleton,1983, p.183)[181] Agreeing with Eagleton this chapter aims to reach this goal, ensuring the paradigms and purposes of the research contribute to each other.

181. Eagleton, Terry, "Literary Theory: An Introduction", University of Minnesota Press, 1983.

4.2 Methodology

4.2.1 Research rationale

This study is overall empirical (situated in this world and being observed as such), aiming to systematically capture events and processes in a real context. In Design Research, besides acting within an empirical context part of the work is imaginative. *"Design research is inherently paradoxical: it is both imaginative and empirical. It can not be simply empirical because the 'typical' consumers that researchers need to understand are rarely able to articulate their needs."* (McDaniel, 2003, p.39)[182] This means that a certain part of the design researcher's work is about making sense - in a broader sense than interpretation - out of what the data offers, so is not purely empirical. This shows why it is very difficult to fit Design Research precisely into any given philosophical system's conceptions about truth, knowledge and reality. Nonetheless, it is crucial to be aware of and consider the different research rationales' perceptions of truth, knowledge and reality. *"You need to make explicit which paradigm(s) your work will draw on, since a clear paradigmatic stance helps guide your design decisions and to justify these decisions. ... You don't have to adopt in total a single paradigm or tradition. It is possible to combine aspects of different paradigms and traditions,..."* (Maxwell, 2012, p.224)[183] It is crucial to set out the basics of the research to help other research scholars better understand the research process and claims. It can be useful to support the data-gathering process, for analyzing and validating the data to justify research insights and outcomes. In this way, building on the knowledge and wisdom of others can help design researchers to define their own concepts better and create new ones that fit their needs.

182. McDaniel Johnson, Bonnie, "The Paradox of Design Research - The Role of Informance", in Design Research: Methods and Perspectives / [edited by] Brenda Laurel, The MIT Press, pp. 39/40, 2003.

183. Maxwell, Joseph A., "Qualitative Research Design: An Interactive Approach", Designing a Qualitative Study, Chapter 7, pp. 214-253, 2012.

Ontology: Reality is constantly negotiated and interpreted depending on different situations and contexts.

Epistemology: Subjective interpretations and/or objective phenomena can potentially lead to knowledge.

4.3 Pragmatism

"Instead of focusing on methods, researchers emphasize the research problem and use all approaches available to understand the problem." (Creswell, 2014, p.39)[184]

184. Cresswell, John W., "Research Design: Qualitative, Quantitative and Mixed Methods Approaches", SAGE Publications, 2014.

This research requires methodology and methods that offer for a flexible and iterative approach, embracing key design features and AI/ML requirements. Pragmatism reflects this openness, with focus on the means to an end, requiring a mindset open to mixing different methods. *"..., for the mixed methods researcher, pragmatism opens the door to multiple methods, different worldviews, and different assumptions, as well as different forms of data collection and analysis."* (ibid., p.40) Although this doesn't mean mixed methods in the traditional sense of using both qualitative and quantitative data; here mixed methods means different qualitative approaches within the same research process. As stated, this research is partly theoretical and partly practical, dealing with social, natural, and technological aspects. *"Several proponents of design science suggest that it is associated with pragmatism as a philosophical orientation in its attempt to bridge science and practical action."* (Iivari, 2007, p.45)[185] This bridging quality is another reason for choosing pragmatism as the overall guide to the methodological framework.

185. Iivari, Juhani, "A paradigmatic analysis of information systems as a design science", Scandinavian Journal of Information Systems, Vol. 19, No. 2, pp.39-64, 2007.

Pragmatism has its origins in America, an attempt to oust the supremacy of philosophical ideas and beliefs from Europe. Its founding fathers were Charles S. Peirce and William James, with later additions from John Dewey, George H. Mead and Richard Rorty. For them America was *"the country of beginnings, of projects, of designs, and expectations."* (William, 1907, p.10)[186] This orientation towards action and the applied sciences was absent in the European paradigms of that time and a new approach was called for. Peirce and James disagreed with the European mindset and definition of truth. In their view, there was no such thing as fundamental or absolute and unconditional truth. Truth depends on the actions taken and results implied. Pragmatism offered new concepts of meaning and truth that were not absolute.

186. William, James, "Pragmatism", Harvard University Press, 1907.

4.3.1 Main concepts and ideas

Besides the pragmatists' concept of meaning and truth, the main ideas central to this work are their concept of inquiry, the importance of (personal) experience, and that knowledge and actions equals change. *"Introducing the word 'pragmatism' in its present sense, Charles S. Peirce used it to name a philosophy that traces concepts back to the action of practical life."* (Barry, 2008, p.2)[187] In their view, meaning and truth are not a given to be found, but developed over time in consensus with others. This is a process, often starting with a problem, then building a hypothesis, testing it, refining it, repeating it and always developing it further, depending on context and experience, which often and in the long run change. A pragmatic stance means the researcher must reflect on her/his own actions. Pragmatism is also pluralistic, meaning it is open to different concepts and makes space for more than one basic substance or principle. Scientific knowledge is meant to have a practical impact on actions - be a means to an end. It's core is also of continuous experimentation and collective development. With roots in empiricism, it goes a step further to imagine a desirable future, not being primarily focused on the past. *"What is philosophically significant in the new science are its experiments and the methods of experimental knowledge. Experimentalism is not mere empiricism."* (ibid., p.2) It can be identified by its processual world-view, embracing and introducing abduction together with deduction and induction as scientific method. Pragmatism can be described as an iterative process of initial abductive arguments (hypothesis or retroductive inferences), extrapolating deductive arguments (necessary inferences) and final testing with inductive arguments (probable inferences) before perhaps going back to deduction or even abduction, to come - potentially - closer to what the truth refers to in a specific set of circumstances, before considering the general implications for theory.

187. Allen, Barry, "Postmodern Pragmatism: Richard Rorty's Transformation of American Philosophy", Philosophical Topics Vol. 36, No.1, pp.1-15, 2008.

Pragmatism should not be viewed as a static school of thought. Classical pragmatists views need to be understood in the context of the time in which they were formed and presented. It is clear those initial concepts need to be adapted to contemporary influences. One crucial common mission still valid and relevant today was to critique and provide an alternative to the dominant ideas at the time, notably empiricism. Given the vast scope and influence of pragmatic thought, any attempt to describe an overview of pragmatism is necessarily incomplete and selective. However, at least one contemporary stream of pragmatic development is referred to here because it supports this research endeavor.

Critical and neo (postmodern) pragmatism as represented by John Dewey and George Mead

Based on the earlier work of James and Pierce, Dewey's perspective emphasizes a more socially constructive view. His idea of inquiry (Dewey, 1938)[188] heavily depends on learning and development process divided into three phases: first, identifying the problem; second, reconstructing the information, context and circumstances found in the initial context of situation and taking action; third is reflection, when constructivist activities take place. Dewey promoted a scientific attitude which involves applying critical thinking to the practical problems of everyday life. This led to the prefix 'critical' pragmatism. Mead's ideas on 'identity processes' (Mead, 1934)[189] which are influenced by external factors such as objects and people and Dewey's scientific attitude are both relevant to design practice.

188. Dewey, John, "Logic: The theory of inquiry", Henry Holt, New York, 1938.

189. Mead, George Herbert, "Mind, Self & Society", The University of Chicago Press, 1934.

4.3.2 Implications for design

The following are relevant in Design Research and complementary to a pragmatic worldview, primarily the focus on the practical implications of every scientific inquiry. *"Pragmatism is a school of thought that considers practical consequences or real effects to be vital components of both meaning and truth. Along these lines I contend that design science research is essentially pragmatic in nature due to its emphasis on relevance; making a clear contribution into the application environment."* (Hevner, 2007, p.91)[190] Second, design theory is strongly tied to abduction, a term Pierce introduced in 1877, which goes hand in hand with the idea that research is not purely empirical, but also imaginative and oriented towards the future and third, it reacts to and reflects on the consequences of its interactions with and within the environment, also a design practice supported by the pragmatic ideas of inquiry and personal experience. *"Schön's account is, to be sure, deeply pragmatic in the ways it captures not just what we're thinking when we act, but also what we're doing when we act, seeing that sometimes we want to ask, 'Do we wish to do more or less of what we did? Was our working theory, our practical expectation and anticipation, spot-on or partially blind? Do we need to reframe our thinking or not?' These are a pragmatist's questions, both about theory and practice, both about how we do what we do and about the connections between our past doing and our thinking, and our future doings as well."* (Forester, 2012, p.9[191]; Schön, 1983[192])

190. Hevner, Alan R., "A Three Cycle View of Design Science Research", Scandinavian Journal of Information Systems, Vol. 19, No. 2, pp. 87-92, 2007.

191. Forester, John, "On the theory and practice of critical pragmatism: Deliberative practice and creative negotiations", Planning Theory, Vol.12, Issue 1, SAGE Publications, pp. 5–22, 2012.
192. Schön, Donald, A., "The Reflective Practitioner: How Professionals Think in Action", Basic Books, 1983.

4.3.3 Alignment design, AI/ML and case study research - focus on outcome

Besides the aspects mentioned above, for design, the focus and interplay of knowledge and action is what makes pragmatism an appropriate philosophy. *"The pragmatist attitude is to intervene into the future with the purpose to construct a better world,"* (Goldkuhl, 2012, p.87)[193] thus creating new knowledge. Göran Goldkuhl examined extensively the core concepts of Design Science and pragmatism and set down how Design Research can benefit from range of pragmatic conceptualization. He writes *"... the as-is world as a starting point for the design process. ... The whole process of going from problems to design and use can be conceived in terms of pragmatic inquiry (as defined by Dewey). The existing as-is is considered as a problematic situation that needs to be settled through an inquiry comprising observation, evaluation, reasoning and intervention."* (ibid., p.88) Besides the complementarity between design

193. Goldkuhl, Göran, "Design Research in Search for a Paradigm: Pragmatism is the Answer", EDSS 2011, Communications in Computer and Information Science 286, pp. 84–95, 2012.

practice and the idea of inquiry, he also relates design process output to the concept of acting for (practical) change. *"The artefact and its features are seen as means to the desired ends of a use-situation."* (Goldkuhl, 2004, p.22)[194] From this orientation, it is possible to include the additional aspect of AI/ML algorithms as an output, as well as the impact of real world scenarios on the methodological basis of pragmatism in a particular context. He suggests three different forms of pragmatism - discussed below - relevant for Design Science Research. Combined they offer the full spectrum for a methodological paradigm that suits the needs of design and the development of AI/ML systems in real world applications.

194. Goldkuhl, Göran, "Meanings of pragmatism: Ways to conduct information systems research", Proceedings of the 2nd Intl. Conf. on Action in Language, Organisations and Information Systems (ALOIS), pp.13-26, 2004.

4.3.4 Functional, referential and methodological pragmatism

Functional pragmatism (knowledge for action)

Constructive knowledge is the fundamental part of functional pragmatism. The guiding question is 'why this knowledge'? The answer is action is the purpose. In this sense functional means that knowledge should be useful and applicable in action. *"Knowledge should be useful for action and change. Functional means that knowledge should be useful and applicable in action. ... Within functional pragmatism, it is also possible to add the growing interest in design science and design theories."* (Goldkuhl, 2008, p.2)[195] It is therefore explicitly prescriptive and guiding attention towards certain phenomena. The knowledge that is constructed in this form of pragmatism can make contributions to a local practice (e.g. action research), but also be transferable to general practice contributions, such as practical theories, models, or methods. In the given set-up this means that the design inquiry serves as a basis for developing knowledge which has an impact in the area of AI/ML development in a specific use case, which can later be transferred to other use cases.

195. Goldkuhl, Göran, "What kind of Pragmatism in Information System Research?", AIS SIG Prag Inaugural meeting, pp.1-6, 2008.

Referential pragmatism (knowledge about action)

Action-conceptualized knowledge is the fundamental part of referential pragmatism. The guiding question is 'knowledge about what'? In this case action is the object. *"This kind of pragmatism is concerned with describing the world (in theories etc) in action-oriented ways."* (ibid., p.3) Referential pragmatism describes the world in action-oriented ways and makes use of action-oriented theories, such as social action theories, symbolic interactionism, activity theory, socio-instrumental pragmatism. In the given set up, this means that the knowledge and insights created draw inferences from the given set-up of designing in the area of AI/ML in the industrial domain.

Methodological pragmatism (knowledge through action)

Experiential knowledge is the fundamental part of methodological pragmatism. The guiding question is 'how to generate knowledge'? In this case action is the source and the medium. *"Methodological pragmatism goes one step beyond pure observation for capture of empirical data. Intervention in the world with the particular intent to apply and test different strategies and tactics is essential in this kind of pragmatism."* (ibid., p.4) Knowledge about the world can be created through action, or knowledge is based on actions, experiences and reflections on actions. The 'true' nature of phenomena only becomes visible or obvious after participation in change, exploration and testing the solution. In the given set-up this means, that the created knowledge and insights derive from a set-up in a use case in the industrial AI/ML domain from the design perspective and actions.

4.4 Postphenomenology[196]

In order to explore a way to complement the philosophical grounding mentioned above, to further elaborate on aspects of understanding humans, technology, and the relations that evolve between them, looking into aspects from postphenomenology presents a promising path. This contemporary strand, which is often referred to as a philosophy of technology, seems to offer a holistic view and concepts that deepen the understanding of human and the many different kinds of relations that can emerge with technology in the context of HCI. With the critical point towards a fundamental definition of truth and reality, it is also a good match for ideas and concepts from general pragmatism. Postphenomenology puts its focus on the integration of human relations with their outside world. *"It is precisely this claim to regain access to an original world that is richer in meaning than the world of science and technology, that postphenomenology refutes. ... Science and technology help to shape our relations to the world... It does not see phenomenology as a method to describe the world, but as understanding the relations between human beings and their world."* (Rosenberger/Verbeek, 2015, p.11)[197] In particular it makes a claim for humans to have relations with technology. *"An essential aspect of the post phenomenological perspective is its focus on case studies of concrete human-technology relations to technologies. This case study approach reflects postphenomenology's commitment to the 'empirical turn' and its pragmatic antifoundationalism."* (ibid., p.32)

196. Don Ihde in his book 'Experimental phenomenology: Multistabilities' (Ihde, Don, 'Experimental phenomenology: Multistabilities', Suny Press (2nd Edition), Chapter 10, pp. 115-130, 2012.) states that pragmatism and phenomenology equal postphenomenology. This is an interesting thought since at the initial stage of writing this chapter, both methodologies seemed in a way to be a good fit for the given research endeavor.

197. Rosenberger, Robert and Verbeek, Peter P., "A Field Guide to Postphenomenology", in Postphenomenological Investigations Essays on Human-Technology Relations, Lexington Books, 2015.

4.4.1 Emphasize design and AI/ML aspects

This focus on technology and with this its shift towards artifacts makes it a relevant paradigm for design in the context of AI/ML. *"Postphenomenology aims to empirically analyze how particular technologies as 'the things themselves' mediate the relation between humans and their world. This has given rise to numerous analyses and detailed descriptions of how human existence is deeply and polymorphously interwoven with artifacts."* (Zwier et al., 2016, p.314)[198] The classical phenomenology by Heidegger and Husserl viewed technology as a fixed instance, whereas postphenomenology views technology as 'multistable'. Pragmatism bridges the gap here, allowing technology being multistable and dependent on use-context. *"For postphenomenology then, anti-essentialism means that the character of technologies is pragmatically defined, which is to say that it depends on use-context. ....the character of things is not essential but is pragmatically constituted in contexts of action, practice, or use."* (ibid., 2016, p.319) Since this work is situated in a multiple case study research (concrete context) investigating the influence and implications for design in the interplay of AI/ML technology, postphenomenological aspects will be part of the research practice.

198. Zwier, Jochem, et al., "Phenomenology and the Empirical Turn: a Phenomenological Analysis of Postphenomenology", Philosophy Technology, Vol. 29, pp.313–333, 2016.

4.4.2 Technological mediation

The definition of technology in the context of postphenomenology is not deterministic, meaning that humans and their actions are controlled by technology, neither is related to a substantivist view, which sees technology as a neutral instrument and also advocates a separation between subject and object. In postphenomenology and its perception of technology as mediation, the idea is that human and technology are interwoven and should be perceived as related rather than dependent. Technology, in that case, functions as a mediator between the human and the world. None of the parts are isolated, but they act on and react to each other. As stated by Verbeek, technology is 'multistable'[199,200], which means that the human perception of technology depends on how it is interpreted while being used and this perception depends on the human that uses it. Technological mediation allows designers of technology, in this case AI/ML, to evaluate how new technologies influence the relationship between humans with their world through technology. Following this concept of technological mediation, technological artifacts (and processes) play an active mediating role in the relations between humans and their world, which will be an important aspect when thinking about the use of methods for this PhD thesis. In certain respects pragmatism also shares the objections made by other

199. Verbeek, Peter P., "Materializing Morality - Design Ethics and Technological Mediation", Science, Technology, & Human Values, Vol. 31, No. 3, pp.361-380, 2006.
200. Verbeek, Peter P., "Moralizing Technology: Understanding and Designing the Morality of Things", The University of Chicago Press, 2011.

methodological stances. They have in common an anti-positivist attitude, asking for postmodernist concepts and ideas that are critical of absolute ideas of knowledge, reality and truth (often so called the 'empirical turn'), giving and leaving room for improvement and something new to happen[201]. (Interactive) constructivism comes very close to some fundamental aspects of pragmatism. Dewey's ideas of experience, inquiry and communication are a great source of inspiration for some constructivist supporters/advocates. The idea of incorporating subjectivism and personal context of the researcher in the theoretical constructions of knowledge is a path worth taking by contemporary constructivist trends. Neubert, who wrote on the discourse from pragmatism and constructivism, makes the point that both align in the idea *"... to refer knowledge claims to the perspectives of the observers who make them."* (Neubert, 2001, p.3)[202] He further writes, *"...for Dewey it is precisely the precariousness and incompleteness of our established systems of belief and knowledge that time and again calls upon us for new experimental constructions."* (ibid., p.4) He sees a lot of consensus between the postmodern methodologies without their supporters taking notice of this. *"At the same time, it seems to be a characteristic of postmodernity that varied interpretive communities of philosophical discourse tend to co-exist while sometimes taking pretty little notice of each other. The present juxtaposition of pragmatisms, constructivisms, deconstructivisms, poststructuralisms and the likes, all operating in their respective circles, meeting at their respective conferences, and articulating themselves in their respective publishing organs, sometimes gives one a troubling feeling of closure."* (ibid., p.7) However, this alignment should only be mentioned here as a trail and that other methodologies were taken into account that made sense of the research set-up.

201. Hickman, Larry A., et al., "John Dewey Between Pragmatism and Constructivism", Fordham University Press, 2009.

202. Neubert, Stefan, "Pragmatism and Constructivism in Contemporary Philosophical Discourse", University of Cologne, pp.1-18, 2001.

Interim results

The methodological set-up for this concludes with a combination of critical and functional-referential-methodological pragmatism informed by Dewey's model of inquiry (1938) and Goldkuhl's investigations of knowledge and action (2008, 2011) supplemented with aspects of technology as a mediator, as proposed by postphenomenological approaches referred to by Verbeek (2006, 2011) and Ihde (2012). The rather isolated concepts of pragmatism and postphenomenology are combined with and incorporate critical and contemporary strands to orient and adapt to the proposed research set-up. This combination is appropriate for the given boundary objects of design in the age of AI/ML based on case studies in the industrial context. Since this is a rather new research area, a novel examination of paradigms was needed, since the requirements for the given research are not fully embraced by a separate methodological approach, especially in the mainly digital context. Equipped with this framework it is possible to decide on methods and tools that complement the research journey. Critical and functional-referential-methodological pragmatism provide the ground for a case study approach based in the industrial domain with the researcher playing an active role in the projects: postphenomenology keeps the focus on the mediation aspects of AI/ML in relation to the humans interacting with it.

4.5 Methods

4.5.1 Qualitative research

This work is overall qualitatively oriented research. It should help generate a deeper understanding of the issues that are relevant for design in the age of AI. It is located in a real industrial context and studies and observes real people in their real environment. It is therefore not a laboratory setting with fixed parameters and static input and output. It is explorative, interpretative and by its nature, iterative. New insights have an impact on the overall research progress. *"..., the researcher may need to reconsider or modify any design decision during the study in response to new developments or to changes in some other aspect of the design."* (Maxwell, 2012, p.215) It is also impossible to determine every single step of the overall research progress. The qualitative approach is meant to uncover unknown challenges and issues and therefore produces insights that haven't necessarily been thought of before, therefore it is in this method's nature to align to those newly found parameters. *"The research process for qualitative researchers is emergent. This means that the initial plan for research cannot be tightly prescribed, and some or all phases of the process may change or shift after the researcher enters the field and begins to collect data. For example, the questions may change, the forms of data collection may shift, and the individuals studied and the sites visited may be modified. The key idea behind qualitative research is to learn about the problem or issue from participants and to address the research to obtain that information."* (Cresswell, 2014, p.235)

AI and ML are typically domains of statistically based methodologies and quantitative methods. However, a lack of qualitative input is missing. This issue is argued, e.g. by Judea Pearl and Dana Mackenzie in their 'The Book of Why'[203]. *"Over and over again, in science and in business, we see situations where mere data aren't enough."* (Pearl/Mckenzie, 2018, p.6) *"I know how profoundly dumb data are about causes and effects."* (ibid., p.16) *"If I could sum up the message of this book in one pithy phrase, it would be that you are smarter than your data."* (ibid., 2018, p.21) Therefore this research wants to put emphasis on qualitative methodology. However, since it is situated in the AI and ML context, it will certainly touch on statistical and quantitative data approaches, too, which is not a negative thing. Combining both approaches adds value by adding accuracy to the findings of the qualitative part, while at the same time, adding meaning and context to the quantitative part, thereby underlining the strength of both approaches and combining them to overcome their weaknesses. But this is not the focus or the main aspect of the research design.

203. Pearl, Judea and Mckenzie, Dana, "The Book of Why - The new Science of cause and effect", Basic Books, 2018.

Qualitative research vs. accuracy and generalizability

Activities related to qualitative research comes with matters of accuracy and generalizability. The openness and flexibility of its use comes with some challenges. *"In the case of qualitative data, the explicit goal is description. The clear issue articulated in much of the literature regarding qualitative data analysis (QDA) methodology is the accuracy, truth, trustworthiness or objectivity of the data. This worrisome accuracy of the data focuses on its subjectivity, its interpretative nature, its plausibility, the data voice and its constructivism. Achieving accuracy is always worrisome with a QDA methodology."* (Glaser, 2004, p.1)[204] Those aspects call for a very transparent data collecting and analyzing process, as well as a clear strategy about which research participants to recruit and which methods to use. Also keeping in mind the size of the data sample, as Udo Kelle points out. *"Qualitative field research is in discredit, due to a very small data sample size and missing objectivity in field reports, to produce insights which misjudge the empirical phenomenon studied."* (Kelle et al., 2017, p.58)[205] A robust qualitative study is supposed to be transparent and correlate to multiple data sources.

204. Glaser, Barney, "Remodeling Grounded Theory", Forum: Qualitative Social Research, Vol. 5, No. 2, pp.1-16, 2004.

205. Kelle, Udo, et al., "Empirische Forschungsmethoden", Springer Fachmedien Wiesbaden, pp.27-63, 2017.

Another aspect is the difficulty generalizing the findings from one or a couple of qualitative field studies to a broader scope of similar spaces. Practitioners in the area of qualitative research therefore prefer to talk about transferability of their research findings. *"The generalizability of qualitative studies is usually*

206. Becker, Howard, S., "Generalizing from Case Studies". in Elliot W. Eisner & Alan Peshkin (Eds.), Qualitative inquiry in education: The continuing debate, pp. 233–242, 1991.
207. Ragin, Charles C., "The comparative method: Moving beyond qualitative and quantitative strategies", University of California Press, 1987.
208. Yin, 1994 see Yin, 2003
209. Guba, Egon, G., and Lincoln, Yvonne, S., "Fourth generation evaluation", Sage Publications, 1989.

based not on explicit sampling of some defined population to which the results can be extended, but on the development of a theory that can be extended to other cases (Becker, 1991[206]; Ragin, 1987[207]); Yin (1994)[208] refers to this as 'analytic', as opposed to statistical, generalization. For this reason, Guba and Lincoln (1989)[209] prefer to talk of 'transferability' rather than 'generalizability' in qualitative research." (Maxwell, 2012, p.246) This is a very important point that is also relevant to this work.

4.6 Multiple Case Study Research

The first sequence of this research is related to multiple case studies located at the Digital Industries division of Siemens AG, Germany. The studies derive insights and findings from the perspective of a mixed team developing AI systems in an industrial context. The researcher is an active part of one of the development teams. A specific project related to the optimization of predictive demand planning for a production site of industrial controls is chosen as the initial focus for the study. Further use cases within the given context, but in different locations, are available and accessible for study. This part is meant to support the hypothesis that a lack of Human-Centered-Design in AI development is a root cause (amongst others) of issues related to the implementation of such systems in the real world. A more detailed project description will be provided in Part IV. Problem Space, Chapter 5.

Within the given research approach an initial hypothesis was postulated, namely that the lack of Human-Centered-Design is posing challenges to the development of AI systems, as well as during their final implementation. This theoretical proposition was formed due to the involvement and the accessibility of the researcher to a development team in the industrial AI context, besides an initial literature review on topics in design and AI/ML. *"..., theory development prior to the collection of any case study data is an essential step in doing case studies."* (Yin, 2003, p.29)[210]

210. Yin, Robert K., "Case study research: design and methods", Applied social research methods series, Vol. 5, Sage Publications, 2003.

4.6.1 Selection criterion

The study was initiated to find out why and answer how to cope with the emerging challenges. *"..., case studies are the preferred strategy when 'how' or 'why' questions are being posed, ..., and when the focus is on contemporary phenomenon within some real-life context."* (ibid., p.1) Besides, the study had already discovered issues in a literature overview and the diverse opinions and perceptions of the participants in the study was additionally aimed for. Since case study research helps to *"... understand complex social phenomena."* (ibid., p.2) it became even clearer to choose this method.

What is a case study? According to Robert K. Yin the definition of a case study can be divided into 'the scope' as well as a 'technical definition'. (Yin, 2003) Both parts conclude in an operational definition of a case study. "A case study is an empirical inquiry that a) investigates a contemporary phenomenon within its real-life context, especially when b) the boundaries between phenomenon and context are not clearly evident." (ibid., p.13) The problem space of this research meets those criteria. "The case study inquiry a) copes with the technically distinctive situation in which there will be many more variables of interest than data points, and as one result b) relies on multiple sources of evidence, with data needing to converge in a triangulating fashion, and as another result c) benefits from the prior development of theoretical propositions to guide data collection and analysis." (ibid., p.13/14)

The three following aspects need to be clarified in order to make an informed decision about which research approach makes sense; "*a) the research question, b) the extent of control the researcher has over the events and c) the focus on contemporary procedures".* (ibid., p.5) If 'a' is focused on 'why' and 'how', 'b' is answered with no and 'c' is answered with yes a case study research is the right choice.

Case Study research and generalizability. As with other methods that focus on real world phenomena and contexts and are not based on a laboratory setting where the parameters can be partly influenced by the researcher and the data input includes a massive amount of predefined data points, case study researchers are confronted with the concern from scientific scholars that it is challenging to generalize from a very specific use case or even multiple use cases in an related context, towards a significance for a broader thematic area.

Furthermore the orientation towards a focus for the case study can be different in its research objectives, either explorative, descriptive or explanatory. *"There may be exploratory case studies, descriptive case studies, or explanatory case studies."* (ibid., p.3) The initial hypothesis and the related research question(s) guide the decision which approach to follow. Case study research is not fixed to one of the mentioned principles, nor is this kind of research only an initial step in a larger research endeavor which needs to be supplemented with additional paradigms from other scientific stances. It is an entire method on its own, which can be used for data collecting frameworks, as well as data analysis. Above those aspects *"..., case studies can be based on any mix of quantitative and qualitative evidence."* (ibid, p.15) Which is a good fit to the flexible and iterative approach to the pragmatic stance.

4.7 Correlation of Expert Knowledge and Design Focus

The second sequence of this research is concerned with the question of how designers can specifically influence and drive the development of AI systems, given that the hypothesis of case study research is proven. Additionally, it poses the question of what needs to be done in order to enable designers to actively take part in the development process. This research step ought to involve input from experts and a broader scope of sources, also outside the given case studies. Furthermore, it is supposed to supplement and validate the findings from the former sequence. It is therefore focused on two input sources: experts from the field of AI and Design and the experience of designers in the context of AI development found in secondary literature. A more detailed description will be provided in Part IV. Problem Space, Chapter 6.

Being not only a researcher, but also an active part of the development team of the Meta-Sample enables the researcher to add an additional expert opinion towards the topic and can therefore be used as supplementary knowledge and data input. While data collection still depends on more sources than purely on the very own experience of the researcher, in pragmatism the bias and expertise of the researcher is taken as a given and as an additional source of making sense of the gathered data. Enriched with the experience and perspective of other practitioners and researchers also involved in the field, this approach aims to generate the necessary knowledge to further support hypotheses and find initial answers on how the enablement of designers in the context of AI can be achieved.

Interim results

The methods used in this thesis, namely an overall qualitative approach represented by case study research, expert interviews and a structured literature review, related to the boundary objects of design, AI/ML and the industrial domain, are supported by the methodological framework, as stated in Chapter 4.2.1. Methodology and methods strongly depend on each other and the given set-up ensures that the criteria and requirements both sections imply are maintained. This also sets the stage for the following chapter that is concerned with the tactics and tools used to conduct the actual research.

4.8 Research Tactics and Tools

4.8.1 Data collection

As stated above the methods section is divided into two parts. It is overall qualitative, but related to case study research and expert input. Therefore the data collection is also split in a twofold way, a) a generative research approach and b) an evaluative research approach. At the same time presenting divergent and convergent activities.

The generative research approach is set out to generate meaning on a new level of knowledge about people or new ideas[211]. These kinds of research tactics are supported through exploratory research tools, such as interviews, observation and co-creation activities. The following data collection tools are planned for use for this research framework:

211. Anderson, Nikki, "Not Sure Which User Research Methodology To Use? Start Here.", 2020. Retrieved from https://dscout.com/people-nerds/how-to-choose-a-methodology. (Accessed on 2022-11-21)

1. Semistructured 1to1 Interviews with the development team, involved stakeholders and management within a multiple case study research set-up (Meta and Beta-Samples).

Based on the initial research questions and the findings from secondary research, an initial interview guide for the Meta-Sample interviews was developed. After the first round of interviews adjustment and reframing of interview questions (theoretical sampling) for Beta-Samples Karlsruhe and Berlin were conducted. This meant starting with a set of questions and interviewing participants in a very open manner. After each interview the researcher had a better understanding of the topic/issue and could focus on the emerging topics. *"Theoretical sampling is the process of data collection for generating theory whereby the analyst jointly collects, codes and analyses the data and decides what data to collect next and where to find them, in order to develop the theory as it emerges."* (Glaser, 2004, p.10)

2. Contextual inquiry, as in situ participant observations and informal conversations.

3. Active role as a team member of the Meta-Sample as a UX designer. Active part in the development of the solution. Detailed in-depth insights on the progress of the project, such as occurred problems, issues, as well as positive aspects and turns.

The evaluative research approach, is set out to evaluate the meaning of something that exists and how usable that thing is. These kinds of research tactics are supported through research tools that focus on certain aspects and narrow down the scope, such as surveys, usability tests and benchmarking activities. The following data collection tools are planned for use in this research framework to bring in focus on design relevant themes:

1. Focused and structured 1to1 expert interviews with Siemens AG internal AI/ML experts, as well as with external consultants and experts in the area of design and AI.

2. A systematic literature review from secondary research conducted by other researchers in the area of UX and AI (paper publications).

4.8.2 Data analysis

1. Immersion in the data. Going through interview transcripts and quotes from papers to gain knowledge and a general overview of the data and the richness of information.

2. Based on interview transcripts tagging[212]/(open) coding (descriptive and thematic) of the themes with regard to challenges during the process (design specific, use case specific, overall relevance) were conducted.

212. Eisenhauer, Karen, "Three Approaches to Tagging that Bring Clarity to Qual Data", 2021. Retrieved from https://dscout.com/people-nerds/three-tagging-approaches. (Accessed on 2022-11-21)

4.8.3 Data synthesis

1. Theme/framework development, here it essentially means taking a bundle of tags or codes and making a meaningful narrative or story out of a set of insights. This stage of the process is usually described as 'synthesis'. Compared to analysis, it's the creation and application of tags or codes (as well as notes).

"..., there is plenty of room for bias in any attempt to explain what you see. We humans like to believe the world is a systematic, rational place, so we tend to fill in gaps with assumptions and causal structures that may or may not be accurate." (Goodwin, 2009, p.222)

2. Evaluate the findings and insights, such as how many participants mentioned the codes (e.g. using cross-tab checks[213]).

213. Eisenhauer, Karen, "Slice and Dice Your Data: Crosstabs 101", 2021. Retrieved from https://dscout.com/people-nerds/crosstabs-101. (Accessed on 2022-11-21)

3. Narrative for the output and how to communicate and deliver the findings (e.g. storytelling[214]).

214. Herzberg, Kyle, et al., "Foolproof Qualitative Analysis Tactics", 2019. Retrieved from https://dscout.com/people-nerds/qualitative-analysis-any-timeline. (Accessed on 2022-11-21)

4.9 Conclusion

This PhD is partly theoretical, as well as practical, hence a kind of 'mixed' approaches are being used (see Fig. 4.2, p.46). Choosing a research set up which reflects this fact is therefore pivotal. Furthermore, as discussed in Chapter 1.3.2, it is necessary for designers to find their own way and means of doing research and representing a voice in the science driven community, which means borrowing procedures and operations from the strong heritage of those scientific resources, but adding their very own flavor to them.

"..., for it begins with the understanding that no single research methodology could possibly account for the diversity of inputs and outputs to contemporary design practice and process." (Lunenfeld, 2003, p.10)

Critical and functional-referential-methodological pragmatism informed by Dewey's model of inquiry (1938) and Goldkuhl's investigations into knowledge and action (2008, 2011) supplemented by aspects of technology mediation in postphenomenology, as provided by Verbeek (2006, 2011) and Ihde (2012), is the methodological set-up of this research. This approach embraces requirements from design and technology (AI/ML) stances, while providing the ground for qualitative research inquiry through multiple case study research as defined by Yin (2003) and the reflective practice of the researcher herself supporting an outcome that can be defined as an artifact and is suited for a practice based approach.

The research paradigm and the research purpose need to be aligned. This work therefore follows an overall empirical approach, mixed with bits and pieces of imagination. Pragmatism, with a focus on critical and design specific pragmatic influences (functional, referential and methodological) being the best fit to align with an advanced practice which deploys research methods appropriately, but flexibly. It embraces overall qualitative methods that provide a deep understanding of the related issues and their causal relations, but additionally presents a mixed methods approach to incorporate quantitative insights[215] from the AI/ML domain as well. To closer link the research approach to the effects of technology and its mediation abilities postphenomenology is added to the overall set-up. This presents a novel methodological approach for this rather new research area.

215. Purpura, Stacey, "Overview of Quantitative Methods in Design Research", in Design Research: Methods and Perspectives / [edited by] Brenda Laurel, The MIT Press Cambridge, pp.63-69, 2003.

The first sequence of the actual research execution is presented by a (multiple) case study research approach. While being based on concrete hypotheses and to use best practice to gather data and validate those hypotheses is the main reason why this method was chosen. It is appropriate for the given conditions of the goal and set up of this research. It is focused around the research question that a lack of Human-Centered-Design is a root cause for pitfalls and challenges when developing AI/ML solutions.

The second sequence adds expert concepts and perspectives. It combines secondary research about the experience of practitioners in the field of AI and design and personal experience from the researcher to bridge the gap to the Solution Space. It is framed by the question of what needs to be done in order to enable designers to strive and have an impact on the development of AI and ML systems, more specifically, what are the design specific issues, what are the key criteria and drivers, and, ultimately, what are the main potentials?

Research Philosophy	Research Strategy	Research Methodology	Data collection, synthesis & analysis methods
Functional, referential and methodological **Pragmatism** + **Postphenomenology** (Technology as mediator)	Design Research + Practice-based research + knowledge-producing & knowledge-using activities	**Qualitative** Research + **Case Study** Research + Expert Interviews, Structured Literature Review	Interviews transcripts Contextual inquiry Project material + Coding (descriptive & thematic) Content analysis Cross-tab analysis

Figure 4.2: Overview and summary of the chosen research approach

Part III. Problem Space

Chapter 5. Case Study Research

as proposed by Yin (2003)

5.1 Introduction

This chapter presents the research from multiple case studies and expert and external input. The relevant research tactics and tools have been derived from the methodological set-up defined in Chapter 4. As such, the first sequence represents a convergent approach exploring a variety of pitfalls and challenges for the development of AI agents in the industrial domain, whereas the second sequence takes a divergent approach while focusing on the design relevant concepts for the development of AI based agents, outside the industrial AI area as well.

Explore the Problem Space: Overall Pitfalls and Challenges

5.2 Case Study 01 - Meta-Sample

This study addresses the hypothesis that current AI development is missing the Human-Centered-Design perspective, such as lack of a) system controllability, b) conformity with user expectations, c) self-descriptiveness and d) error robustness, with the challenges that occur as a consequence. The purpose of this exploratory sequential design is first to qualitatively explore with a small sample and then determine if the qualitative findings are generalizable to a larger sample. The first phase is a qualitative case study related to the development of an ML solution in an industrial setting in which semistructured 1to1 interviews are conducted with the development team and involved stakeholders at Siemens AG DI (Digital Industries) Data Lab in Munich, Germany and its internal customer from a Siemens AG factory which produces hardware components for the factory automation market in Erlangen, Germany. From this initial exploration, the qualitative findings will be used to develop assessment measures that can be administered to a large sample. In the planned cross case validation phase, additional data from two other case studies will be collected from the relevant development team members, one similar Siemens AG factory site which produces another hardware component for the factory automation market in Karlsruhe, Germany and a second one from another Siemens AG business, namely SI (Smart Infrastructure) units hardware production site in Berlin. All three cases use the same ML technology for their factory planning process, namely time series forecasting, which makes them comparable.

Figure 5.1: Map of Germany with locations from case study research

Time series forecasting is based on historic data points for making predictions about the future development of the given data set. Algorithms that are related to this kind of problem-solving use observations from the past as a basis for making a prognosis in the future to drive decision-making.

The purpose of this first study is to explore how the development of AI systems is perceived by the team members and stakeholders of a case study in the domain of industrial AI at Siemens. The initial qualitative semistructured 1to1 interviews with the eight team members' goal was to get an in-depth understanding of what specific issues emerged from their point of view, including key aspects from a design, data (science) and business perspective. The cross case approach aims to further validate the initial findings and explore any additional issues that emerge.

5.2.1 Research design factory Erlangen

Over the course of the following paragraphs 'Meta-Sample' will refer to the initial case study from the factory use case in Erlangen, Germany, which was used to identify the first relevant themes that occurred during the development process, in trying to prove whether the hypothesis of the missing Human-Centered-Design focus was the reason for pitfalls and challenges amongst other concerns. However, 'Beta-Sample(s)' will refer to the cross case validation case studies from similar projects in factory sites in Karlsruhe and Berlin, making sure that the initial findings are transferable to other similar case studies as well as making sure not to miss out on any additional emerging themes.

I. Research questions

What does the development process of industrial AI/ML solutions look like?

» Why do problems occur during the development?
» Why do a lot of AI solutions fail in the implementation phase? What are the pitfalls and challenges?
» How does the industrial context influence the overall set up? Why is this approach different?
» How can HCD and UX influence the development process of AI-infused systems?
» How is the process different to current software/digital transformation projects?

II. Initial propositions

Currently the focus of AI/ML development projects is on technological feasibility. Design, data science and business domain knowledge are not aligned. Design in the development of AI agents is not perceived as a crucial expertise to be included right from the beginning of those projects.

III. Unit of analysis

Technology Assessment describes a process that aims to identify and measure the eventual impacts of aspects of technology early on in its development cycle. It is intended to inform public, political and general decision-making. It examines the short and long term consequences of the application of technology. The assessment is related to societal, economic, ethical and legal issues.

This inquiry is overarching about technology and its impact and relation towards and with humans (philosophy of technology as mediation as proposed by postphenomenology). Concepts and implications such as Technology Assessment (TA), Human-Computer-Interaction (HCI), Human-Centered AI (HCAI), play a central role. It is also about the dynamics and working mode of the development team, as well as their development process.

» Time Horizon: Project start April 2018 (PoC was created at the end of 2017) project end January 2020

The interviews with the eight team members were conducted in August and September 2019. The predictive demand planning system was successfully installed at the factory in Erlangen, final adjustments and a testing phase were the next steps.

» How does the literature review contribute to the selection of the case study?

The field benefits from insights into real life use cases as examined in the relevant literature (see Chapter 3.6). This work wants to be relevant to science and research, as well as practice and industry, therefore the initial step of this work analyzed a use case within Siemens AG Digital Industries factory automation unit, a real world scenario as a basis for scientific analysis. A lack of human input is perceived as a problem for AI systems development. This is the initial hypothesis which should be validated with the Meta-Sample and its cross case validation samples.

IV. Project description

Predictive Demand Planning (Erlangen, Germany) Industrial AI

A use case from Siemens AG, business division Digital Industries, was the initial Meta-Sample for this research. AI is used to predict how many pieces need to be produced for a factory in Erlangen, Germany. ML algorithms predict future demand of their products, so-called predictive demand planning (PDP) with time series forecasting using convolutional neural networks (CNNs are a method from Deep Learning). The business division Digital Industries offers hardware components as well as software to automate production sites. The portfolio represents solutions for Industry 4.0. The factory in this use case is 'Gerätewerk Erlangen'. Hardware components from the model range SIRIUS[216] are produced in this related factory. The production itself is mainly automated. With the hardware components of the SIRIUS range (see Fig. 5.2), Siemens offers a comprehensive portfolio around industrial automation technology. These products can be combined in a variety of possible solutions and installed easily due to their modular components and design. The components are easily integrated into decentralized systems and units which are optimally matched to each other. The downside of this flexible and modular offering to Siemens's customers is the variety of products that can be ordered and purchased, making the planning process an important aspect for the overall success of the production site.

216. Siemens AG: Industrial Controls - SIRIUS. Retrieved from https://new.siemens.com/global/en/products/automation/industrial-controls/sirius.html. (Accessed on 2022-11-21)

Figure 5.2: A selection of the SIRIUS modular system hardware products range

Main circuits
a) Contactor S12 for switching
b) Soft starter S0 for starting
c) Circuit breaker S6 for protecting
d) Overload relay (thermal) S0 for protecting
e) Overload relay (electric) S10 for protecting
Control circuits
f) Function and communication module

The goal of the project is to improve and optimize the factory demand planning process, which is becoming better at estimating the required output of the factory - the quantity of hardware components which need to be produced in order to keep to the date of delivery requested by the customer. In the last two years prior to the setting up of this project, actual demand for ordered pieces exceeded the factory demand plan (see Fig. 5.3) multiple times over, outperforming the capacity of the production sites. The result was a supply chain shortage and the inability to deliver to customers. Besides market behavior and other macro and micro economic factors, the quality of the factory demand plan was perceived as a potential root cause for this mis-planning.

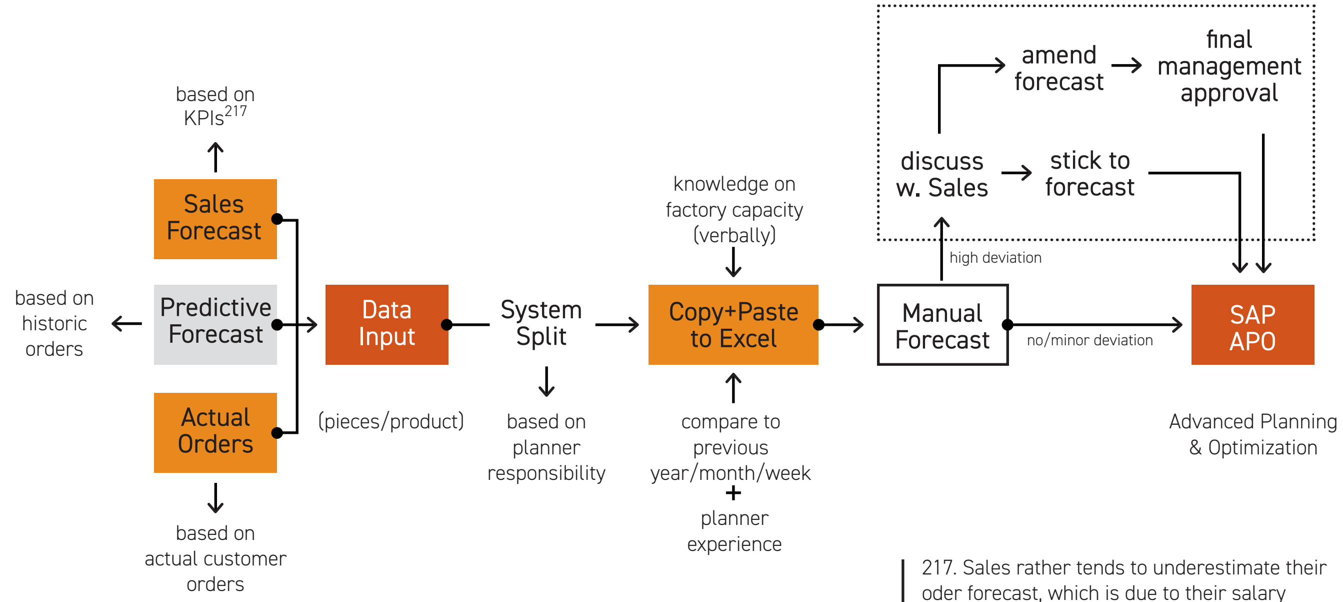


Figure 5.3: Visualization of current factory planning process/workflow, with integrated ML solution

217. Sales rather tends to underestimate their oder forecast, which is due to their salary system based on bonus. They get target KPI's based on their forecast, if they reach or overreach that goal, they get a bonus, if they don't reach it they don't get a bonus. On the other hand, the shop floor and the material procurement rather like to overestimate the order intake. For them it is easier to handle a lower number in actual orders than a higher number of products they need to produce. This is a conflict of interests that is based on different human goals which is a root cause for difficulties in the manual factory plan. None of the mentioned approaches is based on actual customer orders.

That was the starting point for the setting-up of the predictive demand planning project using so-called time series forecasting. An initial Proof of Concept (PoC) with a small data sample was supposed to prove whether or not an ML solution using convolutional neural nets would be a possible improvement to the factory demand planning process. The PoC using ML predictions to support and optimize the quality of the factory demand plan was producing very accurate figures. This proved to be a very promising direction to develop the idea to use ML even further and scale it towards a greater number of products. Digital Industries' own data lab was delegated to develop the solution. The team's task was to further develop the PoC into a productive system which could be implemented and used on a weekly basis.[218]

The Meta-Sample is the starting point for all further investigations and served as an initial source of inspiration and information. The acquired knowledge was then validated and compared to two additional case studies within Siemens AG dealing with the same problem and using a similar technology as a solution, namely a factory in Karlsruhe, producing another range of Digital Industries

218. When the interviews were conducted in 2019 the project was being implemented for the customer in the factory site in Erlangen. This project had a very high priority since the problem exists in many other production sites as well and the need for such a demand planning support was huge and the need to scale such a solution was immense, and had the potential to provide a positive impact for Siemens overall.

factory automation hardware components and a factory in Berlin producing hardware components from the Smart Infrastructure hardware range

Theoretical proposition(s): The case study should show that in current AI development projects, the Human-Centered-Design approach is missing, causing pitfalls and challenges.

Rival theory: The case study should show that no pitfalls and challenges occurred during the development and therefore no changes to the process were needed.

Without the focus on Human-Centered-Design aspects, the full potential of AI systems is ignored. The negative aspects of the technology could be more evident to humans than the possible advantages. Malfunctions and bad user experiences could become more frequent and erode trust in those systems. A fruitful collaboration between human and machine is in peril. In particular, the industrial AI context is potentially at risk, since most of the time, the end users cannot decide which solution is implemented and they are not involved in the development process. Missing out this factor might just be spotted when the goods have already been delivered to the customer. Additionally, the focus of industrial AI/ML use cases is on optimization, which oftentimes is a discouraging measure for human involvement.

If the hypothesis is supported, the research questions regarding the enablement of the designers need to be taken into account as a next step. If designerly ways of working can have a very positive influence on AI development, how can this be done and ensured? This needs to be defined, established and implemented. The necessary methods, tools, processes to reach this goal still need to be analyzed and designed. A mix of theoretical groundwork and real world use cases is needed to reveal the current state of affairs and define what skills and tools are necessary for designers to contribute to the development of AI systems.

V. Data collection

This case study research used various principles of data collection:

1. It used multiple sources of information, such as interviews, observations, project results (presentations, dashboards, software), literature
2. The information was stored in a case study database with anonymous data, transcripts, interview guides and reports
3. With this it has been possible to maintain an audit trail

Data collection for the Meta-Sample was done by direct participation and observation, from the early stages in the development process. Qualitative semistructured 1to1 interviews with all team members, involved stakeholders and management were conducted during the final implementation of the product. In addition, direct observation of and with the factory planners before the implementation and afterwards were conducted.

The upfront interview guide was organized in three different sections, namely a) overall project set up related questions, b) process related questions, and c) HCD/UX related questions. In total eight 1to1 interviews with the team members and relevant stakeholders were conducted (P1 - P8). The chosen sample size represented a variety of opinions and qualitative input, however, it was also shown to be the right amount of input to sustain repetitive information among all participants. It therefore proved the validity and reliability of the initial part of the case study research to establish an informed and data driven decision for the next steps[219], ensuring the quantitative concept of sample size was present, even for qualitative research activities.

All interviews were transcribed[220]. Impressions from contextual inquiry/participant observations supported the process of sense-making and data interpretation - as well as the available project results which were accessible to the researcher.

219. Anderson, Nikki, "Spooky Sample Sizes: Choosing 'The Right' Number of Research Participants", 2021. Retrieved from https://dscout.com/people-nerds/sample-size. (Accessed on 2022-11-21)

220. The first attempt to transcribe the interviews was done using AI. This was in 2019 (otter.ai and trint.com) The results have been very bad, especially on German interviews. Later on in 2021 the language models performance improved seriously and those ML based tools became a helpful support of this data analysis (for more information see Appendix III. page 175).

VI. Data Analysis & Synthesis

This case study research used various principles of data analysis:
1. Immersion in the data
2. Inductive and deductive data analysis tagging/(open) coding (descriptive and thematic)[221]
3. Theme/framework development
4. Evaluation of the findings
5. Narrative and storyline

221. Braun, Virginia, and Clarke, Victoria, "Using thematic analysis in psychology", Qualitative Research in Psychology, Vol.3, No. 2, pp. 77-101, 2006.

The first part of the data analysis followed an inductive approach, it was strongly linked to the gathered qualitative data from the interviews and not to any theoretical framework (Braun/Clarke, 2006). First, the transcribed interviews were read to find meaningful sections. Second, the sections were analyzed looking for patterns and codes, in particular, challenges and barriers which occurred during the development of the AI system were examined, this having organized the data into more abstract pieces of information and the codes attached (see Fig. 5.4). Third, these codes were systematically grouped into categories dealing with similar issues, while the same code could be linked to more than one category. This was an iterative process, going back and forth through the data, refining and renaming the codes and patterns and identifying how they were related to each other, while the next step, grouping the categories again, established a comprehensive set of themes. Data analysis resulted in 59 codes, 4 groups and 15 themes. Fourth, trying to evaluate whether or not the data gathered contained enough evidence to support each of the themes. Making clusters of a) codes that were expected, b) codes that were surprising, and c) codes that are unusual, comparing this to other, overall AI challenges from other domains and external sources. This represents the deductive approach of the research. Fifth and finally, naming the themes with the requirement to find a short phrase that represents the essence of each theme. Also adding a short description to make the concept of each theme obvious, clear and reflect the meaning of the data collected.

Data extract	With code applied
"We really had a hard time evaluating and justifying what a good prediction is." (P1) *"People don't want to hear, or do not understand that maybe I have a couple of products that are simply not predictable."* (P3) *"We were able to prove that our forecast was better than the planning data."* (P6)	‚Good' predictions
"We should have put more emphasis on the definition of done. When is good, good enough." (P2)	Definition of Done
"One key insight from this project is that there is not this one KPI or error metric. We can provide suggestions, but it is worth looking into different numbers and metrics, in order to derive a decision." (P5)	KPI Definition
"What was really convincing about the algorithmic forecast was that we were able to reduce the planning errors." (P7)	Impact of Results

Table 5.4: Sample of interview data extract with code applied

5.2.2 Research execution Erlangen

Interviewed team members and their roles:

Scrum is a framework that supports a specific type of project management. It is characterized by lean processes, step-by-step development - so called sprints - and regular feedback loops. It was originally used in software development, but is now used in many other domains and industries where an iterative approach is valuable.

P1 - Scrum Master (German)
P2 - ML Engineer (German)
P3 - Project Manager / Stakeholder / Supervisor (German)
P4 - Data Scientist (English)
P5 - Sr. Data Scientist (German)
P6 - Data Analyst (German)
P7 - Product Owner (German)
P8 - Planner (German)

The overall project team also included a UX Designer (the researcher of this thesis), as well as other stakeholders involved, such as the upper management, additional planners, and the factory manager.

Meta-Sample
Erlangen

Figure 5.5: Map of Erlangen

Project goal

P3: *"The goal of the project is how can we use Machine Learning to automate a process for demand planning - on a product level - that is running manually today and, based on data, obtain a proposal for a prediction for the next twelve months that is not biased by humans and thus improves not only performance but also process efficiency. To, in the end, optimize material planning."*

5.2.3 Detailed participant input (P1-P8)

P1 - Scrum Master

The first interview was with the SCRUM master of the project. This person has a background in IT and strong expertise in software development projects (not necessarily Machine Learning) following the SCRUM methodology. The person joined the team right from the beginning (April 2018) after the decision was made to set-up a team and a project from the initial PoC. The interviewee was overall very positive about the project, its development and outcome so far. She spoke in high terms about the team dynamics and spirit. However, she was very aware of the problems and unforeseen issues the team was facing during the development. In her opinion a lack of knowledge and wrong expectations on the management and business domain side were the root cause for most of the issues. On the other hand, the iterative working mode helped a lot to offset the problems and support the teams' flexibility to respond to those issues.

Detailed input: AI in general

The interview participant had the impression that a lot of Siemens management, as well as employees, realized that AI and ML are hyped at the moment and therefore perceived it as a solution to every problem without really having any notion about the technologies capabilities and boundary conditions. P1: *"... the management... who sometimes get the KPI to use trendy technologies just for the sake of it."* She also mentioned that she is not an AI/ML expert, but that she has the basic expertise needed to successfully embrace the potential and advantages of the technology.

Detailed input: Project & process related

One of the interview participants main pain points was the ability and agreement from the business domain to judge a 'good' prediction'. P1: *"What was really difficult, is to judge whether or not it is a good prediction."* She said that they had a lot of discussions and disagreements about that topic. In her view the final decision is still to be made at the point of the interview. One reason is the lack of knowledge about AI/ML accuracy measures on the business domain side, as well as the lack of trust in the algorithms output on the planners' side. She perceived the iterative working mode and the sprint logic as a main factor for success.

P1: *"We had a couple of test phases with productive data, two, the one in August was very helpful, because we figured out that we need post-processing steps. We couldn't use the pure algorithmic output."* Collecting feedback in her view was a way to better understand the business domain and build trust in the forecasting output.

Detailed input: HCD/UX related

She perceived design as a way to make something look nice. P1: *"Before I got to know you, design to me was purely a styling issue."* But she mentioned that working with an UX design expert had changed her perception. She now understood HCD and UX more as a way to focus on requirements from users and different stakeholders, shifting the pure focus from technological feasibility. In her view, HCD and UX are highly valuable for focusing and prioritizing the most important project requirements, also meaning that HCD and UX do not only provide new requirements and features, but also eliminate those which are not necessary or useful.

P2 - ML Engineer

The second interview was with the ML Engineer. This person has a background in IT with a strong focus on ML development projects. The person joined the team right from the beginning (April 2018) after the decision was made to set-up a team and a project from the initial PoC. The interviewee was overall not very positive about the project, its development and outcome so far. He was very concerned about the issue of forecasting per se. In his view, making predictions about the future from historic data is more a good guess, rather than a clear statement. He was very aware about the problems and unforeseen issues the team faced during the development. In his opinion, a lot of aspects played a role in the issues that emerged.

Detailed input: AI in general

One point he made were the high expectations of the management and business domain side. P2: *"... I had the impression that the expectations at the GWE were too high, ..."* The initial PoC proved to be very accurate for a very minimal amount of products, but set the stage for the rest of the project. P2: *"The problem is, so to speak, if the results of the prototype are too good.... at the beginning we showed results, with a certain technology and an approach that we could not really operationalize in that way."* By adding more and more products to the data set, it became clear that the initial performance from the algorithmic forecast could not be kept. Instead of looking into the quality and amount of data, the discussion was more around the performance and improvement of the model instead. The involved parties were also not aware of the uncertain and open character of ML development projects, which caused a lack of understanding of certain process steps and loops. P2: *"In ML projects there is the point where everything is open. Everything is new and you can not tell where this will end."* The interview participant also suggested an iterative approach as the only working mode for this kind of project.

Detailed input: Project & process related

Another aspect he mentioned was not having enough resources to properly work on all the issues and requirements for the size of the project, therefore also not being properly able to fully understand the manual planning process. P2: *"I personally think that we do not really grasp and understand the current manual planning process to be able to understand all the questions that are raised by the planners"* this meant not being able to address all the necessary features and steps to produce a solution which was valuable for the planners and therefore the likelihood of their acceptance was very low. He also saw a huge gap between the technology used for the PoC and the possibilities for the implementation of the final solution regarding the software architecture and infrastructure in such a regulated domain. The initial set up was impossible to scale to all the products the factory was producing. A lot of time and effort was put into the search and set up for the final productive environment. P2: *"You sort of had a prototype that you couldn't use productively that way."* He also saw a huge problem in the agreement for the 'definition of done'. P3: *"We should have put more emphasis on the definition of done. When is good, good enough."* The interviewee also mentioned that he felt they were only presenting the results from very accurate and high performing products to keep the management and business domain people with a positive attitude towards the project, but also knowing that this would be a biased representation putting even higher expectations on the final solution. P2: *"We tend to present our forecasts too positively."*

Detailed input: HCD/UX related

He perceived the input from the HCD/UX expertise more comparable to change management. To figure out how the current manual planning process could be changed in order to potentially convince planners to use the numbers produced by the algorithmic forecast, P2: *"We thought the acceptance and trust of the planners in the forecasts improved and they used it and then we got to know it's not."*

P3 - Project Manager/Stakeholder/Supervisor

The third interview was with the initial project manager, later throughout the project this person became more a supervisor and was not actively involved in every process activity anymore. This person has a background in finance and a strong expertise in the business domain of the project. The person joined the team right from the initial PoC phase (end 2017). The interviewee was overall very positive about the project, its development and outcome so far. She was very aware of the problems and unforeseen issues the team was facing during the development. In her opinion the technology and data driven focus of the project were the root cause of most of the issues. For her, any of that kind of digitized project needs to be additionally supported by a change in management activities.

Detailed input: AI in general

The interview participant mentioned that the initial data sample for the PoC was a bit random. Most of the products were so called 'high runners', meaning that the amount of orders was very high and therefore the amount of historic data points was huge, resulting in the good performance of the algorithmic forecast. In the next phase, when the project and team were set-up in April 2018, the product owner and the data scientist put more effort into defining the data sample set. Also, products with a smaller amount of historic data points were used for the algorithmic prediction, resulting in a drop in performance and accuracy. This was a surprise for the management and the business domain experts and a big lesson learned for the development team. The importance of carefully defining the initial data sample set for the first PoC needs to represent a variety of possible data points in order to fully validate a potential model performance.

Detailed input: Project & process related

The technical development team tried to understand the manual factory planning process, but in hindsight, failed to fully grasp it. In her view, this was partly due to the lack of involvement of the planners, as well as the awareness of how important this factor would be. Any technological solution, whatever the accuracy and value might be, equals a change and therefore needs to incorporate change management and building trust. P3: *"This is nothing that you develop from scratch, it is sitting on top of something that is already there and therefore it is a lot about change. And especially with AI it is a lot about trust."* As with the other two interviewees she agreed that the definition of a 'good' prediction was an issue, as well as the lack of AI expertise which led to wrong and too high expectations.

Detailed input: HCD/UX related

She was convinced that HCD/UX expertise was a highly crucial factor for the success of the project. However, she also declared that sometimes, the technological focus was the primary driver. P3: *"We had this a couple of times, that we totally focused on the technological aspects and the model generation and performance. We completely forgot about the users."* She said that the project increased her awareness of the HCD/UX topics and value. AI/ML projects especially, need the perspective of human focus, because just developing a new tool, will not solve all the problems. Technology is too often perceived as the solution. She also mentioned that she thinks that the definition of HCD/UX for a lot of people equals the look and feel of a product. P3: *"I think a lot of people associate it with making applications look nice."* But for her it is a lot about the influence of the development process in order to reach the goal of a human-centered application.

P4 - Data Scientist

The fourth interview was with one of the Data Scientists. This person has a background in data science with a strong focus on ML development projects. The person joined the team right from the beginning (April 2018) after the decision was made to set-up a team and a project from the initial PoC. The interviewee was overall not very positive about the project, its development and outcome so far. She was very aware of the problems and unforeseen issues the team faced during the development. In her opinion, the missing focus and collaboration with the factory planners were the root causes of most of the issues. For her also, the lack of AI/ML expertise on the business domain side was a source of problems, such as unrealistic expectations and the inability to agree on a measure to judge the performance of the algorithmic predictions.

Detailed input: AI in general

Although her own AI/ML expertise is quite high she rated and compared herself to other experts in the field and therefore scored herself lower. She perceived knowledge of AI/ML to be a crucial factor for the overall project, in this case creating challenges. She was able to compare this issue to other projects she worked on where the client also had AI/ML expertise and the flow of the project was therefore a bit more fluent. P4: *"I noticed that was like really, really surprising. They knew their data very well, they could generate it on the fly like, so. Having the customers be technical, like made it really easy for them to try to use AI."*

Detailed input: Project & process related

Similar to P3 she also mentioned how important the choice of the initial data sample set was, setting the stage for the rest of the project. In this case, when the initial PoC was turned into a project set-up, it was her first task to make sure that the data sample represented a large variety of products from that factory. It was her intent right from the start to assist the factory planners and not replace them. She tried to make clear that AI/ML does not equal automation. She was very aware of the potential impact of her work and was hoping that over time, the factory planners would gain trust in the algorithmic forecast, after showing them over and over again how reliable the output was. Another pitfall she mentioned was that the whole project had an issue with translating the business needs into data needs. P4: *"So some sort of like translator, but not like, literally in language per se. Well, maybe it is natural language to mathematical language."* She perceived a gap there, which was partly due to the lack of AI expertise in the business domain. She also mentioned the lack of focus on the users. P4: *"I think it would have been good if the factory planner somehow was also in…"* This was a huge issue for her, because she felt kind of guilty that she did not manage to build a rapport with them. For her this was partly also due to a language issue, not being a native German speaker. The pitfalls and challenges along the way oftentimes caused a shift in requirements and resulted in a lot of discussions and losing focus, another issue she mentioned. This also led to a communication bias where the development team preferred to present the accurate figures rather than the low scoring ones. P4: *"I think maybe we could have been more sympathetic, knowing that perhaps this could be a touchy subject for them that like: Oh, look how well the machine learning algorithm performs, right?"* She also mentioned the issue of agreeing on 'good' predictions.

Detailed input: HCD/UX related

She perceived HCD/UX activities as important, especially in the situation of potential job losses for the factory planners. P4: *"I think if the factory planners didn't have maybe a feeling of insecure, job insecurity, they would have been more cooperative."* However, she also mentioned that the timing for the HCD/UX activities was bad. P4: *"I think the shitty thing was we got the interview done after we had set some requirements,"* which was only after requirements and features had already been defined and the first feedback from the users was not as good as initially wished for when interviews with the factory planners were conducted. It was hard for the development team to incorporate all the feedback, because a lot of work streams were already defined and running. She also questioned her own behavior and attitude towards the factory planners. Primarily the way they communicated the performance of the algorithmic outcome in front of them was often perceived as an offense. Overall she is aware of a missing human focus in AI/ML development. P4: *"I think it's just because AI could seem so cold. Like as the Data Scientist who somewhat delivers the AI we need to kind of show there's a human aspect to it,..."*

P5 - Sr. Data Scientist

The fifth interview was with the second Data Scientist. This person has a background in data science with a strong and senior focus on ML development projects in the forecasting domain. The person joined the team right from the initial PoC phase (end 2017). The interviewee was overall very positive about the project, its development and outcome so far. He seemed to be not very aware about the problems and the unforeseen issues the team faced during the development. In his view, most of the activities went well, as with other kinds of projects he had worked on so far. However, he also mentioned problems and issues which were encountered during the project, which were related to wrong expectations and a lack of the factory planner involvement, but somehow he was more focused on the good performance of the algorithms.

Detailed input: AI in general

The interview participant mentioned that with the roles and skills of the given team it was possible to offer an end to end service, meaning from an initial PoC phase, to the transfer towards production and the ability to scale towards other business units. He said that this is not a given and very often a white spot in the current AI/ML development. He perceived this a unique value proposition by the team.

Detailed input: Project & process related

The interviewee was aware of the fact that the whole project lacked proper user involvement, which was partly due to the factory planners availability. The iterative working mode and the sprint logic was new to him and he appreciated this way of operating. P5: *"To keep the sprints and present results on a regular basis was key for the success of this project."* He also made the point that he was facing a lot of wrong and high expectations by the business domain people. P5: *"... it is necessary to communicate that the part of data preparation and consolidation takes a lot of time and effort, ..."* He saw the lack of AI expertise as one of the reasons for this. He said that he tried to give a lot of input regarding these issues during the team meetings and other conversations. P5: *"... they somehow have a very clear idea of what the problem is, but the translation into a data analytics solution or decision support is definitely a mismatch."* A key learning for him was the fact that defining KPIs and agreeing on an error metric was such a painful process. In the end everybody realized that there is no single answer to this issue. P5: *"One key insight from this project is that there is not this one KPI or error metric. We can provide suggestions, but it is worth looking into different numbers and metrics, in order to derive a decision."*

Detailed input: HCD/UX related

To him HCD/UX activities are very crucial in this kind of project. He sees the practitioner's role as being a facilitator, to figure out what each other's domain is talking about and trying to bridge the given gaps, so translating data inputs and business needs. P5: *"...they somehow have a very clear idea of what the problem is, but the translation then into a data analytics solution or decision support, there is definitely a mismatch there."* For him data, business processes and user requirements need to be aligned in order to unlock the full potential of data science.

P6 - Data Analyst

The sixth interview was with the Data Analyst. This person has a background in data analysis and reporting with a strong focus in data visualization. The person joined the team right from the beginning (April 2018) after the decision was made to set-up a team and a project from the initial PoC. The interviewee was overall not very positive about the project, its development and outcome so far. She was very aware about the problems and unforeseen issues the team was facing during the development. In her opinion the wrong expectations by the business domain and management side, as well as a lack of activities related to data preparation and data quality, together with the challenge to work properly with the factory planners, were the root cause for most of the issues.

Detailed input: AI in general

The interview participant rated her AI expertise below average (4 out of 10). However she said that her expertise was enough to add value to the project. She perceived her role as being a facilitator to bridge the gap between tech and business and named it as an advantage that she was not too technical, as she was also able to understand the business domain needs and negotiate between both sides.

Detailed input: Project & process related

In her view the development team did a lot to communicate the positive performance of the algorithmic forecast to the factory planners. She couldn't understand why they still did not trust in the system's output. P6: *"We were able to prove that our forecast was better than the planning data. Nevertheless, the planners did not trust the AI forecast, only because the line charts looked different from what they expected."* She also mentioned the issue of wrong expectations. In her view the team tried too hard to please the management and business domain side instead of showing them that AI/ML do not always perform better than the human planners. She was overly concerned that the team did not spend enough time looking into the data and doing proper data preparation. P6: *"We did not spend enough time and effort on the data analysis, to evaluate the input data a bit deeper."* She used visualization tools to communicate her findings regarding the trouble with the data input, but also as a way of presenting the algorithmic output. P6: *"..., I often notice that something is wrong. The input data did not remain stable, so to speak, but always deviated."* In her view visualization is an important vehicle to communicate in a way that is accessible to different professions. She was also aware of the fact that the development team did not fully understand the manual planning process, which was partly due to the lack of planner involvement. P6: *"The attitude of the planners was an important factor. They haven't been part of the team from the beginning and had to work with a solution they did not ask for. That was difficult."* She understood their resistance to accepting the algorithmic solution due to the initial project goal to replace the planners and their manual planning process. She liked the sprint logic. The impression that she was not very happy with the project originated from her statement that she thought it is also the duty of the data lab to do some coaching in the direction of not using AI/ML and refusing similar projects in the future.

Detailed input: HCD/UX related

In her opinion HDC/UX activities are not important in every process step, e.g. at the beginning when requirements are gathered, but not during the model's development.

P7 - Product Owner

The seventh interview was with the Product Owner of the project. This person has a background in economics and strong expertise in traditional project management. The person joined the team right from the initial PoC phase (end 2017). The interviewee was overall very positive about the project, its development and outcome so far. She spoke in high terms about the team's dynamism, motivation and willingness to provide the business domain with a successful solution. However, she was very aware of the problems and unforeseen issues the team was facing during the development. In her opinion a lack of knowledge, regarding AI capabilities, as well as projects related to AI development, was the root cause for most of the issues. On the other hand, she perceived the iterative working mode to be a very helpful way to offset the problems and supported the teams' flexibility to respond to those issues.

Detailed input: AI in general

During the interview it became quite clear that the results of the initial PoC were a very positive surprise to the interview participant and set the stage and expectations for the upcoming project. She had a very positive attitude towards the technology, without any AI/ML detailed knowledge. P7: *"We were very surprised by the results of the 1st PoC, we said: What? Really?"*

Detailed input: Project & process related

One of the pitfalls she mentioned right at the beginning of the interview was that the positive impact of the algorithmic forecast is not really used in the productive environment. The factory planners refuse to use the algorithmic figure. They still do not trust in the output. One of their arguments relates to the fact that they cannot integrate the figure into the manual planning process. They still need to apply post processing steps in order to use the number generated by the algorithm, with this basically making a neutral data driven decision of the forecast obsolete. On top, she mentioned the current situation that the management is dictating the numbers and therefore influencing the algorithm, as well as the manual planning process accordingly. Reaching their KPI's is rated higher as the predictive demand plan. She can partly understand the behavior of the planners, since the initial project goal was to replace them, but in the meantime it became clear that this is not possible and she would wish them to change their attitude accordingly. P7: *"My initial task was to rationalize the planner's jobs. So I can totally understand that they did not want to support our project."* She was hoping that a lot of conversations and communications would possibly change this. She said that she underestimated the change management that was needed for this project. She was also surprised at how much effort it was for all the team members involved to translate business needs into data impact. She knew that data quality was an issue, P7: *"We have a lot of data, but the quality is not always good"* but was not aware of the dimension this would have. She appreciated the sprint and iterative working mode.

Detailed input: HCD/UX related

She mentioned the CRISP DM process and that HCD/UX were part of this approach. For her it was very important to conduct those activities at the right time. P7: *"UX impact for the project? At that point we did it, it was too late. At the beginning it could have influenced the direction we went."* In her view the definition of requirements based on user research activities were conducted too late. P7: *"If UX research is done right from the beginning it can be very valuable."* However, she saw a great value in the findings from user research for defining the post processing steps the factory planners were asking for. In her view, being able to deliver those features was essential for establishing trust in the algorithmic forecast.

P8 - Planner

The eighth and last interview from the Meta-Sample was with one of the factory planners. This person has a background in economics with no expertise in software or ML development projects. The person joined the team right from the beginning (April 2018) after the decision was made to set-up a team and a project from the initial PoC. The interviewee felt overall uncertain about the project, its development and outcome so far. He was very aware of the problems and unforeseen issues the team faced during the development. In his opinion, lack of knowledge of AI/ML and its' capabilities in general, as well as a lack of fully understanding the manual planning process, so, this as a solution was not fully applicable to his daily job routine, which combined with the fear of losing his job in the first place, were perceived as the root cause for most of the issues.

Detailed input: AI in general

The interview participant rated his AI expertise as very low. He also took this lack of knowledge as an argument or reason why he wasn't able to contribute to the project. P8: *"I was only a user. ... I always think I lack the knowledge."*

Detailed input: Project & process related

The interview participant was very aware of the initial goal of the project. He admitted that he was afraid of losing his job and therefore was very skeptical about the project. He was more or less forced to contribute to the project, primarily by giving feedback about the performance of the algorithmic figures. It was then that he realized it wouldn't be as easy to replace him and his colleagues as he initially thought. This changed his attitude towards the project. He made the point that the algorithmic planning proposal still needed some post processing steps before it could be used productively. Therefore it is currently not supporting his work, but adding an extra figure to his tool-base which he has to evaluate in addition to the other figures. This is the reason for the low acceptance by the planners. P8: *"The forecast does not support our work. Only if we can directly use it for planning without any post processing it is supporting our work."* He described the process of the project as very uncertain most of the time. He was unable to answer the call to define an error metrics or KPI for the algorithmic forecast. He felt a role was missing for someone who translated business into technology concepts and approaches. He also confirmed the impression from the other team members that they never managed to fully understand the manual planning process and that this was a source of discussion and misunderstanding. P8: *"It would have been very helpful in my opinion to watch the planners do their job. Learning on the job for 2, 3 days. We would have cut down a lot of discussion."*

Error metrics are a way of measuring the error of an ML model prediction, to make a statement about its accuracy, either to compare competing models or to compare against the current status. Different types of error metrics are related to different statistical techniques (e.g. Mean Squared Error (MSE), Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE))

Detailed input: HCD/UX related

The interview participant was not able to answer any of the HCD/UX related questions.

5.2.4 Insights and findings from the Meta-Sample

Each participant described the overall process in very different steps. During the whole project, the team encountered unforeseen problems and tackled a lot of challenges. The project took longer than initially planned. Some members left the team, new ones joined. Acceptance and adoption by users was low. Most of the team members were aware of those issues. Nevertheless, they were mostly pleased with their work and the overall outcome, but also pointed out that they could have done their job better.

The research with and for the Meta-Sample was meant to open up to all the pitfalls and challenges, also shed light on the positive aspects and drivers to gain a better picture and overview without any particular focus areas, so the list of codes and categories is very extensive. However, most of the findings could be sorted and grouped into themes afterwards due to their similar characters and statements.

The established themes can be grouped by their relationship and relevance a) for AI projects and development in general (1-4), b) to the given use case (5-12), and c) to HCD/UX expertise (13-15), whereas some of the themes can be referred to more than one group, the borders being fluid. The participant shortcut indicates who named this issue and this making a ranking by importance possible. A short description is added to support this statement.

01. Missing AI/ML-expertise (all)

The initial part of the interview asked all participants about their AI expertise. It was quite interesting that the AI/ML experts compared themselves to other experts in the field and therefore never awarded themselves the highest score, whereas the non-experts rated themselves higher in relation to the experts in the team. They compared themselves not towards an expert in the field, but their own knowledge at the beginning of the project and again towards the end. There was no agreement amongst the interview participants about which level of AI expertise would be needed, but all agreed that a basic knowledge of AI/ML capabilities would be beneficial for the overall development process.

02. Wrong expectations management (all)

One of the major issues mentioned by all interview participants was the expectations of the technology, either wrong or too high. This goes hand in hand with the first insight about the AI expertise. Whereas the experts knew about the limitations and basic conditions for such projects, this was not similarly clear to the business domain experts. Additionally, the current hype of AI/ML technology also plays an important role in that realm, since AI/ML is perceived as the solution to every problem in the digitization area.

03. Trust in the output (P1, P2, P3, P4, P6, P7)

Related to a lack of knowledge and wrong expectations, a lack of trust on the factory planners' side ('users') in the output of the algorithms was mentioned by most of the interview participants. Fear of losing their jobs can be associated with this concern. It took time, a lot of conversations and testing phases until planners gained trust in the system's output. It was also necessary for the developers to admit that not all products could be predicted with a high level of accuracy by an algorithm, making it necessary to manually plan those products. Both sides had to agree on compromises.

04. Culture and mindset (change management) (P2, P3, P7)

Most of the interview participants were aware of the pitfalls and challenges. A couple of them realized that a lot of concerns also resulted from the business culture and the mindset of the people. In their view, change of management activities should be integrated into this kind of project. This holds good for other projects in the area of digitization. Fear of job loss, new ways of working and a change in habit and attitude go hand in hand with necessary structural transformation.

05. Gap between ML and business domain (P4, P5, P6, P7, P8)

A couple of the interview participants perceived a gap between the AI/ML and business domain. They described it as different languages used and different goals planned. Also slightly going back to the matter of AI/ML expertise, the business domain did not really know if their identified problem was a good fit for an AI/ML solution, and the other way around, the AI/ML expert would not be familiar with the business domain data, its meaning and potential bias or data quality issues. Also, the definition of a useful initial data set for training and testing algorithms is impossible without both - AI/ML and business domain experts - closely collaborating with each other.

06. KPI's ('Definition of Done') (P1, P2, P3, P4, P5)

The team mentioned a couple of times that it was very hard to decide and agree on a measure to judge the algorithmic performance. While the AI/ML experts were more into error and accuracy measures, the business domain experts' views were more related to economic value and comparison with the manual planning process. This led into a lot of discussions, shifting requirements and priorities, making it hard to judge whether or not the initial goal of the project had finally been reached.

07. Analysis status quo (current process)/involvement of the factory planners (all)

All the interview participants identified the current manual planning process as a critical item. Each planner did their product planning slightly differently, which was also related to the nature of their products ('high-/low runner', 'exotic', 'sparse'). It was therefore very hard for outsiders to fully understand it. On top, due to the lack of involvement and availability of the factory planners, any attempt to change this was not possible, making it impossible to fit the algorithmic figure into that process. It became clear that it would be helpful to adapt the process to the AI/ML technology, but this was never the scope of the project and therefore was not touched by the team.

08. Iterative working mode (all)

The nature of AI/ML projects is uncertainty and volatility. A lot depends on data quality and access, but also on know-how and human concepts and expectations, as initially stated. All the interview participants agreed that an iterative working mode with predefined sprints and regular touch points was a fundamental requirement, giving the team the flexibility to react to unforeseen challenges and situations, as well as keeping everybody in the loop, and in the best case, not wasting too much time with backlog items that were unnecessary or error prone.

09. (Project) starting point/goal (P4, P7, P8)

The initial goal of this project was to improve the factory plan, because the manual plan had a very low accuracy level, compared to the actual product orders, with this also replacing the human in that equation. This was the idea of the higher management. The factory planners have been aware of this goal. It was not they themselves who were willing and open to improve their planning proposals with AI/ML technology. For them this was an offense against their expertise, know-how and skills. This set the stage for their motivation and willingness to collaborate to reach that goal, which was obviously not very high. This shows how important and relevant human-focus for technological endeavors should be. At an early stage the set-up can change a lot, in a good or bad direction.

10. Feedback structure, structured feedback - feedback loop (P1, P3, P4, P7)

The team collected user feedback from the factory planners. This was a very unstructured process. Most of the time the team had no idea how to incorporate that feedback, or decided not to incorporate it at all, therefore collecting feedback was not a loop. From the UX perspective this was a very negative experience for the factory planners. They provided the team with feedback, but most of the time, couldn't see their input reflected in the results. This might also become an even bigger issue when the AI/ML predictions need to be retrained. It is actually counterintuitive to the ability of AI/ML, which has the potential to learn and improve over time.

11. Data quality and consistency (P3, P6, P7)

During the course of the project, it became apparent that the data used had a kind of 'bias'. Since the development team received the data on customer orders from different areas of the Digital Factory business unit, it was only after some poor results from the neural networks that it became clear that something was wrong with it. The reason for this was that in the different data-supplying departments, canceled orders were represented differently. This resulted in various revisions of the models and also an additional effort to clean the data.

12. Way of communication/biased presentations (P2, P4, P6)

Three interview participants mentioned that they had the impression that sometimes the team did not do a good job in communicating their results. They often focused their presentation on the positive results, to please the management, but on the other hand, offending the work and expertise of the factory planners, fueling wrong expectations on the management side and increasing the pressure on the factory planners.

13. HCD/UX value and usefulness (P1, P2, P3, P4, P5, P7) vs. (P6, P8)

Most participants agreed that HCD/UX can add value to the development of AI/ML infused systems. To orient, manage, prioritize, eliminate and having human focus were mentioned as positive aspects of HCD/UX activities. However, it was problematic to fully incorporate the insights gained from the user research into the further development of the AI solution. Not all of them could be transferred 1to1 into the statistically based models, showing the gap between human and data-centered approaches. On top, it became also clear that for a couple of participants HCD/UX activities were not perceived as a crucial part of the overall AI/ML development. They mentioned HCD/UX relevant issues, however, they did not really make the connection to practice.

14. HCD/UX timing (P4, P6, P7)

HCD/UX based activities are really about the right timing. If one or the other comes too late in the process it cannot influence the direction anymore. It is supposed to be an activity that needs to be initiated from the start of a project. If insights and findings from research interfere with already set requirements and backlog items they are perceived as a burden.

15. Definition of HCD/UX and awareness (P1, P3)

In Germany, design has a very special connotation and limited meaning. The interview participants' perception was that design is about form and style. In that way, it would only be an activity towards the end of a development process. Since timing in the early stages of the project was mentioned as a crucial requirement for design activities, this perception of design had to be avoided. It therefore made sense to switch to the terminology of HCD and UX.

AI in general	**Use case specific**	**HCD/UX specific**
Missing AI/ ML-expertise (all)	*Analysis status quo (current process) / involvement of the factory planners (all)*	*HCD / UX value and usefulness (P1, P2, P3, P4, P5, P7) vs. (P6, P8)*
Wrong expectations management (all)	*Iterative working mode (all)*	*HCD / UX timing (P4, P6, P7)*
Trust in the output (P1, P2, P3, P4, P6, P7)	*Gap between ML and business domain (P4, P5, P6, P7, P8)*	*Definition of HCD / UX and awareness (P1, P3)*
Culture and mindset (change management) (P2, P3, P7)	*KPI's (Definition of Done) (P1, P2, P3, P4, P5)*	
	(Project) starting point / goal (P4, P7, P8)	
	Feedback structure, structured feedback - feedback loop (P1, P3, P4, P7)	
	Data quality and consistency (P3, P6, P7)	
	Way of communication / biased presentations (P2, P4, P6)	

Table 5.6: Overview and summary of insights from Meta-Sample assigned to clusters

Interim results

Some of the revealed themes were not surprising, since they can be found in secondary research and general literature about AI/ML challenges. The interviews worked as a reality check and set those findings in the context of a real project. However, some of the themes revealed new insights into best practice approaches, combining insights from design, data and business domains and therefore supplement the current research and knowledge base. Not all of the above issues are relevant for or should be tackled by the HCD/UX practitioner, but are related to other roles and expertise. However, it became quite clear how important a holistic approach is. AI expertise, expectation management and gaps in the collaboration of the different domain experts were mentioned by all the participants. A huge issue was the understanding of the current manual planning process and the involvement of the factory planners ('users'), thus supporting the initial hypothesis that a lack of human-focus is a big issue, amongst others. To be more specific the presented case study could not ensure the involvement of the user throughout the design and development phases. The solution therefore did not fully meet the users' expectations and they were not able to integrate it into their working routine. On top, they did not have control over any of the system's features. In case of an error or a missing data point they had no possibility of changing the system's behavior or understanding what caused the malfunction. This shows - in this case anyway - that the core principles of Human-Centered-Design proposed by ISO 9241-210 are neglected by current AI development.[222]

222. These insights have been shared with the research community at the HCI International 2020 (Heier, Jennifer, et al., "Design Intelligence - Pitfalls and Challenges When Designing AI Algorithms in B2B Factory Automation", HCII 2020, LNCS 12217, pp. 288–297, 2020.).

5.3 Case Studies 02 and 03 - Beta-Samples

5.3.1 Research design for the cross-case validation study Karlsruhe and Berlin

I. Research questions
How did the other teams develop their solution?
If their process was different, why was their process different?
Did the other teams also encounter pitfalls and challenges? How did other teams solve the challenges?

II. Unit of analysis
Beta-Samples: Predictive Demand Planning (Karlsruhe and Berlin)

While conducting the initial Meta-Sample research it became clear that two other Siemens factories used the same approach to improve their factory planning processes - a factory in Karlsruhe which also produces hardware components for the Digital Industries unit, namely from the SIMATIC ET200 iSP[223] range, as well as a factory in Berlin which produces hardware for the Smart Infrastructure unit from Siemens, which is related to digital protection relays and controls - SIPROTEC 5[224].

223. Siemens AG: Industrial Controls - SIMATIC. Retrieved from https://new.siemens.com/global/en/products/automation/systems/industrial/io-systems/simatic-et-200isp.html. (Accessed on 2022-11-21)

224. Siemens AG: Protection Relays and Controls - SIPROTECT 5. Retrieved from https://new.siemens.com/global/en/products/energy/energy-automation-and-smart-grid/protection-relays-and-control/siprotec-5.html. (Accessed on 2022-11-21)

Whereas all three projects used slightly different technology approaches, e.g. Berlin used linear regression, instead of neural nets as a ML method for their predictions, the goal of all projects was to improve the factory's demand planning, to better plan the manufacturing lines and support the supply chain activities. Using similar set-ups provided common ground for comparability and cross case validation.

III. Data collection
More qualitative interviews were conducted, however, with a slightly different focus and adapted interview guide. The interviews were meant to foster exchange between similar predictive demand planning projects, meaning that it was also necessary to talk about the pitfalls and challenges of the Meta-Sample.

5.3.2 Research execution Karlsruhe and Berlin

Interviewed team members and their roles (Karlsruhe)
P9 - Product Owner/Management Planners (German)
E1 - Solution Expert/Process Consultant (German)

Start of the project was at the end of 2017

Interviewed team members and their roles (Berlin)
P10 - Management (German)
P11 - Planner/Developer (German)
P12 - Planner Procurement (German)
P13 - Team Lead/Project Manager (German)
P14 - Planner/Data Scientist (German)

Start of the project was January 2017

Beta-Sample 1
Karlsruhe

Figure 5.7: Map of Karlsruhe

5.3.3 Detailed participant input (P9-P14+E1)

Karlsruhe:

P9 - Product Owner/Management Planners

The first Beta-Sample interview was with the Product Owner and at the same time, the manager of the factory planners in Karlsruhe. This person has a background in logistics and strong expertise in the planning process of the project. The person initiated the initial PoC phase (end 2017) together with an external consultancy. He was the single and main contact on Siemens side. The interviewee was overall very positive about the project, its development and outcome so far. He was very aware about the problems and unforeseen issues that occurred during the project. In his opinion, a lot of work still needed to be done regarding changing the manual planning process and adapting the tools used accordingly, a lot of which were very similar to the ones from the Meta-Sample.

Detailed input: AI in general

One major issue the project team in Karlsruhe was also facing was the matter of trust and the need for change management. As with the case in Erlangen, the project was initiated by the upper management and not the planners themselves, resulting in the planner's resistance to trusting and using the algorithmic forecast. P9: *"We have to change on a very small scale. We have to build trust first. The planner gets this new information from the system and we have to find a way for the planner to tell if the forecast from the system is right or wrong."* Although Karlsruhe never intended to replace the planners, as the primary goal was to improve demand planning accuracy and support the planners in their job, still the issue of trust was an obstacle to implementation.

Detailed input: Project & process related

The interview participant also mentioned the current manual planning process as an issue. He was aware of the need to improve it in order to provide sustainable benefit from the predictive demand planning project. In his view, this needs to be a twofold initiative, on the one hand, the predictive part of the process needs to adapt partially to the planners needs, whereas the planners also need to change their behavior and way of working. P9: *"I agree that the planners need a solution which is flexible about their planning figures and which is targeted towards their need in its appearance. But I disagree that this needs to be Excel, because it is not connected to our overall database structure."* The interview participant knew that the algorithmic prediction did not work for all the products. Therefore the planner's expertise was still needed. They have to find a way to see and understand which figures they can use and which they still have to plan manually.

Detailed input: HCD/UX related

There were no specific HCD/UX activities at the Karlsruhe case study. Nor did they employ an expert from that field. Therefore the interview did not generate any new insights or confirm the initially found ones.

Detailed input: Different issues

The team and project set-up at the site in Karlsruhe was completely different to the case study in Erlangen. They hired an external consultancy to work on the issue of predictive demand planning. P9: *"We started working together with the external consultancy, developed the PoC with most of our products. The result was that the system made better predictions than the planners for most of the products. Therefore we decided to implement the solution in order to support the planning process."* The development was completely carried out by the external consultancy with P9 as the single source of contact at Siemens. The interview participant said that this was the right decision, because they did not have the expertise to work on such a project. It would have been impossible to develop a solution in that short amount of time (from start to implementation the project took only 12 months). Another aspect very different was the final solution. The team in Karlsruhe used a 3rd party software application, whereas Erlangen developed their own prediction platform. P9: *"That's a standard tool, but we don't have that in the SOP world, so that's a third-party provider, but it's a standard tool. One with a solution from a consultancy company."* The advantage of such a system is that the architecture and infrastructure are already given. On the other hand, there are limitations and restrictions in both features and customization. However, P9 was very positive about the solution. Data preparation was done with KNIME which allowed adaptation and changes on Siemens side without the need to authorize the external consultancy. P9: *"The solution platform is very transparent. You can look into every step the system runs through. This is very good and important for us so that we can maintain the solution even after the project handover."* Only when a new product is added to the Karlsruhe portfolio does the team depend on technical know-how from external consultants.

E1 - Solution Expert/Process Consultant

The second Beta-Sample interview was with the Solution Expert from the external consultancy and was therefore classified as an expert interview. This person has a background in IT and economics and a strong expertise in predictive analytics and Machine Learning projects (9 years). The person joined the project right from the beginning (end 2017). He was the project lead on the external consultancy side. He was overall very positive about the project, its development and outcome to date. He was very aware of the problems and unforeseen issues that occurred during the project. With his huge expertise in this kind of project he was able to compare the different clients and use cases. In his opinion, most of the issues were not Siemens specific, but occured on most of the AI/ML projects he had worked on so far.

Detailed input: AI in general

The interview participant pointed out that the mission of the external consultancy is not only to develop solutions for their clients, but also to enable them to be empowered to work with Machine Learning after the collaboration. He was aware that the AI expertise was missing from the Siemens side. In order to supply a sustainable solution it was crucial for him and his team to also train Siemens colleague in basic AI/ML concepts and be very transparent about their approach. One aspect he mentioned in that regard was the means of communicating the algorithmic output. E1: *"It is generally important in the area of predictive analytics and machine learning to visualize the output in a way that is understandable, explainable and user-friendly. Therefore I would recommend everybody working in that area to be able to know how to create a report."* The ability to bridge the gap between business and technology is, in his view, therefore twofold: on the one hand, it means training the client; on the other hand, fostering the skills on the data science side to communicate the output in a way that is user-centered.

Detailed input: Project & process related

E1 also made the point that the way results are communicated can be very biased and therefore raise wrong or too high expectations. Also going in the direction of evaluating whether a prediction is good or bad, in his view, it is absolutely crucial to define the KPI's and agree on the measurement metrics. E1: *"... the way I represent the output influences how I perceive the results. Especially in machine learning, I can interpret the output in different directions. The quality of a forecasting model by itself can be quantified and visualized in different ways."* He also pointed out that it is often hard to find an agreement that fits all the stakeholders involved. In his view, this is partly due to a lack of knowledge about AI/ML measurements on the business domain side, but also due to the type of problem AI/ML is supposed to solve. Another point he made was the set-up of the team and their roles. He recommended having a mix of people in the team. People who focus on technological and data issues, but also others who see the bigger picture and focus on communication and facilitation. This was also the set-up for the Siemens project. However, no design or UX expert was part of the team. His biggest project related issue, he revealed, was the analysis of the current manual planning process and access to the factory planners. It was one of the first action items to analyze the status quo, especially its deficiencies. E1: *"... in those initial workshops we talk to the planners and domain experts to see what their process looks like. What kind of data and information are they using to generate their forecast? And if the data is the same as we can access for the machine learning model, then we can estimate that this is a best-in-class approach to improve the forecast accuracy."* This represents the approach also for similar projects with other clients. If this initial analysis reveals that the planners also have access to multiple and additional data sources such as sales colleagues or external data from the Federal Office of Statistics which the algorithm cannot access, he said that they need to change their expectation management regarding the model's performance. The interview participant also mentioned that this initial activity is very important for him to understand or identify the business problem. It is then his role to translate this into a data-mining-problem. He made the point that with Siemens, but also with other clients, it is difficult to raise the awareness

that this step is crucial and important and that the people and experts involved allocate their time to contribute their know-how. He mentioned that it was very difficult for him to talk to the factory planners directly. E1: *"Being able to talk to the planners directly and not through a third person such as their manager is absolutely crucial and I did not emphasize this fact enough in this project. It is very valuable to talk to the planners on a regular basis..."* The reason was, he said, the middle management is kind of hesitant to involve the users of the final solution, because the outcome of the project has a direct impact on their process and the way they work. E1 made the point that exactly for this reason he wanted to involve the factory planners. E1: *"We have this issue a lot, people are afraid to involve the planners directly, therefore they put a third person in between to minimize the risk that they talk too much to the users solution. ..., because we change their process... or let's say our solution has a huge impact on the way they work. All the more important it is to talk to them..."* Within this part of the interview he also mentioned the effects of a lack of user involvement, namely lack of acceptance amongst the users being the reason why no sustainable implementation of the solution can be reached. An iterative working mode is very important in his point of view. E1: *"Those loops, these iterative loops, are more frequent and important than with other software projects. The waterfall process, where you plan step by step from the beginning, just never happened in those kinds of projects so far."*

Detailed input: HCD/UX related

As mentioned above, there was no HCD/UX expert in the team. However, the interview participant pointed out that they generally target their whole approach towards the domain expert, which is not necessarily the end user of the solution. E1: *"Regarding your question about Human-Centered-Design: our whole process set up is focused towards the needs of our domain experts."* While this represents more the concept of Customer Experience (CX), and the relationship between client and consultancy, still the attempt was to incorporate needs and way of working from the factory planners. Nevertheless, it was also mentioned as a challenge.

Detailed input: Different issues

Working as an external partner together with only very limited resources on Siemens side, plus a contact who was not overly technical was a special issue in this project. Transparency about the process and a very structured approach even within a very iterative working mode were the key aspects for client involvement and engagement mentioned by the interview participant. He was very aware that providing a solution without any client enablement during its development wouldn't end in a sustainable result. E1: *"We provide and install the tools we use ourselves, and sometimes we even delegate tasks to our clients themselves during the PoC, this way he or she feels engaged."* However, providing additional headcount for the AI/ML expertise on Siemens side would be a logical next step in his point of view, since AI/ML projects do not end with the first model implemented, but need further maintenance, monitoring and even retraining.

Berlin:

P10 - Management

The third Beta-Sample interview was conducted with the upper management of the factory in Berlin. This person has a background in finance, sales and economics and a strong expertise in the overall planning processes that are run in the factories in Berlin, Goa and Nanjing. He has worked for Siemens in many different divisions and for more than 10 years. The person supplied the budget for the initial PoC phase (end 2017). The interviewee was overall very positive about the project, its development and outcome so far. He had a very high level view on the outcome and development of the project. In his opinion there is a huge potential for the technology in other areas as well. However, his focus was on issues emerging from the mindset of the people and the overall corporate culture. In his view, change management is the main issue that needs to be tackled.

Figure 5.8: Map of Berlin

Detailed input: AI in general

He was making the point that a lot of misconceptions and wrong expectations surround the main ideas and concept of digitization. P10: *"You can automate a lot, without having anything digitized."* This initial statement set the tone for the rest of the interview. The participant was very open to technology progress and saw a lot of potential for Siemens, but had the overall impression that the general attitude and mindset of the people was the main roadblock preventing them reaching that goal. P10: *"You know, nobody wants to change. That is the main problem in our organization, we have a lot of people who stick to the status quo, and they do everything to miss out on opportunities regarding future development."*

Detailed input: Project & process related

He also mentioned the manual planning process as a main source of issues and challenges. The process was such a complex and painful job for the people involved, that they agreed to change it. It was not based on facts and figures from customer orders, but sales and management KPIs. Due to its complex nature, it always took a long time to come up with the final factory plan. It made the whole process very inflexible and impossible to correct. Although the accuracy of the AI/ML algorithm was better compared to the manual planning proposals they still have the issue of acceptance by the sales and product management departments. For the interview participant, this is no surprise. It is strongly tied to the issue of change and mindset. P10: *"People are in love with what they have. The fight for keeping what they have instead of asking themselves how can I use technology to improve my situation."*

Detailed input: HCD/UX related

He did not make the connection that a human focus or UX expertise could help with the issues he mentioned.

Detailed input: Different issues

Hiring a data scientist for the job of the factory planner at the factory in Berlin combined the data science perspective with the domain expertise, and made it possible to choose an initial data sample for the initial PoC phase. P10: *"It was P14 who started dealing with predictive demand planning, firstly for our SIPROTECT 5 products."* This way the best match of products suited very well to be predicted with an AI/ML forecast was given. Accuracy was assured and acceptance among the development team easily established - they being developers and users at the same time.

P11 - Planner/Developer

The fourth Beta-Sample interview was with the second factory planner and at the same time, Developer in Berlin. This person has a background in computer science and strong expertise in the planning process of the project. The person joined the team right from the beginning (April 2018) after the initial PoC. The interviewee was overall very positive about the project, its development and outcome so far. She was very aware of the problems and unforeseen issues that occurred during the project. In her opinion, the manual planning process was the main source for most of the problems.

Detailed input: AI in general

The interview participant has technical expertise and was very aware of the AI/ML limitations. Although she said that she was using most of the algorithmic figures for her planning and that this saved her a lot of time she also mentioned that for new products, where they don't have historic data, the forecast would be useless in the first place. P11: *"..., if we are talking about a completely new product, then no time series, no neural network can calculate anything, because no historic data is available."* This represents the combination of a domain perspective with also AI/ML expertise.

Detailed input: Project & process related

Even for the project in Berlin the topic of trust and user acceptance was an issue. The participant mentioned that within the team of factory planners it was no issue, since they were the ones who initiated the project and also part of the development team, combining and bridging the gap between the tech and business perspective. However, when trying to on board other roles, such as sales, or trying to scale the solution to other factories, they encountered similar issues to the other use cases. P11: *"On the one hand in our small team we didn't have the problem with the change management and acceptance. ... with the PDP tool, we also received some skepticism from this side, because the PLM who has done this for years and of course also knows how much effort or knowledge it means for him, did not immediately believe that some tool can now somehow deliver better results in two minutes than he can, without his expertise flowing in. That was an issue."* For her the current manual planning process is an issue regarding the implementation of the algorithmic solution. Any further development of the algorithms, or the implementation of feedback is hardly feasible due to the rigor of the current process. For her it is really hard to fit the technological solution into the given process. In her view, the goal of the project needs to be supplemented with a change in the manual planning process.

Detailed input: HCD/UX related

There was no HCD/UX expert involved in the project. The interview participant did not make any connections that meant this role would have been a value addition to the overall approach. For her the combination of business and technology expertise was the key to the success of the project. Any new requirements could be implemented by herself. She did not relate the lack of trust and acceptance from the people outside the project to a missing human-focus.

Detailed input: Different issues

The interview participant was hired as a factory planner with a tech background to support the predictive demand planning project. Hence, she was interested in the technological solution prior to having knowledge of the manual planning process. For her it was quite clear from the beginning that the process was the issue and not the technological solution. There was no need to convince her to use the algorithmic figure for her planning. P11: *"..., I took over the role of P14 as a planner. Accordingly, it was more the other way around for me. I didn't have to convince myself of the process, but rather I already understood, more from the tool, how our processes should be adapted if necessary, because the tool has already changed certain long-established processes a bit."* Due to the combination of domain and tech expertise it was also her goal to improve the AI/ML solution. She saw great potential for incorporating more information than the historic piece count data, such as market intelligence information. To her this is a greater goal than trying to on board additional colleagues to trust and use the predictive solution, thus rating model performance over human needs.

P12 - Planner Procurement

The fifth Beta-Sample interview was with the procurement planner of the factory in Berlin. This person has a background in economics and strong expertise in strategic purchasing. The person was not actively involved in the initial PoC phase (end 2017), but was very interested in expanding the solution to procurement planning to improve the supply chain management of the factory based on the forecast figures. The interviewee was overall very positive about the project, its development and outcome so far. He was not aware of the problems and unforeseen issues that occurred during the development of the project, but about the solution. He realized that the team had some issues with trust and acceptance among other people involved in the planning process, but who were not part of the initial development team.

Detailed input: AI in general

The first issue he mentioned was trust and how he perceived this issue. P12: *"You need a certain basic trust in the algorithm. I think that's a basic thing. Do you trust the whole thing from the beginning, or are you rather skeptical about it? I trust in it, because I know the people behind it, who developed it, and also probably over time, how long it has been used already."* For him it is the combination of knowing the people who developed the AI/ML infused solution, as well as developing trust over time, when the output of the algorithm proved to be accurate. He also admitted that he would not be able to easily transfer such a solution to meet his demands because he does not have the AI/ML expertise needed. He would need support, as well as training, but since both are available he would be willing to be a pilot user to test the predictive demand planning algorithm for procurement planning.

Detailed input: Project & process related

He mentioned that the sales staff were not very happy with the predictive demand planning solution. In his view, this is a matter of acceptance and trust. He did not ask himself what potential reasons they could have for objecting. He was convinced that the management of the factory in Karlsruhe did a lot to engage the different people regarding change and new technologies. P12: *"I think we also do a lot of work on acceptance at our plant. ... And if technology is not demonized per se, the employees, even if they are not directly affected, are involved in its development: Hey, we're using predictive demand planning here, not to somehow get rid of colleagues, but simply to better understand the process or to become more precise in order to also improve our planning and support our production."* The interview participant himself is very interested in new tools and eager to acquire new skills. He also mentioned the current manual planning process as an issue, not only on the factory planners' side, but also for him. Even though the algorithmic predictions are very accurate, due to their dependency on data, the numbers are still post processed by humans, such as the management, with different profit goals from the actual customer orders. Therefore the unbiased AI/ML output is manipulated by human intervention, which the interview participant perceived as a problem, making the initial idea and concept of using AI/ML to improve the factory plan obsolete. P12: *"... someone at a very high level says: Put x x x million times on here because we need it now and I look at the numbers, so what kind of value do you use here? How can you break that down? Then you start to do something manually again and then you lose the benefit from the algorithm really quickly."*

Detailed input: Different issues

The interview participant was very eager to use the AI/ML solution for his procurement planning. He was quite convinced of the benefit of the algorithmic forecast. However, he also mentioned that he would need the resources, time and training to be able to transfer it to his daily job routine.

P13 - Team Lead/Project Manager

The sixth Beta-Sample interview was with the Project Manager and, at the same time, manager of the factory planners. This person has a background in project management and strong expertise in the planning process of the project. He initiated the initial PoC phase (end 2017) and hired a new factory planner with a background in data science. The interviewee was overall very positive about the project, its development and outcome so far. He seemed not very aware of the problems and unforeseen issues the team faced during the development. He was very convinced by the solution and did not understand why not everybody saw the benefits of the algorithmic forecast.

Detailed input: AI in general

Like the interviewee from the upper management level, he was very focused on the issue of mindset, culture and a need for change management of those kinds of projects. P13: *"In my opinion, if you want to drive something into the organization or change it, it only works if the people actually want it."* He was also very aware of the issue of AI/ML expertise. He thought that this was an issue for some Siemens plants especially in remote areas, where they are not able to attract new talent, and were also not able to convince the old workforce to take over new roles and responsibilities.

Detailed input: Project & process related

As responsible for the current manual factory plan, he knew very well the problem of accuracy. He made the strategic decision to hire a new person that would be able to support him to use AI/ML to tackle this issue. P13: *"Our inventories were increasing, increasing, increasing like the material for example. The stock grew and we always had the wrong thing at hand, which is about the worse thing you can do from a logistics planning perspective. ...with the change in personnel, I had then the capacity to tackle the whole issue statistically grounded and on the basis of facts and figures."* They developed the first PoC internally and used the predictive demand planning results without giving any notice to the other involved parties, such as sales, product- and upper management. This was a strategic decision. One reason for this was their knowledge of the current manual factory plan and the related issues. Second, the interviewee mentioned that it would be impossible to convince all the involved stakeholders to change this process. They also wanted to first check how the algorithmic forecast would perform in order to get the buy-in from upper management. P13: *"I would rather call it management convincing rather than proof of concept."* This approach implied a couple of issues. Firstly, the sales and product management department was very hesitant about this solution. They tried to defend and justify their current manual planning process. On top, it raised the issue of trust in the output and failed to deliver acceptance by other potential users from other factories. The interview participant had no empathy for such a behavior. In his view, people with that kind of conservative attitude needed to be replaced. P13: *"Maybe you have to do this once and do it a second time, and then say the third time: Maybe the person in this position is a bit overwhelmed, and maybe you have to think about personnel changes in certain key functions, because they don't really understand anything."*

Detailed input: HCD/UX related

It became quite clear during the interview that awareness for the value of HCD/UX expertise was missing. P13: *"We are the users, after all. We are the users and designers, if you want."* He did not at all relate the issues of missing acceptance to the lack of a human-focus.

Detailed input: Different issues

The presented project setup had a great advantage. P13 was able to hire a new employee combining the skills of the business domain and the technical domain. P13: *"I had an open position to fill and I used this to, let's say, get on board very specific know-how, because I wanted someone with a very strong analytical, mathematical and statistical background. And then I sort of brought that person in."* The team was therefore not faced with the business and technology expertise gap the other two use cases had. The development of the initial PoC went very well and was developed very fast. However, when trying to convince other stakeholders and scaling the solution to other factories, they encountered the same issues of trust and lack of expertise and willingness to change the current manual planning process as the other case studies.

P14 - Planner/Data Scientist

The seventh and last Beta-Sample interview was with the primary factory planner. This person has a background in data science and strong expertise in the planning process of the project and was hired to work on the PoC phase (end 2017). The interviewee was overall very positive about the project, its development and outcome so far. He was very aware of the problems and unforeseen issues that occurred during the project. He had a lot of insights and topics that were relevant for the development of the project. He mentioned challenges from a business as well as AI/ML perspective due to his special role.

Detailed input: Project & process related

He mentioned the manual planning process as a big issue. P14: *"A lot of questions are a matter of improving the current process, they have nothing to do with the accuracy of the models."* When he started in the position as a factory planner he had to start from scratch. Nobody really understood and analyzed how accurate the manual planning process compared to the actual orders really was. Everybody just agreed that the planning output was not very accurate and that this needed to be changed. He therefore made the effort of collecting a lot of information and data from different sources and stakeholders prior to any AI/ML modeling. He also faced data quality issues, which slowed down his efforts. P14: *"... I faced a couple of data issues, such as real and unreal zeros, that was painful. That took me a couple of days to solve."* Once these tasks were completed he defined an initial data set and started the first PoC. P14: *"It was me who said, let's see for the last year, how a predictive model would have done the forecast? We compared those figures with our manual plan, and we saw immediately that just one single time series model was better than our manual forecast."* Since he had a deep knowledge of the different products the chosen data sample set already involved a huge variety of products, which made the team immediately realize that not all products are equally predictable, giving them a good idea about expectation management and how to define and measure a 'good' prediction. Although a lot of people were convinced about improving the current planning process, as they were confronted with the results from the predictive demand planning project, some people became skeptical and hesitant. They realized that the algorithm did not necessarily reflect their profit targets. This was when the team started to face a lot of issues regarding the final implementation. From the interviewee's point of view this behavior has to change. He said that they should learn to trust in the forecast and if the customers do not order in a way that reflects their profit targets, it would be time to re-evaluate the market and strategically start to try to answer the needs of the changing customer demand. He was very aware that it would be a very long journey to convince the management and sales people to think and act this way. When trying to scale up their solution and get other factories on board, they were facing very similar issues. For him, there was a role missing. P14: *"This is exactly what was missing, somebody who is responsible for scaling the project to other business units. On the one hand, being a change manager, who is looking into the manual processes, talking to the people to understand what they need to understand the predictive figures."*

Detailed input: HCD/UX related

Although the team had no HCD/UX expertise, the interviewee was aware of the value. He perceived it as a way of communication and visualization. P14: *"I think the topic is very important. In the end the algorithm or the figures are useless, until you see the impact of a good forecast, such as improved accuracy for turnover and sales figures, planning to use a dashboard to make this impact visible and easy to understand, this is a good user experience regarding our PDP."* For him it is more an afterthought rather than a role that is necessarily involved right from the beginning.

Detailed input: Different issues

When asked about the advantage of the team combining the business domain and technological know-how, he said that it is really hard to find people with this skill set and profile. P14: *"It is really hard to find somebody who is willing and able to code, but also is a business domain expert."* It is therefore not a sufficient solution to address all the pitfalls and challenges encountered.

5.3.4 Insights and findings from Beta-Samples

Each use cases followed a very different development process and starting point. Karlsruhe hired an external agency to develop the AI/ML solution, due to missing skills in their own team. Berlin hired a data scientist before starting the project and trained him as a factory planner. In this way the AI expertise, as well as the domain knowledge were combined in one person. The goal of the project was not to replace the factory planners, but build up a headcount with a different skill set. This fact was very helpful during the development. However, when scaling up the concept to other factories, they faced very similar issues to the other teams. This additional research particularly supported the initial findings from the Meta-Sample. However, another theme was added: 16. External vs. internal software. Erlangen and Berlin developed their own software solution and infrastructure for the final product, whereas Karlsruhe used a 3rd party solution. This had a huge impact on the duration of the final phase of the project.

16. External vs. internal software

Karlsruhe used a 3rd party software solution to implement their AI/ML system. Both approaches have their pros and cons, important factors when designing AI systems and added to the list of themes. The Karlsruhe team - from a technical point of view - was faster with the implementation because they were able to use a given infrastructure and there was no need for them to set this up in the first place. However, a disadvantage is that they were relatively inflexible regarding the choice and use of certain models. This was especially an issue with products that were hard to predict, as well as new product releases. On top of this, for any new product that needed to be integrated into the solution, the team in Karlsruhe would need the expertise of the external consultancy.

5.4 Conclusion

This case study research (Meta and Beta-Samples) looked for the overall pitfalls and challenges when developing smart algorithms in the industrial AI domain. It showed that a lack of a human-focus and misunderstanding of the workflow of the factory planners ('users') was a big issue. It became also clear that a lack of Human-Centered-Design and with this a lack of a) self-descriptiveness, b) conformity with user expectations, c) controllability of the system and d) error robustness is not the only problem that occurred during the development. This initial collection of issues in a very open manner revealed that the hypothesis was supported, amongst other potential research areas and subject matters, the two Beta-Samples also confirming those initial findings.

With this, the logical next step is to further emphasize the designer's role within the whole research area, by mapping those themes to further research informed by expert interviews and a structured literature review. The expert perspective would sharpen the industrial AI/ML perspective, as well as bring in knowledge from different case studies and therefore make comparisons between them possible. Further examination of secondary sources conducted by other research scholars focusing on the UX and design component(s), to try to understand what HCD/UX designers would need to add to bring a human-focus to AI/ML development. This combination seemed to be a promising approach to turn the focus on to the HCD/UX issues.

Chapter 6. Expert and External Input

6.1 Introduction

This section is designed to be convergent. It matches the data collected and gathered from the Meta and Beta-Samples with insights from experts and other projects, Siemens internal, as well as external, also from other areas to validate the findings, but also check for unexposed issues. This was done in two ways. Firstly, by talking to experts in the field, secondly, by examining the literature that is focused on the issue of HCD/UX involvement in the field of AI/ML.

Explore the Problem Space: Design Challenges

6.2 Expert Interviews

The interview guide for the expert interviews was different compared to the case study interviews. They were more structured and not targeted towards a specific project, but an overall comparison between different projects, to try to evaluate the initial case study findings. All four experts (1 internal, 3 external) have a lot of experience with many different industrial-, as well as more commercial AI/ML development projects. Data analysis was done in a similar manner to the case study interviews, but additional codes and patterns emerged. Besides the already given cluster of issues, a section about lessons learned and strategic decisions as well as proposed offerings were revealed.

List of interviewed experts:

E2 - AI Consultant/Sr. Data Scientist (English)
E3 - Sr. Data Scientist (German)
E4 - Sr. UX Researcher/ML Designer (English)
E5 - Sr. UX Designer (German)

6.2.1 Detailed participant input (E2-E5)

(External) E2: AI Consultant/Sr. Data Scientist

The second[225] expert interview was with an external AI consultant working in an agency in Munich. This person has a very diverse background in different areas such as engineering and data science, but also change management, both in academia as well as industry. He described himself as being familiar in the qualitative as well as quantitative world. That's why he also likes working in data science and advanced analytics, because perspectives from both worlds are helpful and valuable in this area. He provided a lot of insights and topics from a diverse range of AI/ML projects as well as the different angles he represents due to his diverse background.

225. This interview is counted as the second expert interview, because the one interview with the external consultant from the Karlsruhe Beta-Sample was counted as the first.

Detailed input: AI in general

When asked about the vision of the agency the interviewee made the point that they are not selling AI/ML solutions, but digital transformation. E2: *"... is a digital transformation data science consultancy..."* He said that with this they raise the awareness amongst their clients that a holistic approach is necessary to implement technological solutions. For them any ideation for a technical solution is accompanied by ideation on process improvements, too. As a huge issue he mentioned the gap between PoC and final implementation. E2: *"I mean, there's this problem of pilot status that large corporations think: Right, we need to get in data science and AI, MVP is a fairly low risk way of doing it. But then you just get activities that don't add up to anything. And the initial enthusiasm goes away and executives are saying: Okay, that's it?"* He was also referring to the issue of change management and expectation management, which in the end, both guide the way to digital transformation. He said that it was easy to spot low hanging fruits in all those PoC and MVP projects, but once those were solved the real work starts. E2: *"One side is the kind of the culture of the technical work and how that... you know, what you're trying to achieve in a proof of concept is not what's required for a production like system."* Most companies realize that AI/ML is no magic, that structural change is needed to fully unlock the technologies potential, together with empowering their workforce. These challenges most of the corporations don't want to take on. In that regard he was also making a point about AI/ML expertise. Informed stakeholders would be aware of this and willing to take on this journey, whereas the uninformed others won't.

Detailed input: Project & process related issues

When it comes to concrete project issues he also mentioned the definition of success criteria and how to define and measure them. It is easier to incorporate quantitative factors into the model, but qualitative features that might be relevant to solving the problem are not so easy to reflect in a model. He also made the point about the gap between AI/ML expertise and the business domain. E2: *"...you as the technologist, you need to measure stuff. And even better, you need to optimize stuff. And so you press someone for a number and they say for example: Okay, yeah, I don't know, like, widgets per person per hour, great. ... you're trying to link these two sides, there's always going to be something that is unable to be quantified and you need to be sensitive to that."* He made the reference to a fraud detection use case. He and his team derived features from a labeled data set and the model performed really well to classify fraud or no fraud. But the value added for the customer would have been if the model could also make inferences on how often and why a person would commit a fraud. From a statistical perspective the model performed very well, from a client perspective it was not enough to purely classify the events.

He had a couple of insights which were related to the topic of predictive demand planning, because he worked on some projects in that area. One major point he made was the issue of trust in those kinds of systems. As long as the predictions are very close or even similar to the manual forecast, trust is not an issue. As soon as the AI/ML driven system displays different numbers, that's when humans start to doubt the forecast. In that case they felt their expertise was questioned, which caused them to turn the case around. Additionally, when those forecasts did not fit the profit goals of the managers, they would manually add their numbers. E2: *"And they suggested totally changing it. And they said: You know, you've used this approach for years. But you know, we really think this one is better and look quantitatively, it'll give you these savings. And so there was kind of an agreement that: Yes, we should move to that new approach. But culturally, it wasn't there. So the prediction as a prediction was being made, but then the stock managers are saying: Okay, yeah, times two."* For him this again made clear how important the matter of change management for those kinds of projects is. As well as really understanding the overall process the forecast needed to fit into.

He mentioned some issues that are HCD/UX related without naming them in that way. To him the classical data science approach is very technical. It does not imply a feedback loop driven by the end user, which could completely change the direction of the whole project. He said that this was really an issue he had not discovered how to solve so far. The focus on technology made it really hard for him to involve the user and their focus and the other way around a lot of users did not understand what the data science experts were doing and therefore did not provide their input. E2: *"...what I would like to have is kind of some sort of interactive mock-ups, interactive slides that sort of show the problem with the live data and say: We can go this way or that way, and you can kind of annotate things. ... There's dashboarding tools, and there's interactive notebooks and stuff, which are really good tools for data scientists to use. But not so much for business users."* He was looking for a way to prototype or simulate AI/ML features and capabilities in a way that could be shown to business domain experts, as well as from the technical perspective in order to get their feedback, which should be a part of a proper HCD/UX practice.

Detailed input: Potential solutions/offerings and other learnings

To bridge the gap between ML and the business domain the consultancy introduced a special role. E2: *"So this AI consultant role is in between the data scientist and data strategist. .. the data translator role. And their job is really to understand what's the business problem and to be able to translate that to the technical people. And so it's this kind of go between where you can say: Okay, yeah, I understand what the methods are capable of, and the technologies, but equally, I know that actually, these are the whatever, these are the processes and these are the personalities, and these are the politics going on."*

Another important point he made was that there is a difference between statistics and ML. E2: *"... there's always the split in the AI world between like machine learning, and statistics. And my expertise is much more one the statistics side, so I can do the basic machine learning stuff. But my interest is backwards, which one's statistics, so it's thinking about the processes that are actually generating the data, making predictions, yes, but caring how those predictions were made. So, in other words, being able to make inferences about the models that are predicting them. Not just making the prediction."*

He had a lot of ideas about the HCD/UX perspective. His definition was very open, but very useful. E2: *"I would say, design is the iterative process of creating a solution to a user's problem. And I suppose the main things in that definition would be, of course, it's iterative, you don't just sit down and do it once and be done with it. It's motivated by a problem. But that problem belongs to a user. So the interpretation of that problem depends on who the user is and may not actually be kind of the right problem. And yet, ultimately, you're trying to come up with a solution."* To him the biggest value is created during the initial stage of gathering the user requirements and empathy. But also during modeling he saw a great chance in the designer's perspective of a creative unforeseen use of AI/ML techniques. To him collaboration between data scientist and designer is an important aspect. Both can benefit from each other's knowledge and perspective. E2: *"...people that come from the technical side, have a sort of standard data science workflow. You think you kind of know what the use cases are, and you've got some data. And so away you go."* Designers can heavily support the communication and visualization of the results and bring in the human-focus, whereas data scientists' know-how on data and the capabilities of the models is beneficial for designers. He said that they do not employ a design expert per se, but that they embedded the data science approach into a larger Design Thinking process. E2: *"And so that technical exploration work is embedded in this larger process, which you can kind of conceptualize from a design thinking perspective...you're basically trying to understand, kind of define the problem, I think empathy is in it, empathy, define, ideate, prototype, test, that sort of cycle. So, the empathy and the define will involve technical people in those processes, but that will be led by the strategists typically, the ideate again, we do that almost always through workshops with the clients. And it's very rare, in my experience it's pretty rare that at that stage we would actually have any sort of technical solution to show - it will just be whiteboards. [...] We would spend quite a bit of time on thinking around the ideas and the use case. And then the prototype phase is when you actually start coding."*

When asked about the outlook of AI/ML activities he said that he could imagine two scenarios. E2: *"... I think there's kind of two ways that can go: one, the optimistic route, is that in five years, people have a much better understanding of AI as a technology to augment design and user experience. The negative version of that is that you've got tools that go off and develop as tools and get deployed as tools. And yeah, they're basically kind of* black boxes*. People don't understand how they're predicting things the way they do."* He would prefer the optimistic route.

In computer science and engineering, a black box refers to a system where it is impossible to understand and explain its internal mechanisms, how the output is related to the input. Artificial neural networks are often referred to as black box systems, since it is not obvious how the neural net reaches its conclusions. The opposite concept of a black box is often referred to as a white or glass box.

(Internal) E3: Sr. Data Scientist

The third expert interview was with the internal Head of an AI lab of a different Siemens unit. This person has a strong background in computer science and advanced analytics. He provided a lot of insights and topics from a diverse range of industrial AI/ML projects for different Siemens divisions (mobility, corporate technology, healthcare, digital industries, smart infrastructure).

Detailed input: AI/ML in general

When asked about his vision for the AI lab, the interviewee mentioned 'Responsible AI' and people enablement. E3: *"'Catalyze a meaningful impact of AI technology for Siemens.' Saying that, we take care and promote responsible AI, responsible technology over all. Catalyze meaning that we measure our success with, how fast we can enable our company and clients, not in the typical approach of how many and long the contracts are that you arrange,"* thus presenting quite a strong focus on people and their development. He also mentioned the issue of missing AI expertise and that they targeted their offerings regardingly, through a format called ‚orientation'.

Detailed input: Issues

As a major issue he also mentioned the gap between PoC and implementation. They established a role in their team which specifically focused on the transition from PoC to product. E3: *"We have somebody who focuses on the transition from PoC to a productive environment, because this is a common pitfall...."* Hence, as E2 he said that stopping with a successful PoC is not getting the business anywhere.

Detailed input: Potential solutions/offerings and other learnings

Instead of talking too much about pitfalls and challenges, he offered a deep dive into the AI lab's offerings. He said that in the beginning, they focused a lot on project execution, but that they realized that they often spent too much time looking into data and trying to make the customers problem fit to an AI/ML problem. In the end, they came to the conclusion that the project was not a good fit to a data science approach and they had to convince the customer about their decision. They decided to change their approach because they wanted to prevent everybody from wasting too much time setting-up a project that was not ready for AI/ML. Therefore they offered AI orientation. E3: *"What is supervised learning? What is data driven? What are the problems with complexity? What is feature engineering? What is a neural net? What is unsupervised learning? What is reinforcement learning? These are topics we explain generally, and then context based."* He said that this is their strongest format. They offer this to Siemens internally, but also for their customers' clients. Once their customers have gone through that format and still think they want to go for AI/ML support, they offer a 5 day sprint. During the sprint they try to develop an initial PoC. He said that in the sprints they get a pretty good feeling for the overall feasibility. If after 5 days they decide that the project is not going anywhere, they have not wasted a lot of time on both sides. If the 5 day sprint is successful, they decide together with the customer how they want to proceed. The interviewee said that it is absolutely crucial to make clear that they set up a project together with the customer. E3: *"We develop the PoC, but the implementation needs to be driven by the business. ... This is our so-called inverted responsibility structure and culture. That means it's not us, you're throwing it over to us, it's you in it. And accordingly, you pitch, not us."*

He perceived HCD/UX activities as very valuable. Depending on the project they took this role on board, primarily from the Siemens internal UX department. He said that the main value added is having a diverse perspective integrated into AI/ML development. E3: *"... it is very helpful and crucial to have a lot of different perspectives combined in your network, to spot blind-spots maybe, diversity, but also different competencies, meaning a community. If you can activate this for your projects, to have an extra step of validation regarding the impact of your technology, that is so important."* He also made the point that best practice sharing needs to be established within the different units. Not wasting time in work that somebody else has already done, but understanding how use cases could potentially learn from each other.

He also gave a detailed view of the difference between B2C and the industrial AI/ML landscape. In his view, B2C is targeted towards customization, whereas B2B is focused on optimization. E3: *"We have industrialization, which is increasing efficiency, increasing productivity, and you have the consumer, B2C area, which goes to predictive behavior, attention, and maybe a little bit of manipulation as well. We call it personalization like that."* He said that he sees an issue with this pure focus on optimization. For him, both orientations are valuable, the industrial domain in particular, would heavily benefit from a better understanding of their customer which is currently outside their scope, missing out a very important aspect of AI/ML technology. E3: *"These two worlds, which we would like to treat as separate, because we say we don't want to get into the also questionable application behavior of transparent work, what we call profiling, monitoring, so to speak, that we don't have in industrialization. We do have it. We have to have it. We have to get closer to the customer. Personalization per se is not a bad thing, but simply, we have to get closer. And that is currently still very much separate."*

When asked about his opinion of an outlook on AI/ML, he said that AI is here to stay. The value of a data-driven approach is too big and the influence on business processes too huge to say that it doesn't make any sense to follow this route. E3: *"I've got bets going with the robotics guys and they're going to say, 'At some point, the AI hype is going to be over.' No chance. Data-driven approaches have such an impact on internal processes, internal sales, internal HR, strategy overall. You just can't get rid of this anymore."*

(External) E4: Sr. User Researcher/ML Designer

The fourth expert interview was with an external User Researcher and ML designer working in a big corporation in the San Francisco Bay Area. This person has a background in computational neuroscience, but her interest in user research turned her into a UX Practitioner. She is also the organizer and founder of a meetup devoted to ML & UX topics. She provided a lot of insights and topics from a diverse range of AI/ML projects with a UX perspective. She also arranged additional exchanges and further connections with relevant people from the field of AI and design.

Detailed input: Issues

A lot of the projects she worked for had HCD/UX practitioners, as well as the data science perspective involved. However, based on her experience working in a variety of AI/ML projects, she made the point that it is hard for designers and data scientists to collaborate, not only due to the fact that their processes are not aligned, but that they often work in their specific silos. E4: *"HCD/UX professionals and data scientists work in different departments."* When talking to fellow HCD/UX practitioners she realized that a lot of them have no deep understanding of the technological aspects of AI/ML. E4: *"Design professionals lack the skills and deep knowledge about AI/ML capabilities."* She also faced prejudice when talking about her mix of ML and UX as people thought she would not be good in either area, which is why she set-up a meet-up around the topic of MLforUX. Her goal was to make the technology and activities in that community available to a larger group of practitioners. When she started in 2017, it was only a very small group of people. E4: *"It is a very small community of skilled ML designers."* She was hoping to be able to change this in the long run. In her view, the involvement of HCD/UX experts is much needed in the field of AI, ML and data analysis. E4: *"We can contribute to the lack of human focus and luckily, some companies already understand the demand for Human-Centered-AI. They are hiring for this kind of combined skill."*

(External) E5: Sr. UX Designer

The fifth expert interview was with an external UX researcher working in a big corporation in Munich. This person has a background in engineering and user experience with a focus on product and business development. He did his PhD in intersections of privacy & security, Machine Learning, robotics, and cultural differences in HCI. He provided a lot of insights and topics from a diverse range of AI/ML projects with a UX perspective.

Detailed input: Issues

The interviewee also mentioned collaboration with data scientists as a crucial advantage for his involvement in the field. However, he also mentioned that this is not a given for a lot of UX practitioners. Besides their lack of access to data scientists and that kind of expertise he also said that they often join a project when a lot of the decisions have already been made. E5: *"UX designers join late in the development process"*. HCD/UX in that case is perceived as an afterthought to make a nice interface. He said that this is not a new challenge, but it makes it even harder for designers to influence and understand the guidelines that are necessary to work in the area of AI/ML. He also mentioned that a lot of his design peers do not perceive designing for AI/ML demands a new way of working. E5: *"A lot of design professionals are not aware that AI/ML is a different design material."* For them the same steps and tools apply as for other software development projects. In his view, a lot of designers are also overwhelmed by the technology. They don't understand what the systems are capable of and think that they have no expertise that could be useful when it comes to data, statistics and modeling and the training of the algorithms. E5: *"They don't know what they can contribute to ML development projects."* For them the whole development is a black box, based on advanced math, coding and some kind of magic.

6.2.2 Insights and findings from expert interviews

The expert interviews contained a lot of additional insight from the AI/ML field in general, as well as HCD/UX focused. They revealed an additional challenge that was added to the list of themes. Talking to the experts also revealed in what way some of the case study themes were also specifically HCD/UX related.

17. Gap between PoC and implementation (P2 + E2, E3)

P2 already mentioned that issue. He said that the team had to put a lot of effort and time into the migration of the PoC into a stable productive environment, which is partly also related to the challenge to develop a deployable system from scratch, or to use 3rd party software and infrastructure (theme 16). Since he was the only participant to mention that item, it was not included in the final set of themes. However, since two out of the four experts also mentioned related concerns, it seemed to be an important aspect. E2 mentioned that very often he sees a lot of successful PoC that never get implemented, because the technical know-how needed for a productive system is not necessarily covered by data scientists and ML experts. E3 even revealed that they have set up a special role in their team to make sure that their successful PoC's are implemented.

01b. HCD/UX professionals lack AI/ML-expertise (E4, E5)

A lack of AI/ML expertise is also related to the HCD/UX domain. Most designers are not experts in the field of AI/ML, so also have the wrong expectations of the technology. In addition, they cannot judge and evaluate how the technology can be a value added for their solutions.

05b. Gap between ML and design domain (E2, E4)

HCD/UX experts often have no direct access to a data scientist or ML engineer, either because there is no data scientist in the team, or each professions works in a different department. Neither are their processes and ways of working aligned, which makes collaboration very hard. Furthermore, they also have different focus areas; whereas AI/ML is focused on data, HCD/UX approaches heavily follow the concept of a human-focus, while both are actually very valuable for the development of AI/ML solutions; it is a matter of aligning both worlds.

14b. HCD/UX timing (E4, E5)

A lot of UX professionals join late in the process and are not involved during the development stages. This issue has already been mentioned before, but received additional attention since both experts from the field also mentioned it.

15b. HCD/UX value & awareness (E5)

Most HCD/UX designers are not aware of AI/ML demand for new processes, methods and tools. They don't think that they can add value in such a technically driven process and domain. Besides enabling designers to contribute to the field, it is also partly a matter of building awareness amongst designers that AI/ML need their input and point of view, while also providing them with guidance on how and where to start.

AI in general	Use case specific	HCD/UX specific
Gap between PoC and implementation (P2 + E2, E3)	*External vs. internal software (P9)*	*HCD/UX professionals lack AI/ML-expertise (E4, E5)*
		Gap between ML and design domain (E2, E4)

Table 6.1: Overview of added insights from Beta-Samples and expert interviews assigned to clusters

	Erlangen								Karlsruhe		Berlin					Experts			
List of Codes	P1	P2	P3	P4	P5	P6	P7	P8	P9	E1	P10	P11	P12	P13	P14	E2	E3	E4	E5
AI expertise	x	x	x	x	x	x	x	x	x	x		x	x	x		x	x	x	x
AI hype and consequences	x		x															x	
Management expectations	x					x					x		x		x	x			
Expectation management	x	x	x	x	x	x	x	x	x		x	x				x	x		
Change management		x	x				x		x		x	x		x	x	x	x		
Culture and mindset											x		x	x		x			
Technological focus			x												x				
Technology as the solution			x			x										x			
Human-focus missing				x						x								x	x
Project scope/goal				x			x	x	x		x								
Manual planning process	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x			
Alignment to process								x		x		x			x				
Post processign steps		x					x						x						
Data quality			x			x	x				x				x			x	x
Data access										x							x		
Data analysis/-preparation					x	x									x				
Define data sample set			x	x															
Available resources		x												x					
'Good' predictions	x	x	x	x						x					x	x			
'Definition of Done'		x																x	x
KPI definition					x					x					x				
Error metrics					x											x			
Coaching						x				x						x			
Translate business needs to data needs				x	x		x	x		x							x		x
Bridge the gap - tech & business						x				x					x			x	
Skeptical users	x															x			
Acceptance of the users		x				x	x	x	x	x				x					
Access to the users										x						x			
(Gain) trust	x	x	x	x		x	x		x			x	x		x	x		x	x
Pilot user									x				x						
Focus on user				x														x	
User involvement/availability					x	x				x									
Client involvement										x						x		x	x
Fear of losing job				x				x											
Assistance vs. automation				x															x
Transparency of the system									x									x	
Communication				x	x	x	x	x		x			x		x	x			x
Visualization						x		x		x									
Biased presentations/communication		x		x		x				x									
Management influence							x						x	x					
Impact of results				x			x	x	x		x			x					
Gap between PoC and implementation		x														x	x		
Feedback loops	x		x	x			x		x							x			x
Iterative process	x	x	x	x			x	x		x						x			x
Sprints	x				x	x	x												
Transparent project structure										x									
Uncertainty/open results		x						x										x	x
Expectations towards HCD/UX	x																		
Definition HCD/UX	x		x																
HCD/UX value	x	x	x	x	x		x									x			
Facilitation					x											x			
Requirements/needs	x				x													x	x
Focus	x																		
HCD/UX expertise			x																
HCD/UX awareness			x													x			x
HCD/UX timing				x		x	x											x	x
Frontend									x										x
Value proposition					x														
Data+business+human					x														
Positive attitude towards the technology							x						x						
3rd party software									x										
External partner									x										
Upskilling													x						
Black box models																x			

Table 6.2: Overview of list of codes from Meta-Sample, Beta-Samples and expert interviews

6.3 Structured Literature Review

6.3.1 SPIDER framework and PRISMA matrix analysis

A systematic review of publications in the field of AI/ML touching on the issue of Human-Centered-Design/AI was conducted, following the SPIDER framework[226]. This framework supported the process of defining the eligibility criteria for the systematic review of qualitative research publications. The final list of publications was then filtered through the PRISMA flow diagram[227,228] (see Fig. 6.3). Literature containing all the search terms and were related to industrial AI/ML input was not found, showing again that this is to a large extent, still a white spot.

226. Cooke, Alison, et al., "Beyond PICO: The SPIDER Tool For Qualitative Evidence Synthesis", Qualitative Health Research Vol. 22, No.10, pp. 1435–1443, 2012.

227. Page, Matthew, et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", BMJ Research Methods & Reporting, Vol. 372, No.71, 2021.
228. PRISMA Statement. Retrieved from https://prisma-statement.org. (Accessed on 2022-11-21)

(S)ample: Designers (HCD/UX) of AI/ML-based systems, products and solutions (in the context of industrial AI)

(P)henomenon of (I)nterest: Research that examines the development for AI/ML-based technology by designers (HCD/UX) and their involved challenges

Study (D)esign: All types of research designs

(E)valuation: Research that presents insights and findings on the experience and perspective of designers (HCD/UX) in the area of AI/ML

(R)esearch Type: Peer reviewed research in English and German

Information sources: Google scholar, Researchgate, SAGE, conference proceedings (e.g. AAAI, CHI, HCII)

Search Strategy:
Domain/context (e.g. Industry, 'real world', best practice, art, design)
AND Human-Centered-Design (e.g. Design Thinking, UX, HCD, HCI, HAI)
AND AI/ML related terms (e.g. intelligent agent, AI, ML, deep learning, neural nets, predictions, classification, NLP, voice assistants ,chat bots)

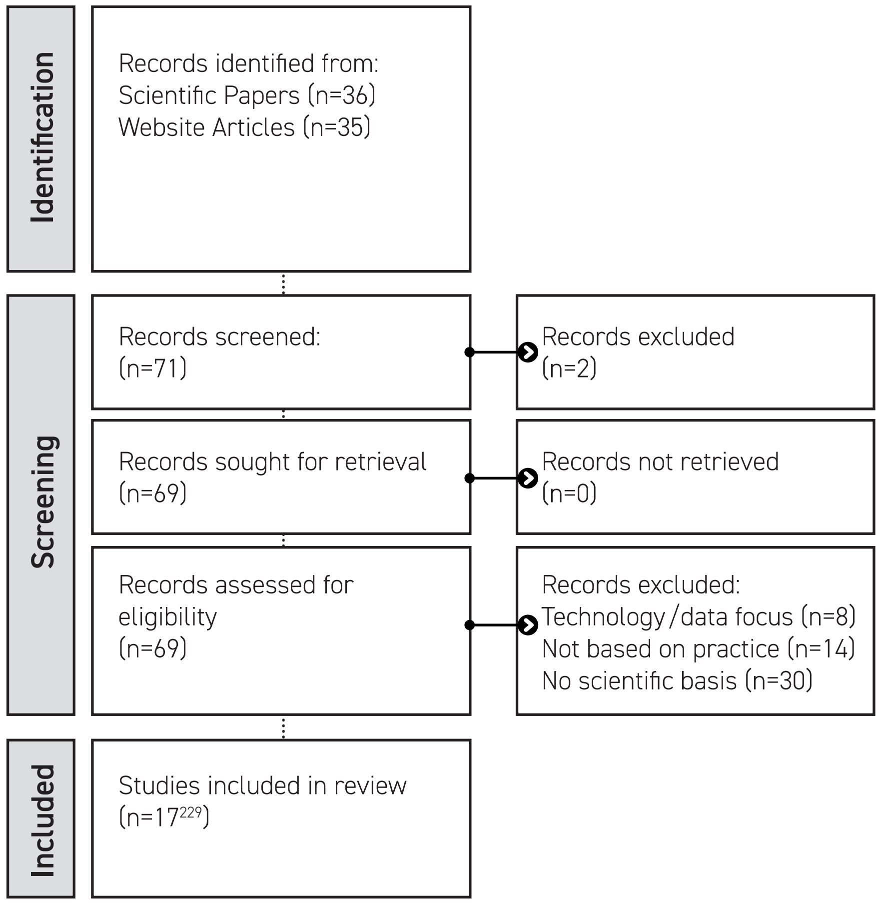


Figure 6.3: PRISMA matrix

229. Allen (2017, 2018), Bergström/ Wärnestål (2022), Dove et al. (2017), Fiebrink/Gillies (2018), Fiebrink (2019), Girardin/Lathia (2017), Kun et al. (2018, 2019), Wallach et al. (2020), Wu/Zhang (2020), Yang (2017, 2018), Yang et al. (2018, 2020), Yildirim et al. (2022), Zdanowska/Taylor (2022)

(The found publications were already included in Chapter 3.)

6.3.2 Insights and findings from literature review

In order to counter and respond to the pitfalls and challenges found in the case study research of the Problem Space and adding the human-centered perspective to the development of AI/ML infused systems, it is crucial to enable the HCD/UX practitioners to contribute their expertise and knowledge. The papers included from the systematic literature review revealed reasons and problems that were relevant and occurred during the development of AI/ML infused projects from a design perspective. A lot of the identified literature from scientific sources was not written by design practitioners themself, but is based on qualitative interviews with them, so this research adds a new angle to the academic discourse, also since the researcher's own perspective derives from being an active member of the development team, being able to judge whether or not the challenges and issues found are also applicable to the industrial AI context.

Overall, the systematic review supported the hypothesis that AI/ML are a new design material, because AI/ML systems are very complex and the designed outcome is non-deterministic, as stated in chapter 3.3.1.

In order to enable designers to work with this new material (Allen, 2017; Dove et al. 2017; Wu/Zhang, 2020) a couple of gaps and missing items were identified. Designers lack, a) AI/ML expertise (Dove et al., 2017; Yang, 2018). They are not familiar with statistical data sets, which are often based on telemetry data (Kun et al., 2018/2019). They understand AI/ML capabilities in a broad sense, but not specifically. Furthermore, there is a lack of AI/ML training targeted at design, HCD and UX practitioners (Bergström/ Wärnestål, 2022; Fiebrink/Gillies, 2018). Further, b) current design tools do not serve the demands of AI/ML development (Allen, 2018; Fiebrink, 2019; Wallach et al., 2020; Zdanowska/Taylor, 2022; Yildirim et al., 2022). They need either to be adapted, such as e.g. user journeys & workflows, prototyping & testing possibilities (Shneiderman, 2022), as well as new ones need to be created, such as e.g. AI/ML systems monitoring, and integrating and reacting to feedback loops (Maeda, 2019), and c) AI/ML exemplars & abstractions / best practice sharing (Yang, 2017; Yang et al., 2018) d) collaboration with AI/ML experts (Girardin/Lathia, 2017; Yang et al., 2020) to partly overcome the challenges referred to.[230]

230. The additional findings from the cross case validation Beta-Samples, together with the insights from the expert interviews and the systematic literature review were published in a paper for HCI International 2021 Conference (see Heier, Jennifer, "Design Intelligence - Taking Further Steps Towards New Methods and Tools for Designing in the Age of AI". HCII 2021, LNAI 12797, pp. 202–215, 2021.). The intention was to start a conversation about possible solutions to the already given challenges by mapping problems to solutions and analyzing how far they matched.

Case Studies	Expert Interviews	Literature Review
Missing AI/ML-expertise (all)	*HCD/UX professionals lack AI/ML-expertise (E4, E5)*	*Lack of AI/ML expertise*
Gap between ML and business domain (P4, P5, P6, P7, P8)	*Gap between ML and design domain (E2, E4)*	*Missing collaboration AI/ML experts*

Table 6.4: Themes mapping from case study research, expert interviews and literature review

6.4 Conclusion

The initial Meta and Beta-Samples revealed a variety of pitfalls and challenges when developing industrial AI/ML solutions, in total 16 themes emerged that touch upon issues from design, data (science) and the business perspective. The missing human-centeredness was one of the main aspects that emerged from this research. The expert angle brought in a transfer to other use cases and projects, as well as the HCD/UX perspective, adding one theme and showing that some of the initially found challenges are even design specific. The systematic literature review shed light on the pitfalls and challenges for HCD/UX designers when working with AI/ML as a design material.

The main aspects and implications that derive from this threefold approach are the recognition that a) non-experts lack of AI expertise was an overall issue with a need for learning material targeted towards different audiences and their levels of expertise, b) a lack of collaboration between the involved professions - such as design, data science and the business domain - perceived as a gap between those perspectives, resulting in c) unaligned approaches and wrong expectations during the development of AI systems, with consequent lack of user involvement and missing trust in the systems' output reported.

The research carried out made it clear that a lot of factors contribute to the development (or otherwise) of Human-Centered-AI. The analysis of the individual steps involved in the development process of AI/ML applications played an important role. Only a systematic, process-driven solution can lead the way to the development of new methods and tools taking into consideration the insights mentioned above. Several measures and actions, as well as collaboration with other professions, can provide the impact needed to enable designers to shape the development of AI/ML agents and algorithms and provide an understanding of the relevant actions which need to be taken when considering a proposed solution.

Chapter 7. From Problem to Solution Space

7.1 Introduction

Human-Centered-AI instructions - a systematic approach

The human-focus in current AI/ML development is important. A lack of user involvement during its development results in trust missing from the output of those systems and one consequence - amongst others - is the adoption of AI/ML infused solutions viewed in a negative way, as illustrated by the research sections in Chapters 5 and 6. These findings open the doors for Human-Centered-Design activities in the age of AI, consequently in turn affecting the decisions and practice of designers, asking for new methods and tools. This section represents the transfer of the findings from the Problem Spaces into practical applications (process, methods, tools) for designers - Solution Space. Integrating AI/ML into design practice - Design Intelligence.

7.2 Summary of Challenges for the Design of AI/ML Solutions

There are many different challenges out there, as mentioned in Chapter 3, as well as shown in part III. Problem Space Chapters 5 and 6 of this work. Most can relate to the following themes:

>> AI expertise - lack of design training material and education (especially data-driven topics, as well as AI/ML capabilities)

Within that area, relevant issues and items are a) challenges to frame what counts as AI/ML, b) challenges to understanding AI/ML capabilities and c) challenges to envisioning novel, practicable AI/ML applications for a given design problem. These issues are also relevant for the business domain expert and strongly related to any challenges that occur due to particular expectations.

>> Missing tools - lack of low fidelity prototyping, dynamic and non-visual UI's, feedback integration

When it comes to the application of current tools designers face a) challenges in iterative low fidelity prototyping and testing human-AI interaction and b) challenges in crafting thoughtful and dynamically evolving interactions.

>> Collaboration - aligned processes (designer/data scientist/business)

Relevant topics that are assigned to this theme are a) challenges to collaborating with AI engineers, and the gap between the involved domains of design, data and business thinking, b) challenge to bringing a human-centered view to AI/ML development, c) HCI/UX experts often only join towards the end of the development process and d) the related experts work in silos.

>> Best practice sharing - missing collection and documentation of AI infused project exemplars

Besides the issues mentioned above, designers face challenges finding information related to actual AI use cases, exemplars, abstractions, which reflect the overall missing focus on real world scenarios in the AI/ML domain.

Different solutions are proposed and have already been implemented in part (see Chapter 3.3.4). However, they are not effective and efficient since they mostly only focus on one of the above aspects, and only on the design perspective. In order to enable designers to access a stream of activities it is necessary to combine the already given solutions, adapt them where necessary and fill the gaps, as well as take the other professions involved in the development of AI solutions into account, such as technical and business experts. This is where the value added is created.

>> Additional need - providing an AI overview and entry point

During a lot of conversations with designers, students, as well as business experts, it became clear that the information about AI 'out there' is overwhelming. People had no idea where a designer could potentially add value during the development process. Non-experts have a hard time finding an entry point. Either material is too generic or too specialized and tech heavy, also missing the notational forms that suit the related target audience of non-experts. The same applies to Human-Centered-AI principles; without a context it is really hard to follow the prompts. Overall any attempt to support the design community to get their heads around AI/ML needs to provide a starting point and from there, different paths to follow, depending on their know- how, skill set and level of involvement.

7.3 Additional Methodological Angle

This part adds an additional component to the overall methodological framing. It follows the Design Science Research and practice paradigm embedded in the context of information technology, systems design and AI/ML data science. It ought to create an outcome that suits the definition of an artifact, based on findings from the Problem Spaces and completes the circle towards the Solution Space. It includes two solutions (AI & design process modules, and an AI use case framework for documenting and sharing use cases) which together enable designers to navigate in the age of AI and seamlessly integrate Human-Centered-Design into the overall development process. The focus audience is the overall design community interested in the AI/ML domain, primarily beginners looking for guidance in that area, but also experts who can benefit from both solutions. Since the process modules are meant to foster collaboration between design, data (science) and the business domain, those stakeholder groups are also addressed by the solution.

7.3.1 Design Science Research and practice

AI and ML can be allocated within information technology (IT) and information systems design. In this domain, Design Science Research is a very common method. It has its origins in engineering and computer science.

"Design Science Research (DSR) is a problem-solving paradigm that seeks to enhance human knowledge via the creation of innovative artifacts. Simply stated, DSR seeks to enhance technology and science knowledge bases via the creation of innovative artifacts that solve problems and improve the environment in which they are instantiated. The results of DSR include both the newly designed artifacts and design knowledge (DK) that provides a fuller understanding via design theories of why the artifacts enhance (or, disrupt) the relevant application contexts." (vom Brocke et al., 2020, p.1)[231]

231. vom Brocke, Jan, et al. "Introduction to Design Science Research", Design Science Research. Cases, Springer International Publishing, pp.1-13, 2020.

A Design Science Research project can either be motivated by an existing theoretical base or by inspiring and informing practice, making it suitable for the given research approach, since it meets all aspects mentioned. Namely, the practical part of this work wants to create innovative artifacts (process, methods and tools) for designers that are concerned with the development of AI and ML systems. This output should be created based on the findings from the Problem Spaces.

7.3.2 Positioning of Design Science

Design Science is a hybrid method. It incorporates aspects of theory and practice. *"While Social and Behavioural Sciences seek to understand reality, Design Science Research (DSR) seeks to invent (design) new means for acting in the world in order to change and improve reality. As a result, DSR re-creates reality through creating and evaluating artefacts that serve human purposes and solve human problems (March/Smith, 1995[232]; Simon, 1996)."* (Venable et al., 2017, p.2)[233]

232. March, Salvatore T., and Smith, Gerald F., "Design and Natural Science Research on Information Technology", Decision Support Systems Vol.15, No.4, pp. 251-266, 1995.
233. Venable, John R., et al., "Choosing a Design Science Research Methodology", in ACIS 2017 Proceedings, pp.1-11, 2017.

Although it is perceived as a different approach compared to traditional social or natural sciences, some Design Science practiced by a certain group of researchers has an affinity with aspects of natural, as well as social (more specifically behavioral-) sciences. *"One way in which design science differs from social or natural science is its stronger dependence on functional explanations grounded in the relationship between functional requirements and the prescriptive components of the design,"* (Venable et al., 2017, p.5) the main difference being the focus on specific practices, processes and artifacts[234,198]. Therefore it is often talked about within both scientific streams when examining information technology and systems development. *"Two paradigms characterize much of the research in the Information Systems discipline: behavioral science and design science. The behavioral science paradigm seeks to develop and verify theories that explain or predict human or organizational behavior. The design-science paradigm seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts. Both paradigms are foundational to the IS discipline, positioned as it is at the confluence of people, organizations, and technology."* (Hevner et al., 2004, p.75)[235] An important aspect mentioned in the remark by Hevner et al. is the position of the methodological stance in the intersection of people, business and technology, also as the sphere of activity of any Human-Centered-Design (for AI) endeavor.

234. Iivari, Juhani, "A paradigmatic analysis of information systems as a design science", Scandinavian Journal of Information Systems, Vol. 19, No. 2, pp. 39-64, 2007.

235. Hevner, Alan R., et al., "Design Science in Information Systems Research", MIS Quarterly Vol. 28, No.1, pp. 75-105, 2004

7.3.3 Guiding principles of Design Science

"Design science is inherently iterative." (Hevner et al., 2004, p.88)

The development of innovative and new ideas, concepts and artifacts is, by default, a process that runs in iterative material, temporal and cultural cycles. It is therefore not surprising that the same counts for Design Science. Being an iterative approach, *"Design is both a process (set of activities) and a product (artifact) - 'a verb and a noun'".* (Walls et al., 1992, p.42)[236] It describes the world as acted upon (processes) and the world as sensed (artifacts). "*This Platonic view of design supports a problem solving paradigm that continuously shifts perspective between design processes and designed artifacts for the same complex problem."* (Hevner et al., 2004, p.78)

236. Walls, J. G., et al., "Building an Information Systems Design Theory for Vigilant EIS," Information Systems Research, Vol. 3, No.1, pp. 36-59, 1992.

The artifact and therefore the practice part plays a fundamental role in Design Science Research. It is the embodiment of the knowledge used and created during its development. *"The fundamental principle of design-science research from which our seven guidelines are derived is that knowledge and understanding of a design problem and its solution are acquired in the building and application of an artifact."* (Hevner et al., 2004, p.82) Similar aspects apply to technology itself. Technology without an application, whether in the form of a physical or digital system, does not exist. The act of coming up with a new technology itself is therefore perceived as a little piece of theory on its own, since aspects of practical reasoning and the use of knowledge are used and a prerequisite for this development. *"Technology has been defined as 'practical implementations of intelligence' (by Ferré, 1988, p.26)[237]. Technology is practical or useful, rather than being an end in itself. It is embodied, as in implements or artifacts, rather than being solely conceptual. It is an expression of intelligence, not a product of blind accident. Technology includes the many tools, techniques, materials, and sources of power that humans have developed to achieve their goals. Technologies are often developed in response to specific task requirements using practical reasoning and experiential knowledge."* (March/Smith, 1995, p.251)

237. Ferré, Frederick, "Philosophy of Technology", The University of Georgia Press, 1988.

7.3.4 Research tactics and tools of Design Science

The first artifact of the Solution Space - AI process modules - is set out to create a solution to the overall accepted hypothesis of the Problem Space, which is supposed to be embedded in the Design Science Research realm. This includes the inductive and deductive steps necessary to get from a practical problem to a set of design principles, the deductive actions to derive more concrete design decisions, the activities which lead to an instantiated artifact and finally methods leading to a comprehensive evaluation concept allowing generalizations and inductive conclusions about the underlying design principles and theories.

I. Build and evaluate

The activities in Design Science Research are split into four overall aspects. The initial sets that follow multiple iterations are 'build' and 'evaluate'[238], including a diverse set of different research methods. They cover the aspects derived from social science research, such as interviews, surveys, literature reviews, or focus groups.

238. vom Brocke, Jan, and Maedche, Alexander, "The DSR Grid: Six Core Dimensions for Effectively Planning and Communicating Design Science Research Projects", pp.379–385, 2019.

II. Theorize and justify

Whereas the initial part of the activities' goal is to establish new theories and to enhance performance, the aspects that are related to 'theorizing' and 'justifying' are aiming to extract general knowledge and test the proposed theories[231].

The second artifact of the Solution Space - AI use case framework - is meant to supplement the process modules. It follows the same process.

7.4 Conclusion

Focus on aligned processes and tools for human-centered and data-centered approaches (+business expertise)

The case study research and expert interviews revealed 17 themes that emerged when designing AI/ML systems in the industrial domain. Missing HCD/UX expertise was one factor mentioned in the HCD/UX specific cluster. 2 out of the 3 cases did not have a dedicated HCD/UX practitioner in their development team.

This picture is also reflected in the literature reviews. HCD/UX are not necessarily perceived as crucial factors in every use case. However, in the teams that were equipped with that expertise, it was perceived as an important part of the overall process, especially when defining the problem and understanding the business domain, as well as when designing the interaction with the end users. On top, it is also very important to find the right timing for the related HCD/UX activities which call for the early integration of design activities in the development process of AI/ML based systems.

The industrial AI domain is very technology and data-driven. It is therefore necessary to align the proposed solution for designers towards this factor. Collaboration between data scientists and HCD/UX designers, also incorporating business domain expertise, seemed to be a valuable asset in that regard. Therefore the idea of integrating both perspectives in a final solution seemed to be an important aspect, also addressing business viability. Trying to map an 'ideal' AI/ML development process when all professions could contribute their valuable know-how is therefore the baseline for the practical part of this PhD, using methods and tools from all three fields were applicable and valuable. The outcome needs to reflect a shared workflow, common terminology and language, as well as boundary objects that help all the professions support the collaboration.

Part IV. Solution Space

Chapter 8. AI Process Modules

8.1 Introduction

This chapter is divided into build and evaluate and theorize and justify activities. Related to build and evaluate is the mapping of the best case scenario for a collaborative approach for designers, data scientists and the business expertise, based on real world use cases in the industrial AI domain, from which are derived process modules that integrate and place the designers tools and activities plus data science and business methods where applicable. Related to theorize and justify is testing and validation with a use case from another domain, and with this additional gathered feedback, being able to improve and transfer the findings from the industrial AI context to a wider spectrum.

Build and evaluate

Connect the Missing Pieces: Process and Tools
8.2 AI and Design Process Mapping

The proposed solutions in this section should primarily suit and address the needs from the design perspective, using different notational forms and mixed representations, such as visualization, mapping and journey techniques presenting an alternative position to a purely data-driven perspective, and with the methods and tools used, being flexible and adapting to the given circumstances. However, the influence of the industrial AI domain should not be denied. It was the source of a lot of insights, technical know-how, conversations and focus topics. This outcome wants to preserve and present this endowment.

The idea is to give an overview and starting point for the relevant AI/ML aspects by mapping the process development steps, showing the aspects which designers could and should touch upon. This should be based on several real world scenarios and use cases directly tied to the development process. Only combining methods and tools with a process and concrete instructions for steps and actions seems to be a promising combination to enable designers in the age of AI to embrace this new design material, therefore the Solution Space has two artifacts, one providing actual guidance and the other supporting this with contextual information from actual use cases. The AI process modules are supplemented with the information and tools already available (as stated in Chapters 3.2.4 and 3.3.4) making it a system's approach rather than a single solution approach. As with every starting point, it is just the beginning of a very personal journey. It should equip the design practitioner with the knowledge necessary to decide which path to follow and where to find input and information for the route ahead.

8.2.1 Inspiration for notational forms

The CRISP DM process and the double diamond process models served as inspirational, as well as guiding pieces. A combination of both was chosen for an initial process prototype. The former represents the data science perspective, whereas the latter includes the design perspective, thus being able to create a shared workflow, use common terminology and language, as well as define boundary objects. The combined design and AI/ML process map should also highlight the points that are relevant for design and UX, as well as special when designing for AI. In addition, the concept of a data flow diagram (DFD) was intended to be the means to visualize the process, as such diagrams manage to express things in a visual way that are usually difficult to explain in words (see Fig. 8.1, p.94). They are also understandable by both experts and non-experts and are therefore suitable for various target groups - from designers, developers to CEOs, this also making it possible to address the business perspective.

Figure 8.1: AI generated mood board[239,240], based on human input[241]

239. Mood Board Search. Retrieved from https://experiments.withgoogle.com/mood-board-search. (Accessed on 2022-11-21)
240. Source: https://github.com/google-research/mood-board-search. (Accessed on 2022-11-21)

241. Human input: Information Theory, DFD'S, layers, pcb's, Claude Shannon, thesaurus maze, process flow, network structures (for more information see Appendix III. page 175).

8.2.2 Requirements for the outcome

This first artifact of the Solutions Space aims to fulfill a couple of requirements to answer the designer's needs. It should be 'modular' meaning to represent the different steps in a manner which groups relevant items together in one module, then be able to combine different modules and leave others out. Designers, HCD and UX practitioners who are very new to the field of AI/ML should have a very hands-on guide to support them step by step to gain more experience, whereas designers with a bit of expertise and experience can use it to experiment and shift things around, trying new and other combinations to see what happens and also use it to facilitate between data and business driven approaches.

The whole AI/ML development is heavily based on iterations. Its probabilistic, complex and partially unpredictable nature is the root cause of this. A non-waterfall approach and appeal are therefore another requirement.

Although the process mapping is derived from case studies from the industrial AI domain, the final terminology, flow and action items are supposed to be domain independent (industrial as well as other domains).

The solution should imply different layers, each incorporating and representing different levels of complexity.

Finally, the main target group are designers who start getting involved in the topic. But it should also be helpful for design and data science experts in this field who can use it to communicate with business domain experts and other stakeholders.

8.2.3 Benchmarking of processes

When the decision was made to create a design and AI/ML process map and its modules, there was no solution out there. However, in the course of this PhD, some publications which address similar solutions became available and for completeness, are mentioned here. Their existence suggests this issue is highly relevant and important, but also what different directions similar findings can reveal, and that the industrial AI domain is still a research gap.

Shared Path - Service Design and Artificial Intelligence in Designing Human-Centred Digital Service

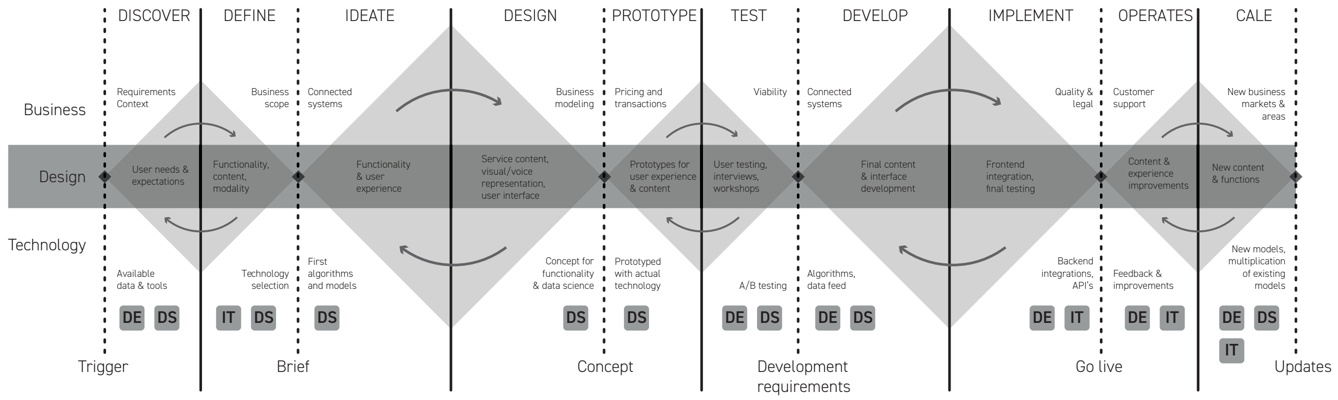


Figure 8.2: The service design process created by T. Jylkäs for AI-enabled services

The focus in this work is on service design and AI assistants, more specifically NLP based intelligent services, such as the text and voice based interfaces found in chat bots as well as AI assistants. The visualized process (see Fig. 8.2) is based on the double diamond approach and divergent and convergent phases have huge emphasis, resulting in a quintuple diamond process[242]. Business, design and technology are mapped as three different streams. However, no specific data science terminology or process is integrated. *"Since the research is drawn from one type of application of AI, namely AI assistants, further research needs to validate the findings in various application forms and design processes of AI-enabled services."* (Jylkäs et al., 2019, p.11)[243] It is based on five service design use cases and seven expert interviews from different industries. The research revealed three main areas: the application of AI in service design, effect of AI in the service design process and role of the service designer in the AI inclusive service design process.

242. Jylkäs, Titta, "Shared Path - Service Design and Artificial Intelligence in Designing Human-Centred Digital Services", thesis, University of Lapland Faculty of Art and Design, 2020.

243. Jylkäs, Titta, et al., "From Hype to Practice: Revealing the Effects of AI in Service Design", Academy for Design Innovation Management Conference, pp.1-14, 2019.

Triple Diamond AI Design Process - Human-centered Design for Data-driven Innovation

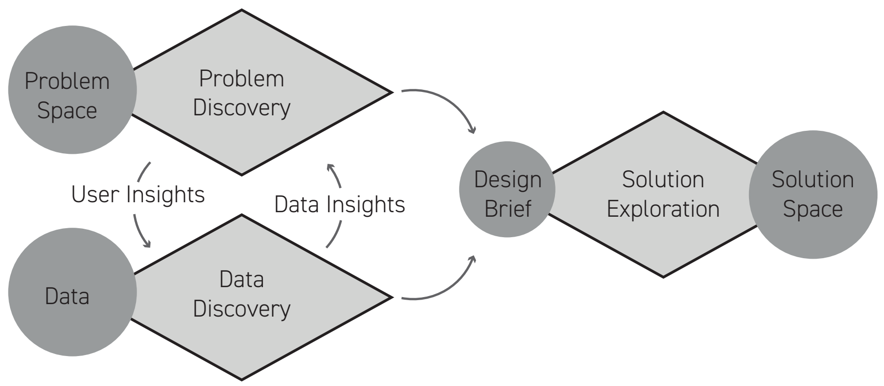


Figure 8.3: The triple diamond process created by J.Schleith and D.Tsar

This process is based on the concept of Design Thinking represented by the double diamond, as well as CRISP-DM and Knowledge Discovery in Databases (KDD) process models (see Fig. 8.3, p.95). The process is based on the hypothesis that there is a huge gap between 'user needs' and 'data constraints' in current AI/ML development. For Schleith and Tsar, the issues around data are their biggest concern when developing AI/ML algorithms. *"... we argue that strong opportunities for AI innovation need to stem from both, a detailed understanding of the problem space, end-user pain points and current processes, as well as constraints and opportunities based on data, its availability and accessibility."* (Schleith/Tsar, 2022, p.139)[244] Therefore their process includes an added section about data, making it a triple diamond. It is a purely theoretical process design not based on real world use cases and not formally evaluated according to specific metrics and practice-related constraints.

244. Schleith, Johannes, and Tsar, Daniella, "Triple Diamond AI Design Process - Human-centered Design for Data-driven innovation", HCII 2022, LNCS 13516, pp. 136–146, 2022.

AI-by-Design: A 6-Step Approach for Building Human-Centred AI Solution

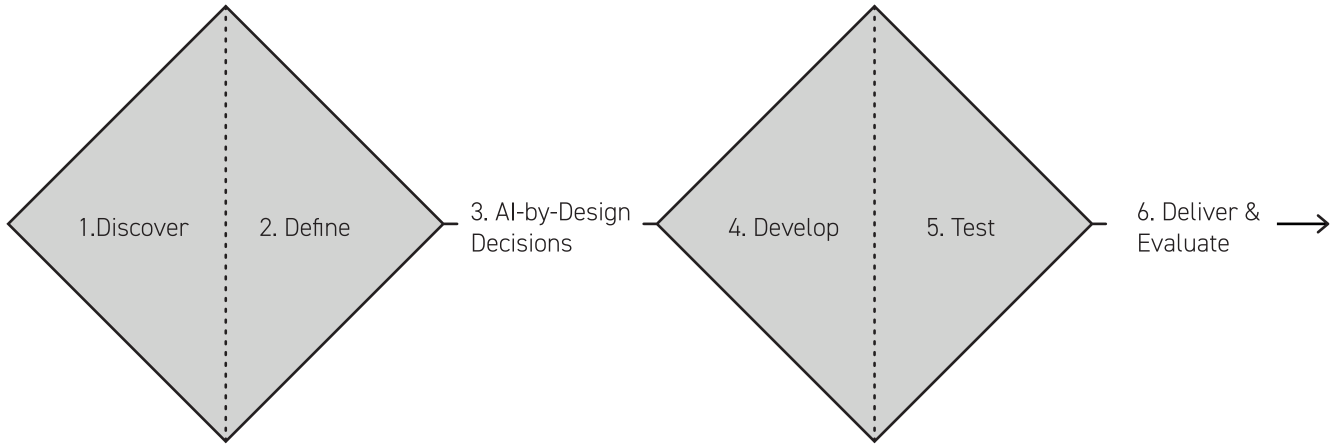


Figure 8.4: The AI by Design process created by S.Westra and I.Zempekakis

This process is meant to combine the design perspective, more specifically, the designer's approach to problem-solving, with the data science perspective on AI/ML technological feasibility. *"Data scientists and designers need each other to create desirable, feasible and viable AI systems. A keen understanding of both the technologies and customer needs are key."* (Westra/Zempekakis, 2022, p.17)[245] It is based on the hypothesis that data scientists tend to develop solutions without the user in mind and jump directly to solutions and therefore solve the 'wrong problems', whereas designers tend to have the wrong expectations of AI/ML technology and for them, AI/ML is not perceived as a solution to their problem because it is too difficult to implement. This process is based on the double diamond, as well as the CRISP DM process (see Fig. 8.4). It is a very high level representation of the different process steps. Each of the six steps is accompanied by an example from a real world project, such as a fully automated AI car inspection tool.

245. Westra, Serena, and Zempekakis, Ioannis, "AI-by-Design: A 6-Step Approach for Building Human-Centred AI Solutions", in collaboration with OLX Group and Koos Service Design, whitepaper, pp.1-44, 2022.

Implications for the AI process modules

The solutions from the benchmark revealed critical gaps and missing items. With a small exception from the first service design process model, the two remaining process representations are very high level with no deep dive layer, concrete activities and their correlations. They also lack modularity and have a waterfall appeal, although their iterative nature is mentioned in the more detailed description of the process steps. None of the above publications address the missing AI expertise and concepts to solve that issue. They do not cover or provide an overview and deeper information about the design specific challenges in the age of AI/ML. They also make no reference to any concrete tools supporting their processes. They seem to have a very low-tech focus, with their information either derived from B2C case studies or not based on best practice activities at all. The perspective from the industrial AI domain is missing completely neither is the domain from the business experts' perspective. In order to provide an adequate solution, these issues need to be addressed and the proposed solution from this PhD can contribute strongly to this research endeavor, filling some of the gaps mentioned and adding relevant items.

8.2.4 Design approach and different iterations

Version 1

As an initial step, the definition of the overall process steps using CRISP DM and double diamond terminology was carried out (Set up, 1. Understand & Define, 2. Data Input, 3. Modeling & Design, 4. Output, 5. Deployment, Post Processing). From there, the sub-categories that each process step contained were defined. These items were then put together as a simple visual in order to start testing out this initial framework with colleagues from data science, business, as well as the UX perspective. After the feedback was gathered terminology was aligned accordingly, and sub-categories where edited and added where needed.

Version 2

Based on the feedback gathered, a second version was produced, this time with a more advanced visualization of the different items, also representing a flow of information and dependencies of steps. This version no longer refers to the visual representations of the double diamond or the CRISP DM processes and also adds an additional layer with relevant methods and tools to the sub-categories, to highlight design relevant process steps. Again, feedback was collected. The solution was then iterated based on the feedback. After this version, the terminology, notations, categories and sub-categories were specified and finally set.

Version 3

As the next step, 'physical' paper prototypes were generated. This step was necessary to turn the idea of a process into the concept of process modules. This activity fostered the development of a shape for the modules that worked separately for each single module, but were also combined together, perceived as a unified whole (see Fig. 8.5). After versions 1 and 2 specified different items, activities and terminology used this 3rd version, aimed at contributing to the requirement of modularity in order to create an adaptable process map, turn the linear appeal into a more holistic picture, while adding different layers and levels of complexity.

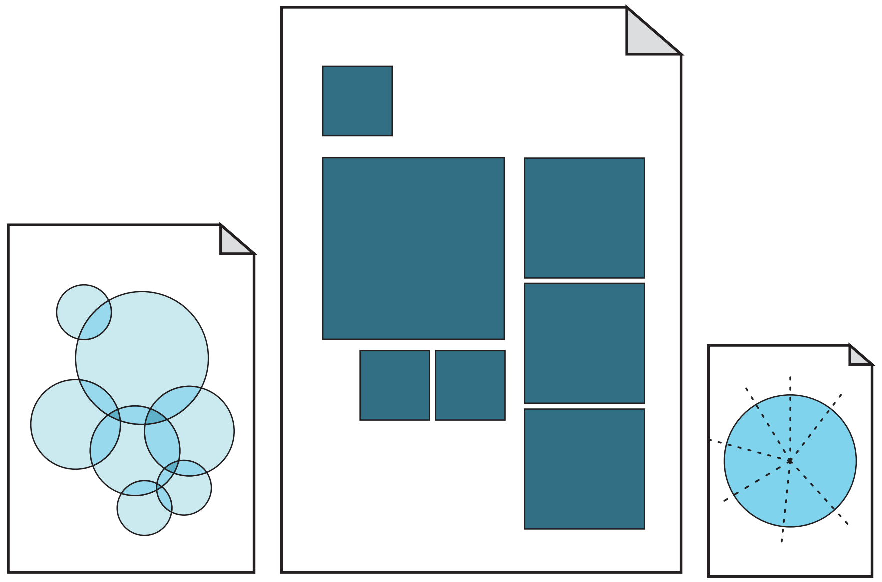


Figure 8.5: Schematic illustration of the different formal elements

8.3 AI and Design Process Modules

8.3.1 Overview process modules and their related layers

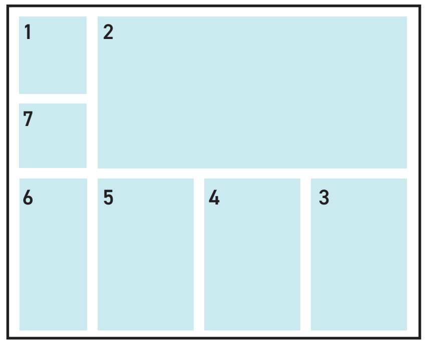


Figure 8.6: High levels: layer 01 overview modules (module size is a code for the design importance and impact); layer 02 modules with related notation (1-7)

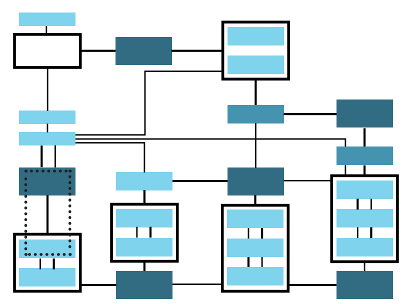


Figure 8.7: Detailed levels: layer 03 modules with related activities their flow and dependencies; layer 04 each activity is related to concrete actions and tools, both 'new' and 'old' ones, with a detailed description (Chapter 8.4)

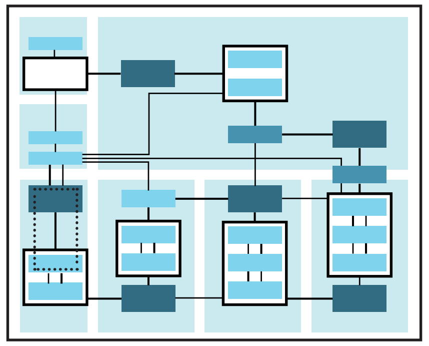
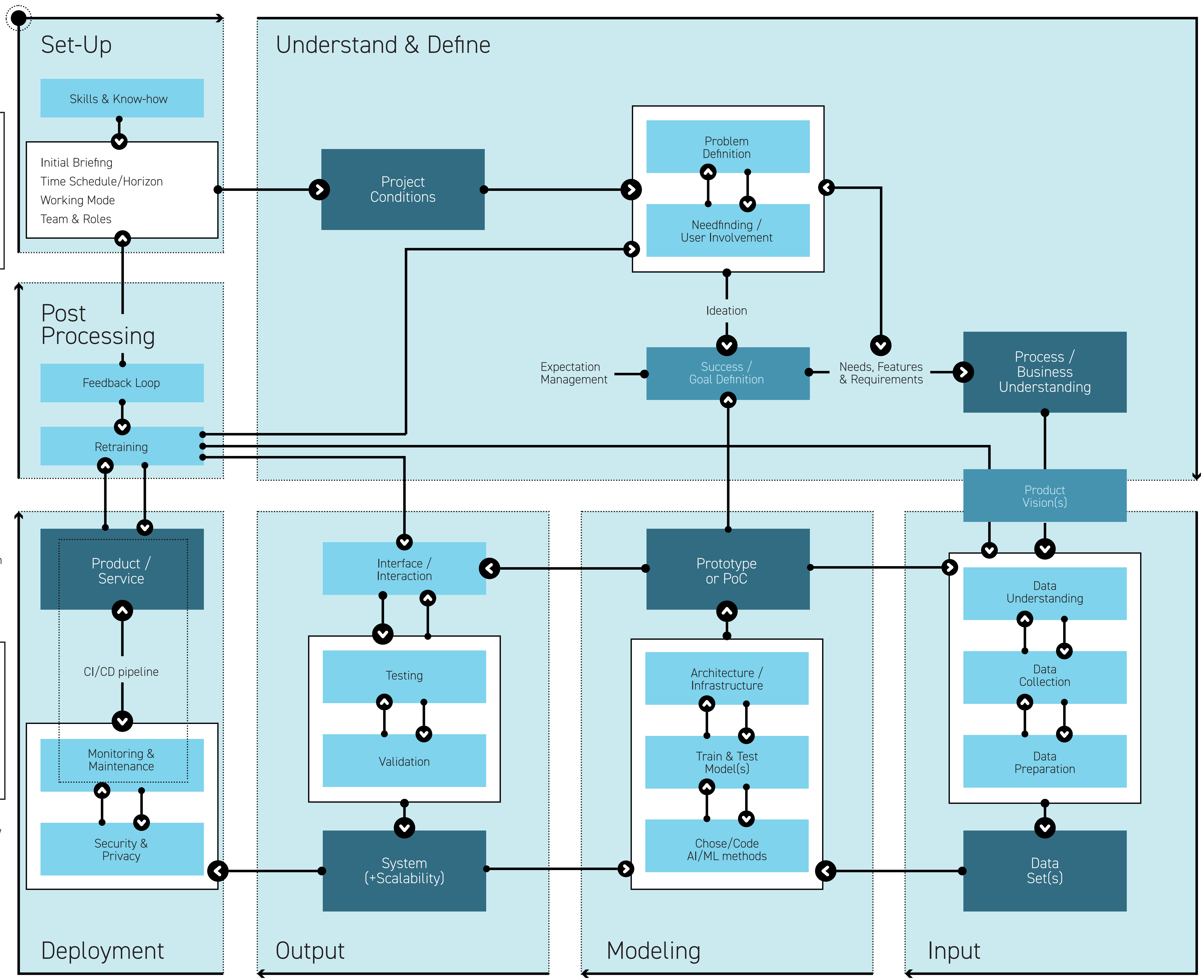


Figure 8.8: Layer 01, 02 and 03 combined in a process modules overview

- Modules
- Activities
- Relations/Dependencies
- Module Outcomes/Milestones
- Validation Item
- Ongoing activitiy



8.3.2 Detailed description of every module

Set-Up

1. Initial Briefing

This activity represents the starting-point for the project. It can be a rough idea, vision, problem, concept, PoC, MVP, data set, or finished product that needs to be redefined. Whatever it is, the initial assumption is that it can somehow be solved by an AI/ML infused solution. It is, most of the time, too early to finally judge whether or not AI/ML methods are the right path to follow. It is also very helpful to gain an initial overview of the data to roughly evaluate and estimate if the quality and amount of data meet the baseline of AI/ML data set requirements.

+ AI/ML methods (pre) selection: In order to decide team members and their related roles, an initial, very high level selection of AI/ML methods based on the initial briefing is necessary. The (1) AI card deck is a tool that can be used.

2. Time Schedule/Horizon

Agreement on the duration of the project (start and wished end point).

3. Working Mode

Research showed that a highly iterative approach is crucial and necessary for this kind of project. In this way, the team can react to unforeseen pitfalls and challenges. The Agile SCRUM method was perceived as a feasible and robust set-up, especially the related sprint logic and time boxing. It is necessary and helpful to make sure that everybody involved is familiar with this method, or a short training unit could be included.

4. Team & related Roles

Based on the briefing, timing and working mode, a choice of team members and their related roles can be made. The recommendation is to aim for diversity and should be emphasized (see ISO 9241-210:2019-07). A purely technical team might be able to do the job but fail to understand the business domain data and focus on the wrong signals and data insights. Research has also shown that a lack of human-focus has been causing pitfalls and challenges and lack of adoption and acceptance by users. Therefore, development teams should be structured with experts from each discipline to make key decisions as a single unit and not work in silos. Depending on the size and complexity of the project, the following roles should be taken into consideration: business domain expert, data scientist, ML engineer, HCD/UX designer, user(s). Other stakeholders involved: management (buy in and budget), IT department (deployment/implementation).

5. Skills & Know-how

Activities 1 to 4 have a huge impact on the necessary skills and know-how in the project team. Research showed that AI/ML expertise is a huge issue, in business, as well as on the designers' side. In order to ensure a certain level of 'AI/ML' knowledge, (2) basic AI training in the capabilities and possibilities of the technology for all team members is recommended as early as possible in the process.

Outcome: Project Conditions

If this is not clear, it is necessary to start over again. If the necessary skills and experts are not available in the company, hiring an external consultancy can be a solution, or also adding to the headcount or making the strategic decisions to get the relevant people on board.

Understand & Define

1. Problem Definition

Take the initial briefing and transform it into a problem statement. Also, try to understand if it is the right problem to solve with AI/ML.

+ Problem Statement: Translating the initial project briefing into a problem statement related to a human benefit.

+ Problem-Technology match: Using the (3) AI/ML or not checklist to see if the problem should and could be solved by an AI/ML algorithm. If the result is not to use AI/ML methods to solve the problem, this activity marks the exit point for the project.

2. Needfinding & User Involvement

Find out which stakeholders and users are relevant for understanding the current issues and for the final implementation. Research showed that industrial AI projects consist of a very complex network of involved stakeholders. Understanding their jobs that need to be done, pains and needs is crucial for making an informed decision about the way forward.

+ Involved Stakeholders & Users: It is crucial to understand and define who needs to be involved, also to understand their current procedures. (4) Stakeholder maps, workflow maps that visualize the status quo are a relevant tool in that regard.

+ Initial Research (qualitative): Understanding pains, problems and deriving needs. Typical methods used are (participant) observations, interviews, co creation workshops, (5) data user stories.

The activities 1 and 2 are strongly related and dependent on each other. They need to go hand in hand. A clear understanding and definition of problem and user engagement are the requirements for starting ideation activities and defining success and the goal. HCD/UX designers can facilitate the conversation and lead the needfinding activities. The integration of other team members is highly recommended to create a first-hand experience.

3. Ideation

Whereas ideation and scenario development are ongoing activities throughout the whole development process, an initial ideation session based on problem definition and user stories to better align and prepare the upcoming activities should be included in this module. It can be done internally with the team or as a part of the co-creation activities with stakeholders and relevant users.

4. Success / Goal Definition

Validation item: research showed that this is a crucial action item relevant to other modules as well. When not following the whole process map, but using modules individually, it is helpful to still clarify this item.

+ Define Success Criteria/Definition of Done: Research showed that this is a highly critical step and needs to be set right from the beginning. It can be adapted during the progress of the project, but not overly stretched. It is an item that serves as a validation point during the whole project. It is not easy to agree on and a balance needs to be found between business and data science focus. Related tools are e.g. (6) confusion matrix, (7) success metrics framework, F1 score, error metrics.

5. Expectation Management

Research showed that setting the right expectations is a crucial action item for AI/ML infused projects. Most of the time, expectations are wrong and too high. Implementing AI/M solutions often calls for a transformation of current processes and job routines and therefore needs to be complemented with change management activities.

- Mental Models: Firstly, understand the mental models of the stakeholders is necessary, in order to set expectations from the start, plan and prepare for co-learning the system, as well as by the user side. Machines and algorithms with human-like behavior are not the best way to go (uncanny valley) making clear that there is a difference is a huge value add on.

- Change Management: AI/ML is not the solution to all human problems. It is a tool that in the best case scenario, augments the human (IA - Intelligent Augmentation) to focus on the relevant aspects of his/her job. Due to fear and wrong expectations, it is necessary to embed transformation and change management activities in the project. Setting-up a role for this and raising awareness are possible activities to address this aspect.

6. Needs, Features & Requirements

Translating the findings from steps 1 to 5 into human needs and system requirements: (8) Analytics Use Case Canvas, (9) ML Canvas can support these activities.

Outcome: Process & Business Understanding

This section is heavily driven by human-centered activities informing the data-driven aspects. In this module, HCD/UX designers max out their expertise. It serves as a way to generate deeper understanding of business domain knowledge and user workflow. If this is not clear, it is necessary to start over again.

Product Vision(s)

Validation item: research showed that this is a crucial action item relevant to other modules as well. When not following the whole process map, but using modules individually, it is helpful to still clarify this item.

- Initial Scenario Ideation: This step is the transition from Problem to Solution Space. Before looking into the data, imagine the best case scenario(s). Map out, visually, what the product(s) or service(s) that answer the human need would look like. Create a shared understanding of the product vision, with focus on human desirability, before jumping into technical feasibility and business viability. In this activity, HCD/UX designers can contribute their imaginative potential and visualization skills. They should include the other team members in the process and encourage them to think outside technological feasibility and business viability. Related tools are journey maps, workflow maps (ideal), visual storytelling, (10) Strategy Pyramid Canvas.

Input

1. Data Insights & Understanding

Activities related to data understanding are the evaluation of the data at hand and which data is relevant to the problem and business domains. Clarify potential data sources, including data that is not easily accessible to an AI/ML algorithm, such as input from human to human conversations not necessarily being reproduced on a database and slicing data into the different iteration cycles, starting small, scaling later. The use of data visualization tools is helpful for understanding the data better, it is also helpful when communicating findings and questions to business domain experts.

- Data Sample Selection & Definition: Making sure that the initial data sample represents a variety of different cases.

- Different Data Sources: Clarifying potential sources such as databases, data lakes, and types of data, domain specific, statistical, qualitative data points from human to human interaction. The (11) Data Landscape Canvas can support this activity.

- Data Strategy: Establishing rules for access rights and data privacy settings, including new data points.

- Data Visualization: Creating visual representations of the data (line charts, box plots, etc.) as early as possible, using tools such as Tableau, Qlik Sense.

2. Data Collection

If the data needed is not already available, or additional data is needed, collecting (additional) data is necessary.

- Existing vs. collecting: Clarifying if an existing data set that suits the project needs is available. This can either be open source or behind a paywall. If existing databases are not an option, collecting data is possible. Depending on the AI/ML method the amount of data points is important. Therefore collecting data might take a lot of time and effort.

- Bias: Checking for bias in the data. (12) What if tool can assist this activity.

- Ethics: There is a lot of ongoing debate and discourse about the ethics of AI/ML solutions. It is its very own research area[246-248]. It is divided between philosophers, psychologists and the technology domain, a very delicate field and unknown, but nevertheless important field for designers. Ethical issues in AI/ML can be related to data privacy concerns, as well as discrimination against certain groups (related to bias in data), amongst others. There are some materials out there that designers and data scientists can use to handle that issue, such as (13) IDEO ethics card deck, (14) obi data ethics canvas. No final code of ethics for AI exists yet.

AI ethics: further resources:
246. IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, "Ethically Aligned Design: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems", First Edition, IEEE, 2019. Retrieved from https://ethicsinaction.ieee.org. (Accessed on 2022-11-21)
247. Institute for Ethics in Artificial Intelligence. Retrieved from https://ieai.sot.tum.de. (Accessed on 2022-11-21)
248. Machine Ethics: Association for the Advancement of Artificial Intelligence on Machine Ethics, AAAI Fall Symposium, 2005. Retrieved from https://aaai.org/Library/Symposia/Fall/fs05-06.php. (Accessed on 2022-11-21)

- Quantitative & Qualitative: Statistical data sets such as financial data (e.g. price development), telemetry data (e.g. GPS tracking), sensor data (e.g. runtime, downtime) are not implying reasons why certain data insights and correlations are discovered from data. It can be a value addition to mix quantitative data with additional information from qualitative data to detect correlations and improve data insights and data evaluation. It is also necessary and helpful to find out if all the data is available in the database that the AI/ML solution has access to. Sometimes relevant data and information is exchanged verbally between humans, knowledge about certain issues which the AI/ML algorithm cannot react to. This might lead to wrong expectations of model performance.

3. Data Preparation

Once data is understood and collected, the related data set needs to be prepared for the model's training.

- Different data types: Classifying the different data types. This activity helps to choose the AI/ML method. Generally, in ML there are two different types of data, structured and unstructured. Sensor data, weblog data, financial data, weather data and 'point-of-sale', as well as click-stream data are related to structured data. This type of data is typically stored in relational databases and has a defined length and format. Text, images, voice, videos, radar or sonar data are related to unstructured data. This type of data has some implicit structure, but it does not follow a specific format. Cloud, mobile devices and social media are typical data sources.

- Data labeling: In certain cases, labeled data is necessary (supervised learning); if the data is too domain specific, setting up a data labeling pipeline is necessary, meaning the domain experts have to take care of this activity.

- Verify quality: For data quality, a couple of factors are relevant, such as the number and amount of data points, their consistency and available history. In most cases, more data is better than little data.

+ Clean: Cleaning data, standardizing data formats such as dates, getting rid of duplicates, outliers, negative numbers, etc. is necessary. There are a couple of tools out there to support this process, such as e.g. KNIME, or easydatatransform.

+ Feature extraction/generation: The concept of feature extraction is taking an initial set of data and transforming it into a reduced set of features (feature vectors). This step is necessary when a data set is too large to be processed by an algorithm and most of the data points are perceived to be redundant (e.g. repetitive, containing the same measurements in different units). For designers working closely with data scientists or having expertise in statistical techniques (15) dimensionality reduction is a commonly used method.

Steps 1 to 3 heavily depend on and influence each other. Sometimes the borders are blurred and activities cannot be separated as stated. However, it is crucial to understand that AI/ML algorithms heavily depend on the input data and that this module is therefore very important overall. Designers can contribute with their human-centered perspective and data visualization skills, but it is also important to understand statistical data sets and be familiar with data preparation activities. The level of knowledge on the designer's side is vital for the involvement of their expertise in this module. Here the data scientist and ML engineers also work closely together to make sure that data and AI/ML method are aligned.

Outcome: Data Set(s)

This module occupies a lot of time and resources, more than 50% of AI/ML projects are data work. The better process knowledge, business domain and product vision are defined and understood, the easier it is to focus on the data necessary to answer the challenges. If something is not clear with the data at the end of this module, it is necessary to start over again.

Modeling

1. Chose & Code AI/ML method

Based on the problem statement and the data set, an AI/ML method that solves the problem can be chosen. Sometimes this is the starting point for a couple of projects where problems and data are already given, without going through the steps above first. It is possible to combine different AI/ML methods or try different approaches in order to verify the best solution for the given problem.

+ Machine (Deep) Learning types: For an overview of different AI/ML methods (16) cheat sheets can be very useful.

2. Train & Test models

The data set(s) from module 'Input' needs to be separated into training, validation and testing data to judge the AI/ML model's performance. The training data is used for model-training, as the name implies. The validation data set is used as a reference for the model's performance. The testing data is provided to a trained and validated model in order to finally test the model with a 'new' data set (see Fig. 8.9). This is very important to understand, because it means that model accuracy is always tested and compared against data from the past that is already available to the development team and that splitting the data into training, validation and test set needs to be allowed for in the amount of data points needed to actually train a model. The validation and testing data cannot be included in the training data set, depending on the division ratio (½:¼:¼) validation and testing data reduces the amount of data overall on which the model can be trained. This is why more data is better than little data.

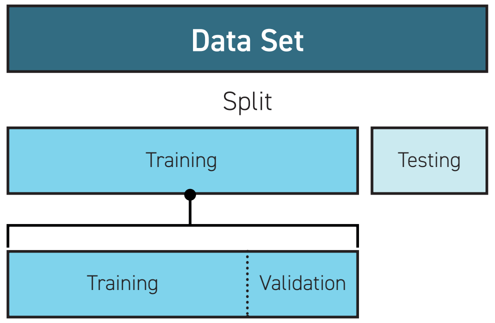


Figure 8.9: Data set split in training, validation and testing data

+ Existing tools: It is very common in AI/ML practice to use a model that has been pretrained and targeted towards the specific use case (e.g. GPT3 - Generative Pre-trained Transformer used for text generation, BERT - Bidirectional Encoder Representations from Transformers used for natural language processing, GAN - Generative Adversarial Network used for image generation, R-CNN - Region-based Convolutional Network used for object recognition). It is then used with its very own data set. The data set is separated into training data and validation data in order to judge the model's performance, as mentioned above. Most AI/ML modeling frameworks have a frontend that incorporates some visualization features in order to judge the model's accuracy and performance (heat maps e.g.). With streamlit, and shiny, it is easy to quickly prototype and share data apps. Other relevant tools and services in that regard are for coding: python, processing; autoML solutions: AWS, Azure, IBM, google teachable machine, lobe and for designers specifically: wekinator and Delft AI toolkit. The tools section is referring to existing tools (17) overview.

3. Architecture / Infrastructure

Many AI/ML models use a lot of computing power and can therefore not be trained on a private PC but depend on cloud computing. Also, when thinking about a productive system and automation of data upload, as well as other features, it is necessary to take the systems architecture and infrastructure into account. It can be helpful to integrate an IT department with this decision in advance.

+ External vs. internal solution: A decision has to be made whether to use a 3rd party solution, which might already provide a frontend, architecture and infrastructure set up, as well as maintenance and monitoring capabilities. On contrary, the flexibility of an in-house development may be the better way to go. Both solutions have their pros and cons, which need to be weighed and acted upon.

+ Cloud vs. on premise: Data privacy and security might be the main decision drivers here. Take the cost for a cloud service, compared to setting up the hardware for an on premise solution, into account.

AutoML solutions provide ML methods and tools for non-experts. These systems often support the data handling process by providing tools for data preparation and cleaning. These systems also provide pre-trained models with the possibility to adjust settings to control the output. However, the problem for non-experts is the untransparent nature of these systems, often referred to as a 'black box', and lack of knowledge about how to overcome failure or understand the error messages provided by the system.

Steps 1 to 3 heavily depend on and influence each other. Sometimes the borders are blurred and activities cannot be separated as stated. The level of knowledge on the designer's side is vital for the involvement of their expertise in this module. Coding skills would help here but are not necessary. AutoML solutions provide a framework that can also be used by designers. However, prototyping in a low fidelity and fail fast manner is hardly possible. Model behavior and performance need to be measured with real data. In this module, ML engineers maximize their expertise.

Outcome: (High fidelity) Prototype/PoC or MVP

This module is meant to prove, or in later iterations make sure, that whether or not the data input creates a meaningful model performance that the AI/ML approach is the way forward. However, a bad model performance can be for different reasons. One reason can be the wrong choice of AI/ML method, in which case, it is necessary to start over again with this module. It is also possible that the problem lies within the data input. Going through the 'Input' module is the path to follow in this case. It can also be helpful to have second thoughts on the success and goal definitions, making sure the error metric or level of accuracy are not too optimistic. If the model performance is bad, it is necessary to start over again. Or if additional iterations are not going anywhere, this marks the exit point for this project.

Output

If the 'Modeling' module successfully leads to a (high-fidelity) prototype, PoC or MVP the next module is related to the output.

1. Intelligent User Interfaces (IUI's)

To move on and for a final solution, the modeling results from the backend need to be displayed in a frontend. This can be an app, a dashboard, any other interface. Since AI/ML infused systems are based on statistics and the probability of coming up with their conclusions, their behavior implies a certain level of uncertainty. The AI/ML system might also change due to its ability to learn and adapt to the users' behavior over time. Building and maintaining trust under these circumstances is a key factor in AI/ML system behavior. A couple of activities can support the team in providing the user(s) with the information needed to judge whether or not the system's output is trustworthy. AI/ML solutions turn the concept of a static interface into smart interactive operations. (18) HAX Toolkit from Microsoft and the (19) People+AI Guidebook from Google can be a helpful set of advice for this activity.

In ML, confidence scores or levels are used to illustrate how confident the underlying algorithm is that it has derived the correct value. It is meant to provide more transparency about the model's decisions and output.

When the AI/ML system produces an error that does not make sense in the given context of the user, these are so called context errors. The systems' output is perceived as awkward or irrelevant from the user's perspective.

+ Transparency & Explainability: Making clear what the system can and cannot do, as well as articulating the data sources are necessary steps in that regard. Two directions can guide this activity, general system explanations; explaining how the AI system works in general terms (e.g. types of data used, what the system is optimizing for, and how the system was trained), and specific output explanations; explaining why the AI provided a particular output at a particular time (e.g. confidence scores (categorical, n-best classifications, numeric confidence level(s))).

+ Failure: Identifying a) user, b) system, and c) context errors. User errors occur when users use the solution in an unintended way, so trying to make failure safe, boring, and a natural part of the product. Avoiding making dangerous failures interesting, or over-explaining system vulnerabilities which can incentivize users to reproduce them. System errors occur when the system does not work or can't provide the right answer, or any answer at all, due to inherent limitations to the system. Context errors occur when user expectations and system assumptions are mismatched, e.g. an AI/ML system makes incorrect assumptions about the user (true positives or true negatives) (20) error message guidelines can support these activities.

+ Feedback: Feedback in AI is perceived as a loop of continuous learning and improvement. It should be used to improve the AI/ML system, making sure that the feedback signal being collected can actually be used to improve the model. This means that the feedback needs to present a structure that can be translated into data points that the AI/ML algorithm can benefit from. There is a difference between implicit and explicit feedback. Implicit feedback is collected while the solution is being used. It is stored in log files. Explicit feedback is actively provided by the user(s). It is therefore necessary to communicate value and time to have an impact.

+ Human-in-the-loop: The concept of the human in the loop is letting the user decide if/when to opt out. The user should be able to edit system settings (e.g. data collection) and take over control. This is strongly related to the Human-Centered-Design approach (controllability).

+ non-visual UI's: The actions above are helpful and necessary for AI/ML systems that have a user interface. Sometimes the AI/ML system just generates a numerical output that is directly fed into a database. Even so, feedback from the user is necessary and the team needs to find a way to collect it. Gaining trust is a very tough task here since it is hardly possible to incorporate transparency and explainability features to the user(s). Most probably, use over time and an accurate AI/ML output will establish trust amongst the user(s). Marketing and communication activities can support this process.

+ Interaction: Intelligent AI/ML based systems also modify the digital interface through which users interact with digital systems. The input can be based on natural language, gesture, mimic or visual representations such as pictures and video. Effective, intuitive and natural interaction enhancing the user experience needs to be established. interactive Machine Learning (iML) is an area of research that tries to offer a solution to this challenge. As an example, IBM offers (21) AI conversation guidelines.

2. Testing

+ Detect & check for outliers and errors: Mislabeled or misclassified results, poor inference or incorrect choice of ML model and related settings, missing or incomplete data can be reasons for a poor systems performance. It is therefore necessary to check the output quality for relevance errors and disambiguate systems hierarchy errors.

+ Usability testing: Only a small number of users will interact with the system as initially planned by the development team. Investing in beta-testing and conducting pilot programs is necessary to spot unintended system dead ends and negative user experiences. User testing, observation, A/B testing, are typical actions that are used within this area.

3. Validation

+ Check success criteria: Monitoring accuracy and performance over time and with different use cases and users to have more chance of uncovering issues with the system.

+ Check expectations: Evaluating if the expectations that were set at the beginning are still valid or need to be adjusted.

This module implies a lot of actions that are related to HCD/UX design tasks. Close collaboration with data scientists and ML engineers to predict system behavior and potential functionality on a positive, as well as a negative spectrum need to be taken account of and made visible and reasonable for the user(s). The turn from static interfaces to smart and dynamic interactions represents a new design material. Potential outcomes and outputs are too complex to be planned in very detail. Failure and malfunction are inevitable and need to be incorporated as a design feature.

Outcome: System (+ Scalability)

'Input', 'Modeling' and 'Output' modules are strongly interdependent and a couple of iterations will be needed to reach the status of an AI/ML system that is accurate, usable and time and cost efficient (combining business viability, technological feasibility and user desirability).

If the AI/ML system is very error prone and transparency and explainability are hard to achieve, it is necessary to start over with the 'Modeling' module, which might guide the team back to the 'Input' module. If test results show a bad user experience, it is necessary to start over with the 'Output' module and redesign the interface/interaction.

If the outcome of this module results in an AI/ML solution which produces stable and accurate output, on small, as well as larger data sets, and the user interface supports its user in reaching his/her goal and trust in the systems output and the business domain experts perceive it as a value addition, either from a time or cost efficient perspective, the transfer from a PoC to a productive system can be made. Scalability refers to the notion that an implemented system, in a best case scenario, could be transferred to similar use cases or other business units and problems as well.

Deployment

For the final deployment, the following need to be handled: Decisions such as the architecture and infrastructure from the 'Modeling' module play an important aspect, as well as the connection to the data sources from the 'Input' module. A lot of the data handling, such as preprocessing and cleaning, or running the AI/ML model on that data have been performed manually until this module. For a productive system, those tasks need to be automated, taking data security and privacy into account, as well as managing access rights and ongoing activities such as monitoring and maintenance (DevOps). A lot of this module's activities are hard coded software development, often the responsibility of an IT department.

1. Security & Privacy

+ Access authorization: (Industrial) AI/ML applications often deal with sensitive data. Different users might have access to different information and features. This needs to be set-up before the system can finallybe installed.

2. Monitoring & Maintenance

+ Responsibilities: System performance and settings need to be monitored, system failures, data input, bug detections maintained. This is an ongoing process (MLOps). Responsibilities need to be agreed on and respective roles assigned.

3. CI/CD pipeline

An integrated CI/CD pipeline is the link to make sure that the ongoing processes are aligned and managed.

Outcome: Product/Service (productive)

This module turns the output from the former modules into a productive environment. This is a rather low area of activity for HCD/UX design. An IT department or related roles might take over from here. Best case scenario is to integrate them as early on in the development as possible.

Post Processing

There are tasks such as the retraining of the models and incorporating new data points from feedback in excess of regular monitoring and maintenance (CI/CD) activities. Strategies and concepts on how to deal with these items is helpful and partly the responsibility of the development team.

1. Retraining

+ Strategy & Concept: During its use, product or service accuracy and performance levels might drop. Retraining might be useful. Adding additional data points might also be cause for a retraining. Setting-up who is responsible or enabled to do so needs to be established.

2. Feedback Loop

+ Strategy & Concept: Developing a strategy and a concept to integrate the information from the user feedback into the AI/ML system was already part of the 'Output' module. However, in the productive environment, this needs to be implemented and even automated on a specified basis, making sure that the amount of collected data points is enough to increase the model performance.

(potential) Outcome: new project

Those strategic decisions can be supported by the HCD/UX as well as data science and ML engineers together with the business domain expert and the IT department. The final implementation of these strategies and concepts might be done by the IT department. This module might result in a completely new project, when over time, the product or service shows that a new problem

has occurred, or developing a new solution would be beneficial for the user and the business. Also, new data points might make it necessary to go back to the 'Input' module, or a new AI/ML method might support going back to the 'Modeling' module.

8.3.3 Different module compositions, equals different project patterns

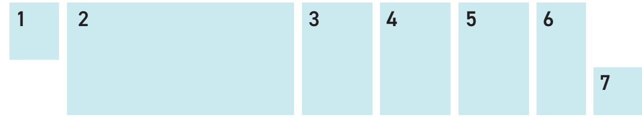
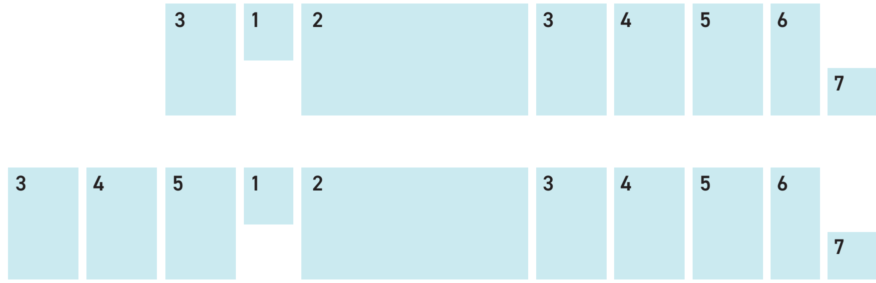


Figure 8.10: Project pattern for an 'optimal' run from module 1 till 7

This pattern presents a project where the team started with module 'Set-Up' and ran through all the modules till the 'Post Processing' module as stated in the overview. Diverse teams which include all the recommended roles and who have a lot of experience with ML projects and a very clear handling of the module outcomes might be able to proceed like this.



Figures 8.11: Project pattern for initial exploratory data or PoC/Prototyping[249] phase before project set-up

This scenario is very common for ML infused projects. In order to judge whether or not a model's performance is suitable for the problem at hand, it is usually necessary to train and test the model on a concrete, but small data sample set which has been cleaned and prepared in advance. This takes some time, resources and effort, but on the other hand, is often a necessary validation item before a porper project set-up is made.

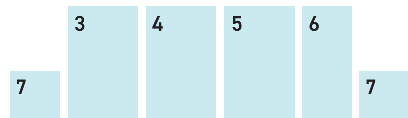


Figure 8.12: Project pattern where 'Post Processing' module creates completely new input and modeling needs

Another possible module combination can be derived from the outcome of the 'Post Processing' module. If the collected feedback from users creates completely new data points, or if a new feature is requested and retraining a model is not enough, it is possible to set-up a mini project that runs through modules 3 till 5 and is added to the already deployed system. Design expertise involvement might be rather low in that project pattern.

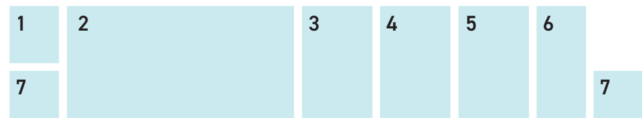


Figure 8.13: Project pattern where 'Post Processing' module results in completely new project

These new data points or feature requests might also result in setting-up a completely new project.

249. As stated before, low fidelity, 'quick and dirty' prototyping possibilities for designers, as well as for data scientists and ML engineers are rarely available, as AI/ML algorithms depend on data and user interaction, neither are static, they are dynamic. More concrete a) for this type of generated content, the AI/ML system needs to incorporate pretrained results. Training the model with user testing input would lead to latency in response making the system behavior unacceptable and useless for the user, b) in order to evaluate a system's performance, the model needs to be trained on actual data that represents a broad range of data points. Training on dummy data or a subset of data could result in misleading model performance and results, c) the architecture that is needed to run a model that generates dynamic content is very difficult to prototype as a low-fidelity solution.

8.4 Overview Toolkits and Additional Resources

The most detailed layer of this solution provides concrete prompts and tools for designers in each AI and design process module. As found during the research for the State of the Art chapter, some proposed steps, guidelines, tools exist that should be integrated into the process modules. The chosen tools are presented and analyzed in the following paragraph, not a complete list but provides a great supplement to the process modules and represents different focus areas. These tools are either 'new' or known but adapted to the AI/ML domain, making their integration an important step towards the enablement of designers in the age of AI. They come from the fields of design, data (science) and business.

Module 'Set-Up'

AI/ML methods (pre) selection: (1) AI card deck
The card deck can be used for ideation to prompt creative idea generation based on AI capabilities to explore opportunities for AI within the given context. It can be used for initial brainstorming sessions and communication between design, data science and business personnel to get to know basic ML concepts and methods, to spark critical discussions around possible solutions.

The cards represent 6 categories, each including 4 'what-if' statement cards that further elaborate on the category, in total the deck contains 24 cards (see Fig. 8.14, p.115). Further information on how to organize brainstorming and ideation sessions with these cards can be found online[250].

250. Toolkit: aimeets.design. Retrieved from http://aimeets.design/toolkit. (Accessed on 2022-11-21)

Skills & Know-how: (2) Basic AI/ML training/knowledge

Research showed that a basic knowledge of AI capabilities is missing among design and business experts but is very valuable for collaboration during AI development. There is no particular one that fits all the basic AI/ML training needs available. Designers, data scientists and business users have different focal points and the area of AI and ML is so broad it is difficult to provide this knowledge in one training or course, neither is it the intention of this thesis to provide a comprehensive solution; this would be another research endeavor. However, it is able to provide the initial resources to get started with.

Basic concepts and definition of AI, ML and DL can be found in Part I. Foundations, Chapter 1.3. For further information, see the map of resources, names of relevant actors and their related work, institutions and artifacts in Part II. Framing, Chapter 3.2.4 is a valuable addition. As well as section (17) overview of existing tools posterior to this paragraph.

There are also online courses that support non-experts to gain a basic understanding and knowledge about the basic concepts of AI and related skills:
Andrew Ng - AI for Everyone[251]
Gene Kogan - ML4Art[252]

251. AI for Everyone. Retrieved from https://deeplearning.ai/program/ai-for-everyone. (Accessed on 2022-11-21)
252. ML4Art. Retrieved from https://ml4a.github.io. (Accessed on 2022-11-21)

Coding resources that are relevant in that regard can be found online as well:
Python for Designers[253]
Coding with Processing[254]

253. Python for Designers. Retrieved from https://pythonfordesigners.com. (Accessed on 2022-11-21)
254. Processing. Retrieved from https://processing.org. (Accessed on 2022-11-21)

Module 'Understand & Define'

Problem-Technology match: (3) AI or not AI checklist[255]
This activity is intended to make a case for or against AI/ML as a solution, based on the insights from user research (the checklist can be found in the Appendix). Depending on the result of the checklist, final statements following this framework can be phrased:

255. People+AI Guidebook: User needs and defining success. Retrieved from https://pair.withgoogle.com/chapter/user-needs. (Accessed on 2022-11-21)

AI [can/cannot] help to solve.............................. [user need],
because..!

Involved Stakeholders & Users: (4) Stakeholder Analysis Canvas[256]

Identifying all the relevant people (and their different related roles) who have a stake in the solution of the project. Firstly, who are those people, secondly, what is their role or function (they can have more than one), and lastly, who to talk to in order to better understand the domain, problem and how to convince them to buy, use, or pay for the solution (the canvas can be found in the Appendix).

256. Datentreiber: Stakeholder Analysis Canvas. Retrieved from https://datentreiber.de/en/method/stakeholder-analysis-canvas. (Accessed on 2022-11-21)

Initial Research (qualitative): (5) Data User Stories

System requirements, based on user research, and requirements elicited through agile software development projects are commonly captured in 'user stories' (a user can also be a stakeholder or a member of the development team). The typical user story is represented by the phrase:

As a .... [persona],
I want to .... [task],
so that .... [goal]!

In ML projects, data plays an important role. Current user stories ignore the available data sources and do not refer to the related data and systems' outcome or additional requirements like adding information about available input (data) which can be data points accessible via a database, but sometimes, even information or knowledge is only available from human-to-human conversations or exchanges, which in that case is, not accessible to ML algorithms. The specific output (data) related to task and goal achievement is a proposed additional item in AI-infused user stories.

As a .... [persona],
by/with .... [expected input (data)],
I want to ....[task],
as a result .... [desired output (data)],
so that .... [goal]!

Define Success Criteria/Definition of Done: (6) Confusion Matrix Canvas[257]

A confusion matrix illustrates the two kinds of correct model behavior - true positives and true negatives - and two kinds of errors - false positives and false negatives - any AI model can make. Mapping any possible results from the AI model supports the team in weighing the cost of false positives and false negatives, which is a critical decision for any AI-infused project. Considering precision versus recall trade-offs in the model's performance is a necessary task, with this limitation of potentially negative outcomes. Taking into consideration the domain and context of the system, errors in medical support systems are more dangerous than in a movie recommender system, so that background information needs to be taken into consideration (the canvas can be found in the Appendix).

257.Intelligence Augmentation Design Toolkit. Retrieved from https://futurice.com/ia-design-kit. (Accessed on 2022-11-21)

Define Success Criteria/'Definition of Done': (7) Success Metrics Framework[258]

It is crucial that everybody on the team is agreed on how success and failure are defined and how they can be evaluated. Defining success criteria and how to measure them is crucial. The success metrics framework supports the team in an agreed success definition for both as well as a metrics to measure failure, with the relevant steps necessary to solve those concerns.

258. People+AI Guidebook: User needs and defining success. Retrieved from https://pair.withgoogle.com/chapter/user-needs. (Accessed on 2022-11-21)

If .... [specific success metric],
for .... [AI feature],
drops below/goes above ....[meaningful threshold],
we will ....[take a specific action]!

Needs & Requirements: (8) Analytics Use Case Canvas[259]

The 'Analytics Use Case Canvas' illustrates the pain points of users and customers. It also conceptualizes data and analytic solutions with their related value additions. The canvas can be used to better understand the users and

259. Datentreiber: Analytics Use Case Canvas. Retrieved from https://datentreiber.de/en/method/analytics-use-case-canvas. (Accessed on 2022-11-21)

to critically reflect on concepts and ideas about the problem solution fit (the canvas can be found in the Appendix).

260. Machine Learning Canvas. Retrieved from https://ownml.co/machine-learning-canvas. (Accessed on 2022-11-21)

Needs & Requirements: (9) ML Canvas[260]

The 'ML Canvas' helps to refine ideas and describe how the ML system will turn predictions into value for end-users, data the system will learn from, and how to make sure it will work as intended. The 'ML Canvas' also allows costs to be anticipated, bottlenecks identified, requirements specified, and a road map created of the necessary steps for the final implementation of the system (the canvas can be found in the Appendix).

261. Datentreiber: Strategy Pyramid Canvas. Retrieved from https://datentreiber.de/en/method/strategy-pyramid-canvas. (Accessed on 2022-11-21)

Product Vision(s): (10) Strategy Pyramid Canvas[261]

Develop a common product vision and mission in collaboration with all team members to define the objectives together. This helps find the right objectives and path for your project. It is a collaboration tool that makes concrete and visualizes the essential parts of the AI system, based on the human perspective (the canvas can be found in the Appendix).

Module 'Input'

262. Datentreiber: Data Landscape Canvas. Retrieved from https://datentreiber.de/en/method/data-landscape-canvas. (Accessed on 2022-11-21)

Different Data Sources: (11) Data Landscape Canvas[262]

The 'Data Landscape Canvas' supports the exploration of data sources and discovery of potential data suppliers. It helps to assess the data at hand and to identify the appropriate data sources for the project. It sheds light on the data supply by classifying data sources according to their origins, as well as differentiating between different kinds of data (the canvas can be found in the Appendix).

263. What-If Tool. Retrieved from https://pair-code.github.io/what-if-tool. (Accessed on 2022-11-21)

Bias in data: (12) What if tool[263]

ML models depend on data therefore the quality of the data is crucial for a responsible system output. Bias in data such as discrimination of certain ethnic groups, or gender bias or skin tone preferences in those systems is a huge issue. The 'WIT' developed by Google, visualizes model behavior across a range of data inputs. Testing the performance of different models and different subsets of data input is possible, using different preset ML fairness metrics. This is a tool from the data scientist's toolkit. Coding skills are necessary.

264. AI & Ethics: Collaborative Activities for Designers. Retrieved from https://ideo.com/post/ai-ethics-collaborative-activities-for-designers. (Accessed on 2022-11-21)

Ethics: (13) IDEO ethics card deck[264]

IDEO's 'AI Ethics Cards' were created as a collaborative design research effort of business and data science experts. It is a tool to help guide such practitioners to develop ethically responsible, culturally considerate, and humanely based data-driven, smart systems. It was developed by talking to experts, practitioners in the field and citizens around the globe to better understand the relevant concerns and issues which needed to be reflected in an ethical card deck.

The deck is made up of four core design principles and ten activities, all meant for use by teams working on the development of new, data-driven, smart products and services (see Fig. 8.15, p.115).

265. Data Ethics Canvas. Retrieved from https://theodi.org/article/the-data-ethics-canvas-2021. (Accessed on 2022-11-21)

Ethics: (14) odi data ethics canvas[265]

The odi (Open Data Institute) 'Data Ethics Canvas' is a tool to identify and manage ethical issues. It is meant for any practitioner who collects, shares or uses data and provides a framework that suits any context and project scope. It is meant to be used at the start, as well as throughout the project, posing important questions about the use of data and the related consequences (the canvas can be found in the Appendix).

266. Featuretools. Retrieved from https://featuretools.alteryx.com/en/stable. (Accessed on 2022-11-21)

Feature extraction/generation: (15) Featuretools[266]

Featuretools is a framework to perform automated feature engineering. It excels at transforming temporal and relational datasets into feature matrices for Machine Learning. It is useful for handling a huge amount of data. This is a tool from the data scientist's toolkit. Coding skills are necessary.

Module 'Modeling'

Machine (Deep) Learning types: (16) cheat sheet

Several different algorithms and ML methods are available. Cheat sheets provide an overview of the different approaches and possible concepts to make an informed decision with algorithms to choose from. It is based on the problem which needs to be solved (task-driven: regression/classification, data driven: clustering/dimensionality reduction, context driven: autonomous robotics), as well as on accuracy and performance.

Existing tools: (17) Overview

The most commonly used programming languages in data science/ML engineering are python[267], C/C++ [268], and R[269]. Python is currently the most popular. It is a so-called 'high-level' programming language meaning that the commands used are closer to natural language and represent many abstractions compared to a 'low-level' programming language. It is easier to learn, because the commands are readable and understandable using words and phrases from natural language rather than computer jargon.

267. Python. Retrieved from https://python.org. (Accessed on 2022-11-21)
268. C++.Retrieved from https://cplusplus.com. (Accessed on 2022-11-21)
269. R. Retrieved from https://r-project.org. (Accessed on 2022-11-21)

A lot of the currently available ML frameworks are open source. A very well-known general purpose Machine Learning framework is scikit learn[270]. It provides a variety of source code and libraries for different ML concepts, from linear models, decision trees, naive bayes, support vector machines and neural networks, to mention just a few. It is based on python. For practitioners looking for Deep Learning frameworks Pytorch[271] and TensorFlow[272] are currently state of the art. Also Matlab, Keras, Caffe (2), should be mentioned here.

270. Scikit Learn. Retrieved from https://scikit-learn.org. (Accessed on 2022-11-21)
271. Pytorch. Retrieved from https://pytorch.org. (Accessed on 2022-11-21)
272. Tensorflow. Retrieved from https://tensorflow.org/resources/models-datasets. (Accessed on 2022-11-21)

Streamlit[273] offers python developers the possibility of creating browser-based high fidelity frontend prototypes. Shiny[274] is a very similar solution based on the programming language R.

273. Streamlit. Retrieved from https://streamlit.io. (Accessed on 2022-11-21)
274. R-Shiny. Retrieved from https://shiny.rstudio.com. (Accessed on 2022-11-21)

AutoML solutions offer a hybrid approach. Those platforms support low-code solutions with minimal effort and Machine Learning expertise. These systems provide a lot of presets and pretrained customizable Machine Learning models as well as (server/cloud) infrastructure, making it also possible to deploy ML models to a productive system. Some knowledge of statistics, data science and programming skills is helpful to tap the full potential of these systems. Using them implies costs, mostly based on a pay per use business model. AWS from amazon[275] actually also provides an open source solution[276], Microsoft Azure[277], IBM Watson Studio[278] and Google cloud[279] representing the cloud native companies being active in that area of AI/ML.

275. Amazon SageMaker: Machine Learning. Retrieved from https://aws.amazon.com/sagemaker. (Accessed on 2022-11-21)
276. AutoGluon. Retrieved from https://auto.gluon.ai/stable/index.html. (Accessed on 2022-11-21)
277. Azure Automated Machine Learning. Retrieved from https://azure.microsoft.com/en-gb/services/machine-learning/automated-ml. (Accessed on 2022-11-21)
278. IBM Watson Studio: IBM auto AI. Retrieved from https://ibm.com/de-de/cloud/watson-studio/autoai. (Accessed on 2022-11-21)
279. Google Cloud: Auto ML Custom Machine Learning Models.Retrieved from https://cloud.google.com/automl?hl=en. (Accessed on 2022-11-21)

There are also a couple of smaller no code autoML solutions available. They are a great resource to start with and understand ML in practice. They are mostly specialized in one type of application such as image recognition or natural language processing. They are free of charge. The choice of model or setting model parameters is very limited. Examples are teachable machine[280] and lobe[281].

280. Teachable Machine. Retrieved from https://teachablemachine.withgoogle.com. (Accessed on 2022-11-21)
281. Lobe. Retrieved from https://lobe.ai. (Accessed on 2022-11-21)

There are also some existing programming languages and frameworks for designers. Processing[245] is a coding language within the context of visual arts. Using a python mode for processing is currently under development[282]. The Wekinator[283] is an ML based system that allows artists, musicians and designers to build interactive systems and interfaces based on mappings of human actions and computer responses, such as gesture controllers, computer vision and listening systems, instruments and more. It implies some basic coding skills and technological know-how. The Delft AI Toolkit[284] enables quick hardware prototyping, experimentation and iteration of AI interactions with powerful nodes that support behavioral sequences, sensing, decision-making,

282. Python Mode for Processing. Retrieved from https://py.processing.org. (Accessed on 2022-11-21)
283. Wekinator: Software for real-time, interactive machine learning. Retrieved from http://wekinator.org. (Accessed on 2022-11-21)
284. Delft AI Toolkit. Retrieved from https://github.com/pvanallen/delft-ai-toolkit. (Accessed on 2022-11-21)

state management, and the simple invocation of AI techniques such as speech to text, text to speech, and visual object recognition. RunwayML[285] was, formerly, a kind of app store for Machine Learning models. However, the company decided to focus on video editing.

285. Runway ML: AI magic tools. Retrieved from https://app.runwayml.com/ai-tools. (Accessed on 2022-11-21)

Module 'Output'

Intelligent User Interfaces (IUI's): (18) Guidelines for Human-AI Interaction[286]

The guidelines from Microsoft recommend best practices for how AI systems should perform interaction with the users. They are intended to evaluate existing ideas, brainstorm new ones, and collaborate with the multiple disciplines involved in creating AI interfaces and interactions.

The card deck contains four categories - upon initial interaction, during regular interaction, when they're inevitably wrong, and over time - which are related to 18 cards with prompts and examples (see Fig. 8.16).

286. HAX Toolkit. Retrieved from https://microsoft.com/en-us/haxtoolkit. (Accessed on 2022-11-21)

Intelligent User Interfaces (IUI's): (19) People+AI Guidebook[287]

The guidebook from Google represents a very useful source of knowledge. It features a set of methods, best practices and examples for designing with AI. Their input is based on data and insights from internal projects, industry experts, and academic research. Their web-page also contains additional resources, such as case studies and design patterns. Their resources are updated on a regular basis, showing that they still improve and work on the input for Human-Centered-AI.

The guidebook contains six deep dive chapters. Workshop material to use the guidebook in action is also provided.

287. People+AI Guidebook. Retrieved from https://pair.withgoogle.com/guidebook. (Accessed on 2022-11-21)

Failure: (20) error message guidelines[288]

Good error messages should be polite, precise, constructive, clearly visible, reduce the work required to fix the problem, and educate users along the way. A more detailed description of each aspect is provided by Jakob Nielsen from the Nielsen Norman group.

288. Nielsen, Jakob, "Error Message Guidelines", 2001. Retrieved from https://nngroup.com/articles/error-message-guidelines. (Accessed on 2022-11-21)

Interaction: (21) conversational user interfaces

Natural language processing capabilities and voice interfaces require the design for those emerging interactions. The goal is to create a human-like conversation with attributes such as empathy, curiosity, humor, compassion, and patience, but still maintain the transparency of talking to a machine-based system. IBM[289] provides advice on how to craft meaningful and effective conversations.

289. IBM: Conversation overview. Retrieved from https://ibm.com/design/ai/conversation. (Accessed on 2022-11-21)

Figure 8.14: (1) AI card deck categories

Figure 8.15: Selection from (13) IDEO ethics card deck

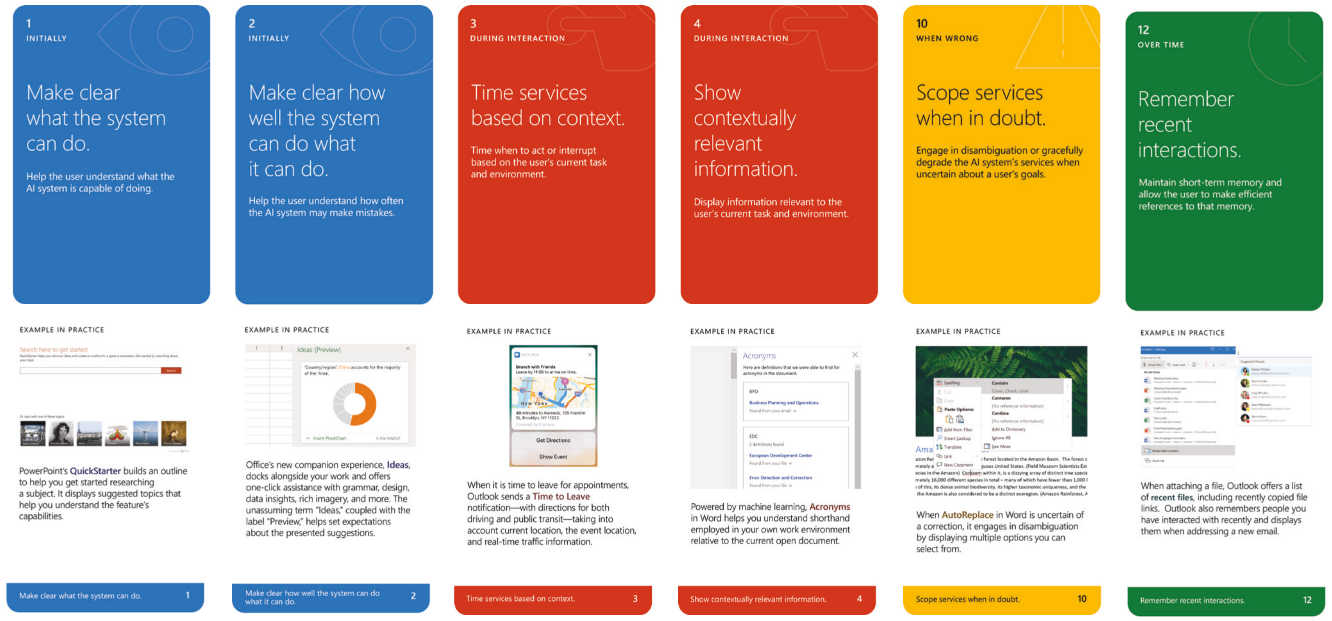


Figure 8.16: Selection from (18) guidelines for Human-AI Interaction

8.5 Testing Case Study Quantified Trees

This section concerns the mapping of the (prototypical) process modules to the project development of an actual case study, to gather feedback regarding the validity of the process modules from practitioners outside the industrial domain, test the modules derived from case study research based in the industrial AI domain on a project from the public sector currently being developed and to validate if the proposed solution is transferable to other areas outside the industrial AI domain. Two online sessions of expert interviews with four out of the ten team members were conducted, of which two have the technology expertise (E6 - IA & AI Expert and E7 - Intelligence Architect) and the other two, the project planning and HCD/UX expertise (E8 - Project Manager and E9 - UX/UI and HCD/HCI expert). Additional material such as project artifacts from workshop results and wireframes have been provided and complement the project description below.

8.5.1 Detailed project description related to the process modules

Qtrees[290] - Intelligent irrigation prediction for city trees

290. Quantified Trees: Intelligent irrigation prediction for city trees. Retrieved from https://qtrees.ai/en. (Accessed on 2022-11-21)

A project based in the public sector sponsored by the Federal Ministry for the Environment, Nature Conversation, Nuclear Safety and Consumer Protection (BMUV)

Testing module 'Set-Up'

Initial Briefing: Use AI for predicting water supply for city trees in Berlin Mitte

E6: *„What drove us? The fact that the current climate changes are causing problems for the trees, especially in cities and very specifically, in the city of Berlin. They are watered by the SGA-Mitte Berlin (Roads and Parks Department), quite heuristically, on average that's 200-300 L of water per tree. We thought, couldn't we do this more efficiently with AI, i.e. less water for a tree that is in the shade compared to a tree that is exposed to a lot of sunlight? The tree then only needs 50 L, so we can save 150 L or use it to water the trees that have an increased water demand."*

Time Schedule: October 1, 2021 to September 30, 2023 (24 calendar months), the project is still ongoing.

E7: *"Two years are the right amount of time to really properly run through all the modules, including deployment and retraining. To understand AI projects also as IT projects that need CIO attention. I wouldn't even start planning for less than a year. Otherwise it will always stay a PoC that in the end, generates no added value for the company."*

Working mode: Circular approach, highly iterative

E7: *"However, very specific work packages and milestones had to be defined in advance for the funding application, very waterfall-like. Such a project cannot be run in that kind of way, but for planning purposes, it makes kind of sense."*

Team & Roles:

I. SGA-Mitte Berlin (Roads and Parks Department): The SGA-Mitte Berlin (Roads and Parks Department) supports the project as a cooperation partner. Due to the responsibilities of the Roads and Green Spaces Office and as part of the Berlin administration, the SGA is the domain expert in water management, irrigation and green spaces.

II. Technologiestiftung Berlin[291]: The team at the Technologiestiftung Berlin has proven expertise in the implementation of participatory digital projects and draws on a network of science, business, administration and civil society that has grown over many years. They lead the project and method using methods and tools from service design and UX, have a strong expertise in frontend, and open data applications.

291. Technologiestiftung Berlin. Retrieved from https://technologiestiftung-berlin.de/en. (Accessed on 2022-11-21)

III. Birds on Mars[292]: The 'Birds' bring a wealth of experience in the latest Machine Learning processes, data science methodologies and IT infrastructures to the network. They complement the technology foundation with many years of experience in the practical implementation of digital innovation projects with focused expertise on technology and backend.

292. Birds on Mars. Retrieved from https://birdsonmars.com. (Accessed on 2022-11-21)

Using approaches from service design, Design Thinking, co-creation and Scrum methods was the common thread combining all the roles and people.

Testing module 'Understand & Define'

Problem Definition: The initial idea was to provide all the information deriving from the gathered data to citizens, as well as SGA-Mitte Berlin, with responsibilities combined in one big platform, for both target users to take action, which then changed to the development of a data lake combining the given data and the newly generated data from actual use and deriving different data driven apps from this input - expert platform and citizen app.

E7: *"Our scope shifted over the progress of the project due to a 'clash with reality' aka the needfinding activities. I would even postulate the hypothesis and claim that projects that are really great projects end up with something completely different from what was assumed at the beginning. This is due to the fact that the world is so complex, and you can't think about everything that is crucial and necessary and what is really needed with a top down approach right from the beginning."*

This statement confirmed the strong dependence on 'Problem Definition' and 'Needfinding' activities and their importance for the orientation and focus of the whole project.

Needfinding / User Involvement: Interviews and co-creation workshop activities with experts, citizens and SGA-Mitte Berlin, as well as other government representatives were conducted. Also actual field studies to check and place additional sensors was part of this activity.

Expert workshop

E8: *"Within the scope of the work package 'requirements analysis', we talked to some tree experts and held a first expert workshop on January 25, 2022. The aim of the workshop was to delve into the topic of 'watering urban trees' and to understand which parameters can be used to calculate the watering needs of trees."*

The expert workshop revealed a better understanding of the domain knowledge, the challenges for the trees and with this, for their caregivers, more data insights as well as ideas about already used mathematical models and methods. Those findings were used to support the needs and requirements analysis activities.

Besides actively watering the trees, the trees would also benefit from additional actions, namely more space for the trees and their roots, implying less soil sealing. On top, watering sacks can improve the situation for younger and older trees, as well as using gravel to cover the tree grates.

The workshop also revealed the relevant data types and parameters for the assessment of the state of the trees, namely weather data, such as precipitation and temperature, soil type, as well as tree type. These are the basic data types required to develop a ML based predictive model to improve the irrigation of the trees in Berlin Mitte (see Fig. 8.17). While the weather data is easy to obtain, information about the type of soil is difficult to gather, because many different soil substrates can be found such as sand to clay and construction areas and trash can negatively influence the soil structure. But that information is very important since it helps to calculate root space, oxygen and with this the availability of water for each tree. The data on the type of the tree, such as age and height are available via Berlin's Green Areas Information System (GRIS) and can be downloaded via the FIS-Broker portal.

Regarding the methods and calculation models that are already used, it became clear that this varies from simple rules of thumb to complex formulae which can be included in the ML models.

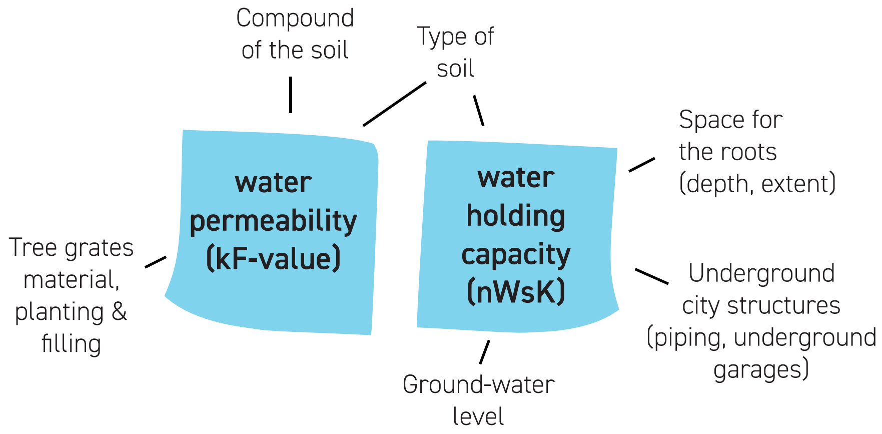


Figure 8.17: Parameters that influence the watering needs for city trees as derived from expert workshop

Citizen Workshop

E9: *"On May 16, 2022 we organized a workshop with motivated citizens which was designed and organized as a hybrid event, the workshop aimed to get to know the needs and wishes of the watering-communities."*

Besides the citizens being generally very eager to water the trees, they also said that they have a general interest in understanding more details about the trees, such as what kind of factors are relevant for knowing when and how much water a tree needs (see Fig. 8.18).

Based on this need, it became clear that providing the citizens with more facts and figures about the trees and their needs would be an added value for them. They wanted to better understand why a tree needs water and what kind of other factors influence the well-being of a tree. In the workshop, they mentioned that the information about tree type and with this, its water needs, as well as soil type and the related water storage capacity would be good to know. Another aspect that was mentioned as one of the challenges from the citizens was the integration of tree watering into the daily routine. Providing them with timing and scheduling possibilities would support them in taking care of the trees. They also mentioned that the possibility of seeing and knowing that a tree had already been taken care of by another citizen in the neighborhood would be very valuable information. Similarly, networking with peers in the area to share resources and experience was identified as a need.

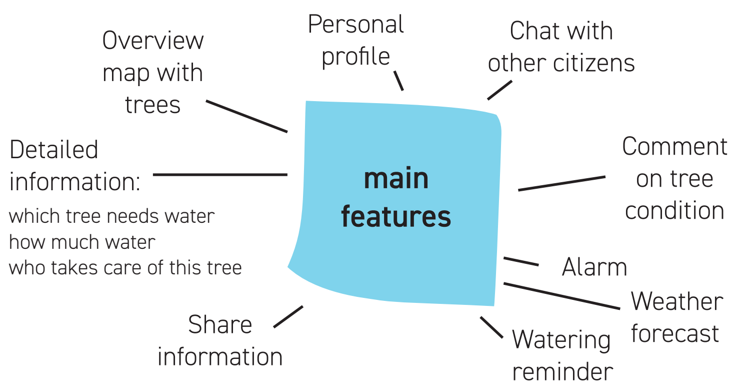


Figure 8.18: Features of the solution as derived from the citizen workshop

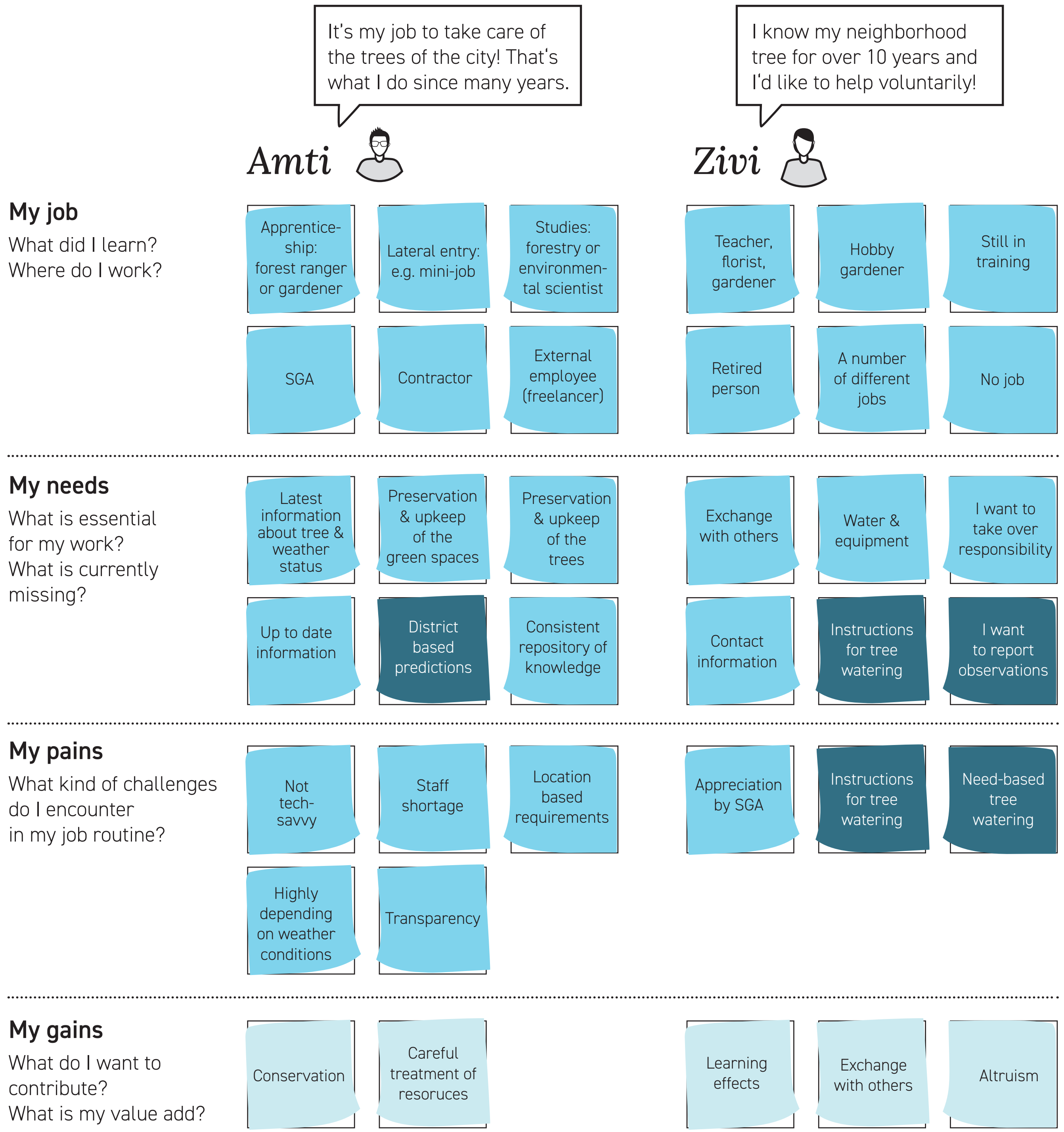


Figure 8.19: Derived profiles with details, pains and gains from expert, as well as citizen workshops

Success / Goal Definition: One success criteria was defined as, if the solution is used by SAG-Mitte Berlin, citizens and other users. Another was if the solution helps to save water or improve the distribution of the water supply (not with any specific values).

E7: *"We want this information and solution to be used. What is the point of a highly sophisticated ML model if no one uses the output in the end?"*

Expectation Management: SGA-Mitte rather underestimated ML capabilities. They were not aware that ML could support them in their job. This is also having a negative effect on the trust in the system because they did not believe initially that ML would create usable information.

E7: *"We present project progress on a regular basis in order to establish trust in the algorithmic outcome. If the SAG-Mitte employees see that we can really provide the information about the shading of the trees they are already seeing the value add-on of the technology."*

Needs & Requirements: The initial activities of the 'Understand & Define' module revealed that the project should keep the focus on watering the trees. There are also other important factors such as tree cutting and pest control, but that is outside the project scope since the amount of data that would be needed to take care of all the issues is overwhelming and difficult to obtain.

The current watering activities are based on generalizations from sensor data derived from one tree transferred to a larger number of trees. SGA-Mitte Berlin employee: *"I don't need a forecast. We have the sensor data. I take that and then calculate in my head what the other trees in the area need."* An ML based solution would, with the help of data, provide customized tree information.

E7: *"Ideally, each tree would have a physical sensor integrated into the soil. But that's not the case, so we create 'virtual' sensors for each tree with the data we have."*

Required information for an accurate prediction of water needs for a single tree come from weather data, type of soil and type of tree. Later on, the team realized that the information about shade is very important, too. This calculation can be provided by ML models and was added as an additional requirement. The prediction has to be made for 2-3 weeks into the future, because this is the time the SGA-Mitte Berlin needs to inform their contractors to react.

An idea for the future is to create location-based decision support systems that inform the city of Berlin where to plant which kind of trees.

As an 'Amti',
I need ....,
so that ....!

Amti

As an ‚Amti',
I need a simple user interface
so that I can get my job done also not being tech savvy.

As an ‚Amti',
I need district based information of the trees
so that I can work efficiently.

As an ‚Amti',
I need weather forecasts (regarding rain and thunder)
so that I can plan my work for the long term.

As an ‚Amti',
I need daily weather forecasts (regarding rain and thunder)
so that I can plan my work for the short term.

As an ‚Amti',
I need daily route planning
so that I can plan my watering route.

As an ‚Amti',
I need to get in touch with local people
so that I can optimize water supply for the trees in case of emergencies.

As an ‚Amti',
I need a way to access / add (tree) data
so that I can optimize the data availability.

As an ‚Amti',
I need a way to edit the ML model settings based on my experience
so that I can optimize the model output, because data can be wrong.

As an 'Zivi',
I need ....,
so that ....!

Zivi

As a ‚Zivi',
I need reliable information about the needs of the trees
so that I do no harm.

As a ‚Zivi',
I need reliable information about watering needs of a specific tree in my neigbourhood
so that I can help.

As a ‚Zivi',
I need to be responsible ‚officially'
so that my support is tolerated.

As a ‚Zivi',
I need to get in touch with other ‚Zivi's'
so that we can exchange information.

As a ‚Zivi',
I need to get in touch with other ‚Zivi's'
so that we can work together.

As a ‚Zivi',
I need to lable the tree that I take care of
so that the others in the community know about it.

As a ‚Zivi',
I need a way to flag observations and ask questions regarding a specific tree
so that others can help.

As a ‚Zivi',
I need a way to provide the status of a specific tree
so that I can provide more useful data.

As a ‚Zivi',
I need the information when a tree needs water
so that I can water the tree.

As a ‚Zivi',
I need the information which tree in my neighourhood needs water
so that I can help this tree.

As an 'Dev',
I need ....,
so that ....!

Dev

As a ‚Dev',
I need to test my data and models
so that I can maintain my code and algorithms.

As a ‚Dev',
I need a lot of data
so that I can train and evaluate my ML models.

Figure 8.20: User stories based on the insights from needfinding and research activities

Testing Product Vision

One specific user story was translated into a data user story. Based on this specific user story, a journey map was created (see Fig. 8.21). This journey and the related touch points with the solution was mapped to the available data and backend items to estimate whether user needs and technological feasibility were aligned.

As an ‚Amti',
by/with data and information available from the backend
I want to see predictive information about the watering needs of a specific tree
as a result in a dashboard with a simple user interface
so that I'm able to react.

1. Frontend (User Interface and Dashboard)
2. User Input (Authentication, Query and Actions)
3. Backend (Data sources /-bases, ML model and predictions)

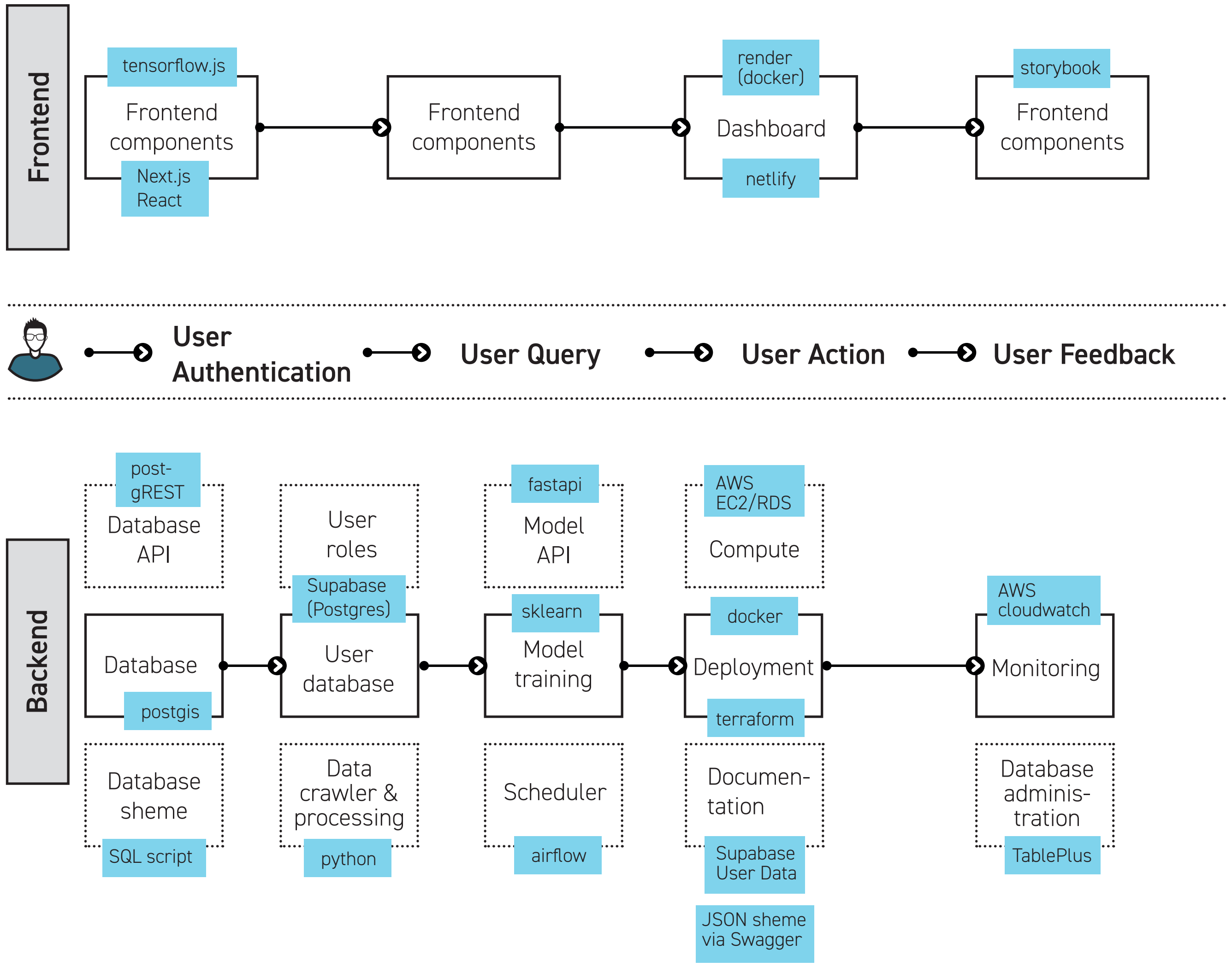


Figure 8.21: Journey and mapping of technology stack for user input, backend and frontend

Testing module 'Input'

Data Understanding: A few trees are equipped with sensors (sensor technology provider is Arbor Revital[293]), in Berlin Mitte there are now 220 watermark sensors. Specifically, these are moisture sensors for suction power and soil moisture. In addition, there is weather data, such as precipitation, temperature, sun exposure and evapotranspiration. There is additional open data (daten.berlin.de), which includes tree master data, such as the type of tree, age or stand age, height and water requirements. Information on soil data, which includes information on composition, degree of sealing and groundwater. From another project of the Technology Foundation Berlin, the team also has citizen irrigation data[294], as well as actual watering data from the Berlin Roads and Parks Department. In the course of the project, it became clear that the influence of sun and shade, i.e. the location of the tree and thus the information about the shade are also very important and needed to be collected as well.

Data Collection: Data understanding revealed that the information about shade is very important for calculating the water needs of specific trees. Part of this information comes from a database created through a project of the Technologie Stiftung Berlin[295], but adding satellite data was also necessary.

Data Preparation: The many different data sources and the complexity of the data input made data cleaning necessary, but overall, very structural data was to hand. The actual data from the SGA-Mitte Berlin is the most difficult to obtain because it is manually collected in excel files from the employees and takes some time to be available, resulting in gaps in the database.

Testing module 'Modeling'

Chose/Code AI/ML methods: Some mathematical models are already used to calculate irrigation needs. Evapotranspiration, i.e. the calculation of evaporation of water close to the ground, as well as transpiration (i.e. the release of water vapor through the stomata of the leaves), is a frequently used model for determining irrigation recommendations. The model for evapotranspiration is based on the Penman-Monteith equation and is used worldwide. Other models, such as Prof. Roth-Kleyer's take account of other parameters, such as soil type or tree type, to determine irrigation needs. The team compared and analyzed those models and used aspects of them for their own model.

The decision was made to use a supervised learning algorithm. A regression model, called random forest, was chosen for the initial ML methodology. The complex nature of the data sources and the amount of structured data and a couple of rule-based heuristics were the reasons for choosing such an approach.

E6: *"It would be nice to also work with neural networks, but the historical data from the sensors is from 2021, or even 2022. That is not enough to train a neural network but is absolutely a possible path to follow when we have collected more sensor data."*

Train & Test models: The satellite data to calculate shading form GIS python script performed badly, which made the team switch to another geo library[296].

Architecture / Infrastructure: Due to the amount of data, a cloud based solution was preferable. The backend is set up in AWS infrastructure using a ML flow pipeline for training the models to ensure versioning, as well as the possibility of understanding and changing the settings, especially regarding the final implementation and the responsible party that will take over MLOps.

293. Arbor Revital. Retrieved from https://arbor-revital.de. (Accessed on 2022-11-21)

294. Gieß den Kiez. Retrieved from https://giessdenkiez.de. (Accessed on 2022-11-21)

295. Erfrischungskarte Berlin. Retrieved from https://erfrischungskarte.odis-berlin.de. (Accessed on 2022-11-21)

296. A Free and Open Source Geographic Information System. Retrieved from https://qgis.org. (Accessed on 2022-11-21)

Testing module 'Output'

Interface/Interaction: The project has two target audiences, namely the citizens of Berlin Mitte (users) and the SAG-Mitte Berlin employees (expert or power users).

Citizen users - the initial idea was to provide them with the Qtree information and ask them to water the trees. After talking to the SGA-Mitte Berlin employees and experts from the ministry of the environment, it became clear that they don't want the citizens to water the trees. This is because the amount they are able to provide to the trees is not enough (5 L vs. 200 L), that would encourage the trees to grow their roots close to the surface of the soil, whereas it is better to have the roots deep in the ground. The direction was changed to an awareness-building solution to inform the citizens about the status of the trees, for example, that sometimes the soil might be dry, but the water deep underground is still enough for the trees, therefore no action is needed.

E7: *"This is very political terrain, because there is also the giessdenkiez initiative and we are pretty much going in the opposite direction."*

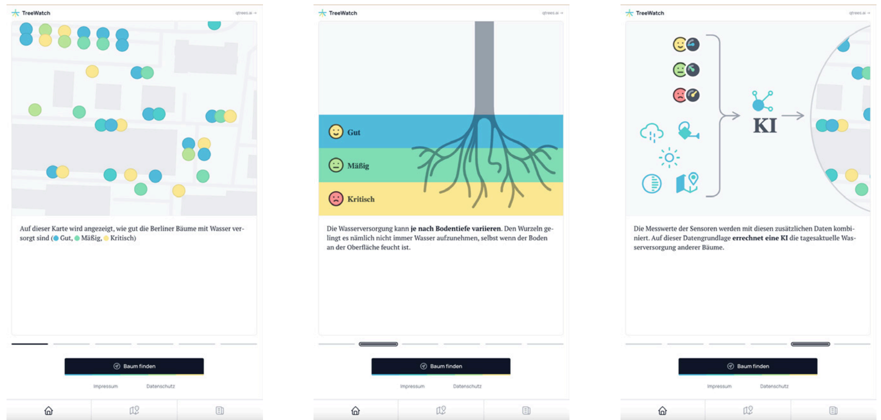


Figure 8.22: Example wireframes citizen information and awareness app

SGA-Mitte Berlin employees - web based dashboard to have an overview of the data sources, but also able to drill into data details and analyze specific data points.

E6: *"They currently get an email from the sensor provider regarding the information from the 220 sensor equipped trees. We think a web based dashboard would be the better solution, but an additional email report would also be possible."*

Testing: Some users asked for an invisible AI assistant instead of a massive dashboard that asks them to analyze and juggle a lot of data. This feedback could be responded to by complementing the web based dashboard with a mobile app.

Validation: For 2022, the predictive model performed very well, but a shift in technology is very likely. This is related to the data from this very 'special' summer. With this kind of open source project in particular, it is necessary to communicate this fact, as just taking over the ML framework of other similar projects without any adaptations based on the data might result in inaccurate model performance . The current model was the right choice for the given data input, but different circumstances with an impact on the trees for the coming year might make it necessary to change the choice of ML model.

E6: *"It will be interesting to see if the data from 2022, which was a very special summer, will perform similarly well in the summer of 2023. We therefore have to re-evaluate the model performance over and over again, an ongoing monitoring activity."*

Scalability: Since the current irrigation prediction for Berlin is very promising it would be beneficial for other cities to set up such an ML based approach. The team is already in conversation and exchange with other cities, such as Dublin and London. Those cities also have city labs[297], similar to the Technologiestiftung Berlin with the expertise to potentially make the necessary adjustments to the set up as well as having their own ongoing tree based projects[298]. Dortmund, which is starting giesdenkiez activities, as well as Essen, which has already developed a project called 'treecop'[299], are similarly interested in the Qtress project outcome and development.

297. Dark Matters lab. Retrieved from https://darkmatterlabs.org. (Accessed on 2022-11-21)

298. Trees as Infrastructure. Retrieved from https://treesasinfrastructure.com. (Accessed on 2022-11-21)

299. Treecop. Retrieved from https://uni-trier.de/universitaet/fachbereiche-faecher/fachbereich-vi/faecher/erdbeobachtung-und-klimaprozesse/umweltfernerkundung-und-geoinformatik/forschungsprojekte/treecop. (Accessed on 2022-11-21)

Testing module 'Deployment'

It is not finally decided who will be responsible for the productive system. This work package is planned for next year.

Security & Privacy: Since the Qtrees project is publicly funded, all the results and data input are open source. Everybody is able to use the work package results and outcomes, so data privacy is not the biggest issue. However, the system collects data from users which needs to be anonymized.

Monitoring & Maintenance: Currently, it is already clear that re-evaluating the model's performance when data from 2023 is available, will be necessary.

Testing module 'Post Processing'

Retraining: not applicable yet

Feedback Loop: Currently, structured feedback from citizens about the condition of the trees is collected and used to verify and map the ML model output. However, it is only a soft factor since watering a tree is not the only measure of the well-being of a tree. In future it is planned to ask citizens to provide additional unstructured data such as pictures of the trees to better judge the well-being of each tree. Image recognition / computer vision features for the citizen app are planned to supplement the overall set up.

8.5.2 Insights and findings from Quantified Trees

While mapping the process modules to the development of the current status of the Qtrees project, it became clear that the process modules were overall suitable for the development of this project. Due to the high level of expertise among the involved team members, they were able to also add insights and comparisons from other use cases from other domains and make connections between the different approaches, confirming the usefulness of the modules. E7:*"This is exactly how we run this kind of project. It was very helpful to have this visualization to reflect on and name the working packages we have to take care of."* The main focus of the project was on needfinding activities, mainly facilitated by the team members from the Technologiestiftung Berlin. The HCD/UX expertise was part of the project team, a very important aspect since projects in the public domain imply a complex network of stakeholders and users with mostly very diverse needs and requirements and the same applies to the industrial AI domain. This is why a lot of information about the 'Understand & Define' process module is included in the case study. The public domain also had an influence on the scope and focus of the project. Business viability was not as important as with industrial AI use cases; however, domain expertise was still needed. Less importance was given to the validation item of 'Success/Goal Definition'. The team mentioned that an early concept of architecture and infrastructure was proposed in the 'Modeling' module, this also having an initial concept for the final 'Deployment' module, which was very helpful for them. While currently, they would separate those concepts, they realized how much they depended on each other and therefore the process modules approach would be something they would take into consideration in forthcoming projects.

Besides the process modules for the development of AI infused systems, the two technologically focused team members mentioned that they offer an additional 'meta process' to their clients. This process goes along with the development and is devoted to all the change management activities, such as supporting strategic orientation towards AI/ML through coaching and people enablement activities. This approach is called 'Intelligent Architecture' by the consultancy and also offered in this way to clients.

8.6 Conclusion

This artifact of the Solution Space proposes a process based collaborative approach between designers and data scientists, as well as business domain expertise for the development of AI infused systems. The result are 7 process modules and their related activities and flow, and dependencies. Each activity is related to concrete actions and tools from all the domains. The process modules provide a systematic arrangement for the application of design principles and tools that are relevant in the age of AI and therefore foster the development of Human-Centered-AI systems. The process modules incorporate and combine the research findings from Problem Space, offering a system's approach, rather than separate activities. The initial version was derived from the Siemens use case samples from the industrial AI domain, with the final solution being tested and evaluated outside this scope, namely in the public sector, presenting a solid approach that can be transferred to other domains and sectors, set-ups and use cases.

A further collection of case studies and mapping of their related development steps towards the proposed process modules will provide more insights and findings about different collaborative approaches and the challenges that occur. The second artifact of the Solution Space makes an additional contribution, with a framework for collecting and documenting AI infused project exemplars and supporting the additional information retrieval for the process modules, as well as answering the research gap of a lack of best practice sharing.

Chapter 9. AI Use Case Framework

9.1 Introduction

A unified framework for AI and design collecting use cases, exemplars and abstractions

As an additional artifact, a framework for collecting example use cases, based on a workshop in the context of the 2021 AI in HCI Conference, affiliated with the HCI International Conference and the process modules from Solution Space is a complementary tool and part of this work. Sharing best practice should provide designers with hands-on examples that make the process modules more concrete and relate them to real world scenarios, combining theory and practice. This whole section addresses the very specific research findings and gaps discovered in both case study and secondary research, namely a lack of best practice sharing. It also provides a concrete project context for the theoretical and high level process related activities.

Since it has been successfully illustrated how AI/ML can operate as a new design material (as discussed in Chapter 3.2.1), it is important to share design war stories, as well as success stories. This is especially relevant since the design community lacks AI expertise. Offering training material and education is one attempt to answer this challenge. Research also revealed that some HCD/UX experts working in the field of AI/ML related their knowledge and the capabilities of the technology to example solutions. *"They instead used designerly abstractions and popular exemplars to explain what ML is and to communicate design ideas with each other."* (Yang et al., 2018) The practitioners with the largest selection of project examples seemed to also be the most successful practitioners in adopting AI/ML algorithms in their work routine. *"Extending, evaluating, and documenting these abstractions offers a clear space for design research. The goal is to develop a large suite of these abstractions, possibly by deconstructing current products and services that employ ML."* (Yang, et al. 2018) Current suggestions and solutions regarding new methods and tools entail design principles, but hardly any specific use cases, best practice sharing or exemplars, nor do they provide a unified framework or any advice on how to document this kind of use cases. This research aims to make a contribution to the given research space. This chapter elaborates on the steps that were taken to propose a solution which addresses the issues mentioned above, namely a lack of documented best practice sharing.

This chapter is divided into build and evaluate and theorize and justify activities. Related to build and evaluate is the organization of a workshop to collect AI-infused project exemplars from various HCD/UX practitioners working in different domains to derive relevant framework items from the workshop activities and relate them to the process modules. Related to theorize and justify is the conduct of a feedback session with the HCD/UX practitioners who provided their use case and with this gathered feedback to improve the framework and make it accessible/usable to a wider audience.

Build and evaluate

Connect the Missing Pieces: Best Practice Sharing
9.2 Workshop on: 'Use Cases of Designing AI-enabled Interactive Systems'

In order to respond to the above research findings and offer a solution that includes knowledge from other domains and experts in the field of design and AI, a workshop in the context of the 2021 AI in HCI Conference, affiliated with the HCI International Conference[300] was conducted. It set out to clarify the research question, if it were possible to develop a 'unified framework' to collect and document the use cases/exemplars in order to advance the State-of-the-Art in the

300. HCI International 2021 - AI in HCI: Workshop On "Use Cases of Designing AI-enabled Interactive Systems". Retrieved from https://2021.hci.international/AI-HCI_Workshop-II.html. (Accessed on 2022-11-21)

field of UX and HCI, using AI and ML as a design material. The outcome is also intended as an additional tool to enhance the AI process modules.

9.2.1 Setting-up of the workshop

The workshop was organized as a remote (on-line) workshop. Besides the requirement to apply with and present a concrete use case, the workshop employed creative co-creation concepts to facilitate participants' knowledge exchange and creative thinking. The focus and aim of the workshop was to collaboratively share, collect and document the use cases in a unified manner.

Workshop agenda

1. Introduction to the workshop
2. Opening speech by Head of Advanced Analytics at a car manufacturing company[301]
3. Use cases presentation
4. Collaborative co-creation activities
5. Workshop summary and conclusions

301. Due to miscommunication the speaker did not join the session at the foreseen point in time. Presenting the use cases came before he gave his talk. This worked perfectly well and was not perceived as a problem by any of the workshop participants. In the end, everybody agreed that this was the best order of presentations.

Submission details

Prospective participants had to submit a short description (800-1.000 words) of a use case describing the design of an AI-enabled interactive system. Proposals included a short description of the use case, as well as lessons learned and/or problems faced. The abstract was submitted in either DOCX or PDF format, but no special formatting guidelines applied. After a peer-review process, a successful application was communicated to the authors and they were able to participate in the Workshop and give an oral presentation describing their use case.[302]

302. Deadline for proposal submissions: 25 May 2021 (extended deadline)
Notification of review outcome: 1 June 2021
Deadline for conference registration: 30 June 2021 (new deadline)

9.2.2 Online workshop execution

The workshop took place on Thursday, 29. July 2021 - 2:00 till 6:30PM (CEST). Overall, 35 participants joined the session related to the presentation of the use cases and the introduction speech by the invited speaker, who shared insights from his role as Head of Advanced Analytics, setting the stage for a practice based focus in the workshop. The collaborative co-creation activity was conducted in a smaller group, mainly with the use case contributors (9 participants) who joined the session.

Presented use cases

Smart Environments
1. Benefitting Users from an ML-enabled Root Cause Analysis | United States

Smart Environments
2. Virtual Control Panel API: An Artificial Intelligence Driven Directive to Allow Programmers and Users to Create Customizable, Modular, and Virtual Control Panels and Systems to Control IoT Devices via Augmented Reality | Canada

Education
3. Using Cobots, Virtual Worlds, and Edge Intelligence to Support On-Line Learning | United States

Assisted Living
4. Can low-cost Brain-Computer Interfaces control an Intelligent Powered Wheelchair? | Canada

Health and well-being
5. Developing a User-Centered Interface for Sensor-Based Health Monitoring of Older Adults | United States

Health and well-being
6. Dementia Caregiver Assessment Using Serious Gaming Technology (CAST) during Covid-19 | United States

Collaborative co-creation activities

Organizing this part of the session was primarily the responsibility of the author of this work, by guiding the activities to meet the needs of her very own research endeavor, namely collecting, documenting and sharing design and AI-infused use cases to generate a 'unified framework' to offer to the design and wider HCD/UX and HCI community in order to generate more content and momentum. To collaboratively work together in the given remote set-up, the tool 'Conceptboard'[303] a digital whiteboard, was used and prepared prior to the workshop (see Fig. 9.1).

303. Conceptboard: An infinite canvas for your whole team. Retrieved from https://conceptboard.com. (Accessed on 2022-11-21)

The following five steps were provided as an instruction to the workshop participants:

Step 1 (15 minutes)
Discuss relevant items for the documentation of the use cases/exemplars, e.g. team roles, time horizon, technology used... using the provided use cases/exemplars

Step 2 (15 minutes)
Try to cluster and group those items according to e.g. a process (HCI process , CRISP DM, other)

Step 3 (15 minutes)
Fill in and provide the concrete information and content from your own use cases/exemplars

Step 4 (15 minutes)
Try to define overall themes/abstractions/patterns, e.g. "screen-free interactions", "deep personalization", "an evolving relationship with the users", "data-driven decision support"

Step 5 (optional and outside the scope of the workshop)
Share with your network and gather feedback, as well as more use cases / abstraction

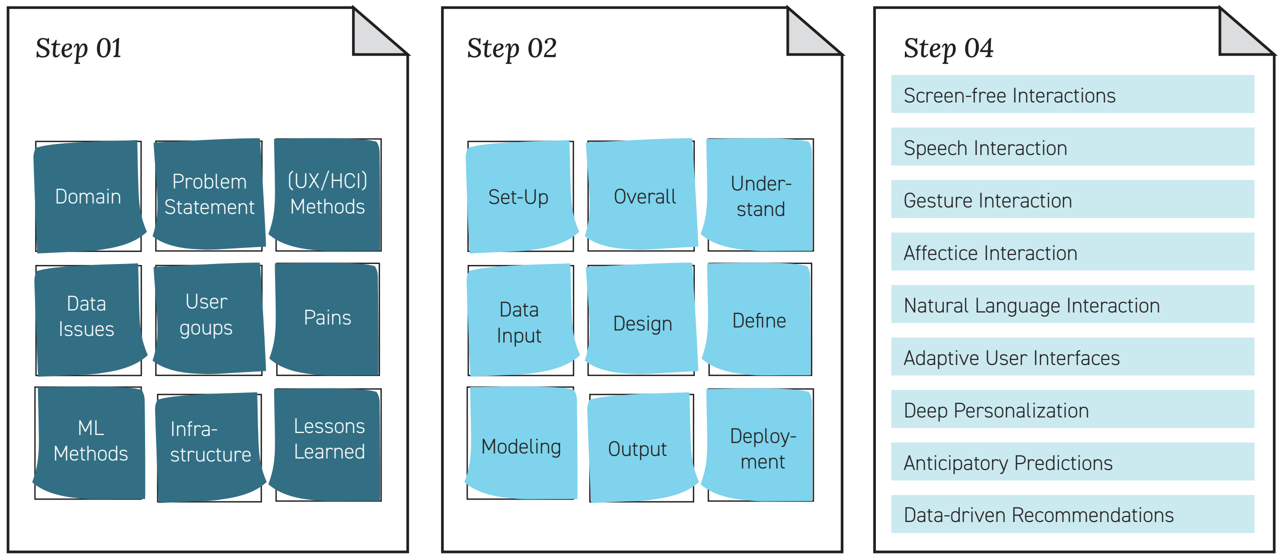


Figure 9.1: Prepared whiteboard items for the activity sessions

The participants were split into two teams related to the domain of their use case (industrial and medical/others). Each team had a communication channel on the webex meeting platform, provided for the workshop overall by the conference organizers. They were given a link to the conceptboard with a password, followed by a short introduction to the tool, such as navigation, creating new text, post its and other shapes. Each team got a moderator from the workshop organization team to guide them through the activities as well as being the time keeper. The collaborative activity session started a bit later than initially planned, at about 5:30PM. Team 01 managed to go through steps 01 and 02, as did Team 02, which also managed to start on step 03. Neither team was able to define overall themes/abstractions/patterns due to time limitations.

Workshop results

After being introduced to the prepared material, the teams were asked to begin with step 01 of the activity items. The first team started with the provided items and discussed their appropriateness for the entailed use cases, following a top-down approach, whereas the second team started from the use cases and tried to describe them using the provided components following a bottom-up approach.

Team 01 were Stravoula Ntoa as a moderator plus 4 participants. This team was linked to the thematic area of the industrial AI use cases. They developed four thematic areas accompanied by 20 related items (see Fig. 9.2).

The four thematic areas that the activities of Team 01 identified used the same high level phases as any kind of development process to group their items. When presenting the results of both teams, one team members said, that *"... this might be due to the fact that we tried to merge this to the industrial phases and wording we are used to."*

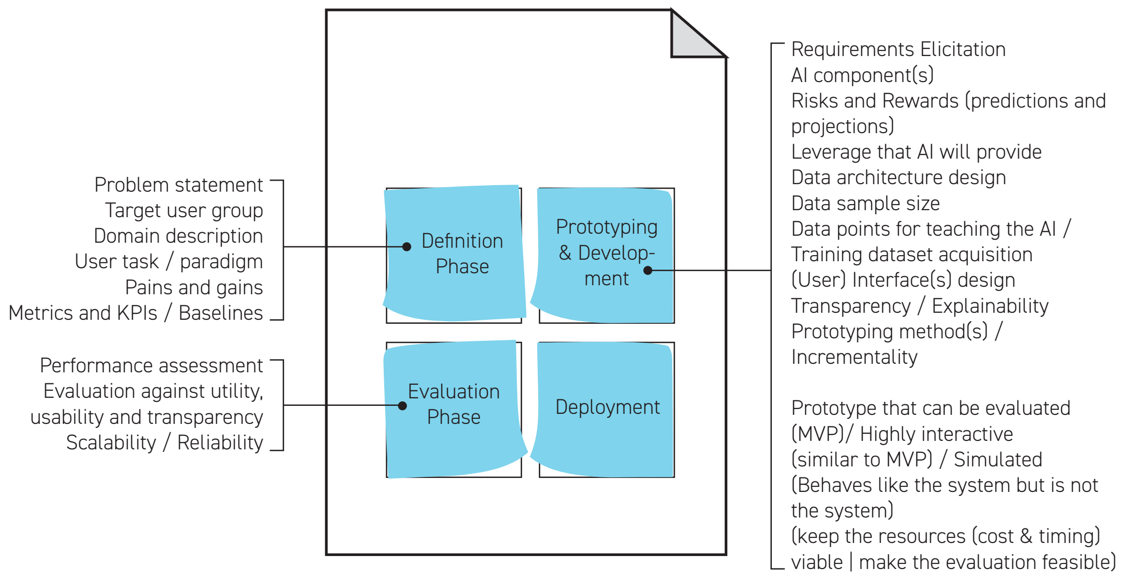


Figure 9.2: Visual representation of the whiteboard from Team 01

Team 02 were Jennifer Moosbrugger as a moderator plus 5 participants. This team had links to the thematic area of AI for medical domain use cases, including domains that weren't included in the industrial team. They developed seven thematic areas accompanied by 13 related items (see Fig. 9.3).

The seven thematic areas identified from the activities of Team 02 include a lot of items related to the user(s) and the stakeholders involved; data privacy and ethics. The team realized that the medical domain/sector poses special issues for the overall project set-up, such as data privacy and ethics, which are the main challenges around which all the rest of the process is based. This was not so strongly represented and reflected in the work of Team 01.

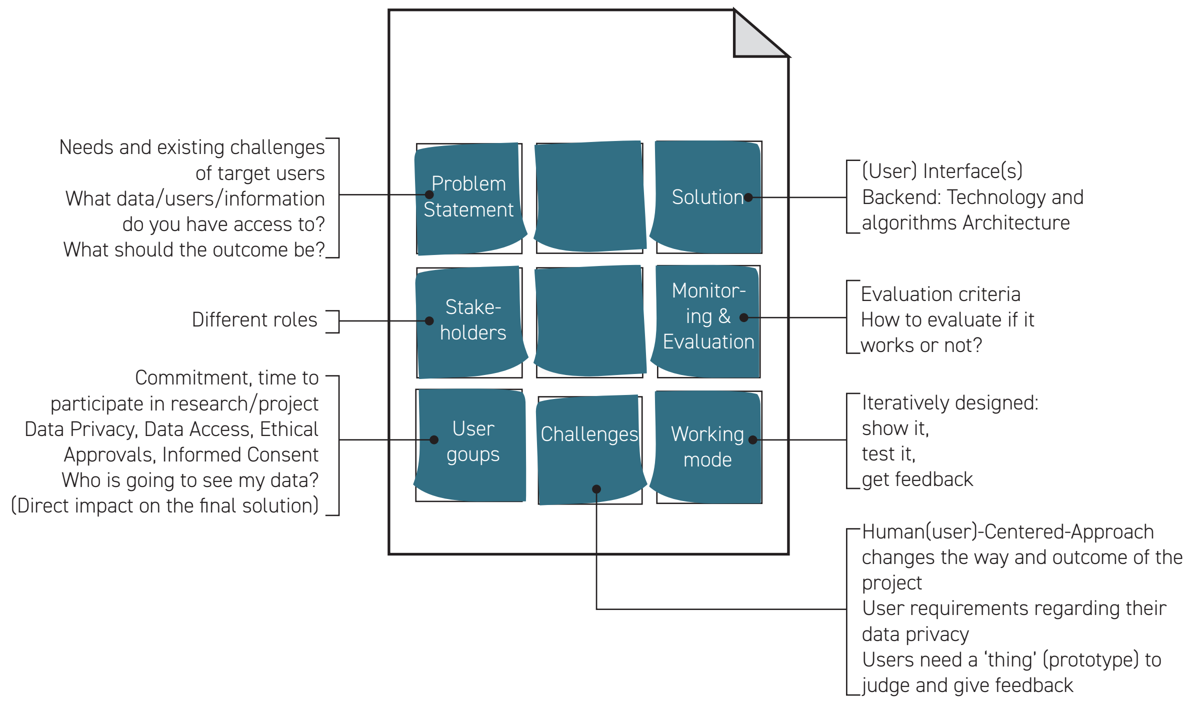


Figure 9.3: Visual representation of the whiteboard from Team 02

9.2.3 Insights and findings from the workshop

The overall set-up and concept of the workshop was shown to work. The formal application with a short description of a concrete use case was productive, making sure that actual scholars and practitioners from the field dealing with AI use cases were part of the workshop. It was also very helpful and interesting for all participants to get a short introduction to the different use cases and being able to ask questions where further information was needed. Six use cases seemed to be a suitable number to provide a great overview, leaving enough time for everyone to present their use case in detail.

There was not enough time to run through all the planned collaborative activities, indicating that co-creation activities cannot be fully planned. Introducing a new tool for the participants to get used to, such as the conceptboard, needed more time than initially planned. None of the teams managed to work on step 4, the themes/abstractions/patterns section. Therefore it is hard to tell whether or not this is a useful add on to the overall collection and documentation of AI infused project exemplars.

Both teams adopted very different approaches to develop their framework items. Team 01 used the suggested process structure provided in the prepared whiteboard, whereas Team 02 used their use cases to derive thematic areas from. These different approaches might be partly due to the division of the teams according to their domains. Team 02 was more related to the medical sector, whereas team 01 was primarily based in the industrial domain. However, the presented areas and their related items still showed some similarities and it was possible to combine them in a first version of a unified framework.

9.3 AI Use Case Framework Version 01

The results developed by each team were slightly different, due to their different approaches to come up with the necessary items. As co-creation activities are expected to yield diverse results in terms of quantity and quality, it was therefore important to carefully analyze and organize them in thematic categories in order to reach meaningful and concrete results. This analysis highlighted all the elements that should be included in the documentation framework based on the workshop, enriched with insights from secondary and the case study research of this thesis. Those elements were finally organized into categories. The initial version contained four thematic areas (see Fig. 9.4) and 24 related items. This section presents the output of the analysis and the outcomes in the form of a framework for collecting and documenting AI-enabled projects.

Effort was made to organize all the information on one page, but making the point that if more space were needed, the project could be documented on more than one page (see Fig. 9.5).

1.Set-up & Understand
Present the core attributes of your project and system, those which were decisive for the next steps

2.Data Input
Identify and describe the parameters which were considered during the data input phase

3.Modeling & Design
Expand on all the aspects of the modeling/design phase, addressing front-end and back-end aspects

4.Output & Deployment
Present results and evaluate your output, in terms of performance, usability, usefulness, transparency and scalability

Figure 9.4: Overview of the 4 categories of version 1 of the proposed framework for collecting and documenting AI-infused project exemplars

An additional worksheet was created to provide an overview of the framework with the related items that could be used to input the use case information.

1.Set-up & Understand	2. Data Input	3. Modeling & Design	4.Output & Deployment
Present the core attributes of your project and system, those which were decisive for the next steps	Identify and describe the parameters which were considered during the data input phase	Expand on all the aspects of the modeling/design phase, addressing frontend and backend aspects	Present results and evaluate your output, in terms of performance, usability, usefulness, transparency & scalability
Introduce: Problem statement/definition Target users & stakeholders User needs Domain description Risks & challenges Rewards & gains KPIs/baselines that should be considered	*Define & Explain:* Data analysis/understanding Data training set Data collection Data preparation Data privacy issues & concerns Ethical issues Overall process & iterations	*Present*: AI component and the leverage it will provide (backend technology & algorithms) Prototyping & ML technology AI training process User Interface Transparency & explainability Architecture & infrastructure	*Analyze & Evaluate:* Evaluation methods & criteria Performance assessment results User testing results (utility, usability, transparency) Feedback with learning loop Scalability & reliability issues Adherence to KPIs

Figure 9.5: Version 1 of the framework worksheet for inputting related use case information

9.4 Framework Evaluation

An evaluation sequence with all participants was organized[304] to introduce version 01 of the framework and worksheet and explain both documents to the workshop participants. One participant (there were 6 in total) from each use case joined the session plus both moderators from the workshop. After the call, the framework draft, including an example use case as a filled out template, was provided to the participants and they were asked to fill in the information from their AI use case until 6th January 2022. They were asked to provide feedback in 1to1 sessions after the submission deadline. From 10th to 19th of January 2022 1to1 feedback sessions were conducted, lasting for about 45 minutes each. The interviews included a first unstructured exchange on the overall opinion of the framework, followed by a structured set of questions as follows:

304. The call was scheduled for Friday, 10. December 2021 - 5:00 till 6PM (CEST).

1. What is your overall impression of the framework?
2. Did you miss any items or find that any items were inappropriate? If yes, please specify.
3. Did you agree with the order of items? If not, what needs to change?
4. How easy or hard was it to fill in the framework?
5. Based on your experience in describing your AI-enabled projects, do you believe that the framework offers any advantages to this end?
6. What would you use the framework for?

Additional questions to quantitatively measure participants satisfaction - UMUX-Lite[305] with the framework and their potential loyalty - NPS[306] were used as follows:

305. Lewis, James, R., et al., "UMUX-LITE: when there's no time for the SUS", in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2099–2102, 2013.
306. Reichheld, Frederick, F., "The one number you need to grow", Harvard business review, Vol. 81, No. 12, pp. 46-55, 2003.

7. The framework's items meet my requirements. 1-7
8. The framework is easy to use. 1-7
9. Would you recommend the framework to others? 1-10
10. What would you use it for?

9.4.1 Consolidate participant feedback

The feedback provided by the six participants was very positive. For most participants, no items were missing and the order was agreed on as well. The framework was easy to use and everybody was able to fill in their content. It helped them reflect on the overall project set up and outcome. The participants actually appreciated the information being presented and condensed in one page. Half the participants stated that the example template was helpful and that they used it to fill in their information. Overall the framework met the participants requirements and everybody agreed that it was easy to use. They would recommend it to their peers as well and promote it amongst their colleagues.

When being asked about a potential use of the framework the following aspects were mentioned:

- summarize a project in a succinct manner ('one pager')
- share project information with others
- justify what you have done and why
- use it as a checklist/project template to track progress and identify missing items
- status report for higher management/sponsors
- communicate content with other team members or peers
- focus on relevant topics instead of getting lost in e.g. technical aspects
- baseline to collaborate on when writing a paper

However, there were also two main criticisms made. Firstly, regarding the different terminology used for research and industry contexts (e.g. using the term KPI's, which was not understood by some of the research-based participants).

Secondly, was the possibility of including additional notations such as images (e.g. user interface), code (open source) and figures (e.g. line charts). Both are to be taken into account for the next iteration (as outlined in the next section).

9.5 Framework Iteration Version 02

Based on the insights and findings from the evaluation, a second version of the framework was proposed. It is more closely aligned to the AI process modules from Chapter 8.3 and represents the HCD and UX relevant topics with the space for input provided. It also takes account of the feedback from the interview participants, more space for additional material if applicable, as well as adapted terminology (see Fig. 9.6, p.136).

9.6 Conclusion

The overall framework was perceived very positively and the possibilities mentioned for its use matched the initial idea of a unified framework to document AI infused use cases to share with the UX/HCD community. The collection of use case exemplars has the potential to address current problems faced by the UX community with regard to AI and ML as a new design material, while further enhancing their understanding of ML through practical examples thus empowering them to engage in AI activities. The validation revealed that the framework and collaborative documenting of the use cases also supported the collaboration between team members, offering a significant supplement to the process modules. By providing the relevant context and best practice examples to guide designers in the age of AI and foster collaboration amongst the different team members and experts involved in the development of AI solutions.

Although each project had a different focal point, they could still benefit from a unified approach. During steps 01 and 02 of the workshop, the second team realized that the medical domain/sector poses special issues for the overall project set-up. Data privacy and ethics are a major challenge that all the rest of the process is based around. As a consequence, it was pointed out that a lot of items are related to the user, the involved stakeholders, and data privacy and ethics. This was not represented and reflected in the work of the other team in the same way. It focused on industrial applications. This fact also made it clear that the medical sector is already focused on the 'user' (patient), whereas the industrial domain is more focused on technical viability. Thus, each use case contributed its unique points of view to the unified framework, in a mutually beneficial approach. For example, although ethics was emphasized by projects related to health, it is an issue that all AI-enabled systems should attend to so ensure that they are reliable, safe, and trustworthy. On the other hand, all projects would benefit from technical validity, be they research or industry oriented.[307]

307. A paper publication together with the co-organizer of this workshop, Stavroula Ntoa (who is a post-doctoral researcher at the Human-Computer Interaction Laboratory, of the Institute of Computer Science, FORTH, Greece. Her work and research focuses on adaptive and intelligent interfaces, universal access and accessibility of modern interactive technologies, and user experience design and evaluation in intelligent environments), for the HCI International 2022 was an additional outcome of this work (Moosbrugger, Jennifer, and Ntoa, Stavroula, "A Unified Framework to Collect and Document AI-Infused Project Exemplars", HCII 2022, LNCS 13518, pp. 407–420, 2022.).

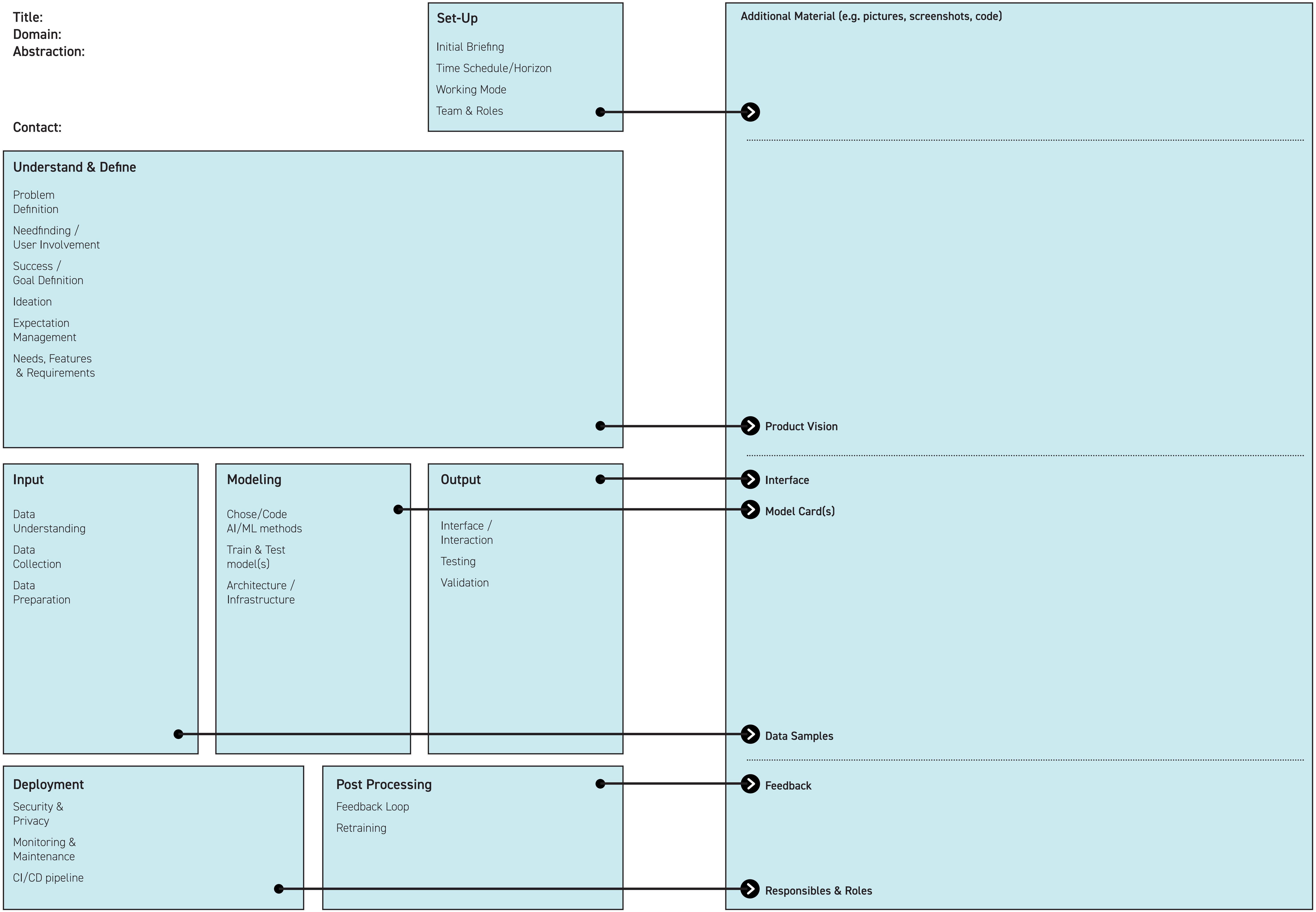


Figure 9.6: Iterated framework for collecting and documenting AI-infused project exemplars

Part V. Reflections & Results

Chapter 10. Summary and Conclusion

10.1 Summary of Results

The starting point of this work was initially very generic, with a broad look into the field of AI and design, as discussed in Chapter 3. The scope was then narrowed down by the focus on very specific case studies in the industrial AI domain within Siemens AG (see Chapter 5.2 and 5.3). The insights and findings that derived from case study research, expert interviews and structured literature review revealed the importance of Human-Centered-Design activities during the development of AI-infused solutions. Lack of AI expertise amongst design and other non-experts and missing structures to support collaboration amongst the different practitioners were identified as gaps needing to be filled to ensure the successful implementation of these activities (see Chapter 6.4). A systematic guidance - AI process modules and their related activities and dependencies - fostering collaboration between design, data (science) and business experts, as well as providing a starting point is the proposed solution to overcome these gaps. The solution is flexible and modular, to support different project patterns and contribute a very general result, and at the same time, proposes concrete activities and related actions (for further detail see Chapters 8.3 and 8.4). The applicability to different project domains was validated by transferring the AI process modules to a case study in the public sector, as well as collecting feedback from practitioners working in the field of designing for AI. A framework to support collecting and documenting concrete AI-infused project exemplars is also proposed (see Chapter 9.5). The framework aims to foster best practice sharing and at the same time, supplement the AI process modules with the information about actual context.

The methodological framework introduced in Chapter 4. supported the thesis's theoretical and practical orientation. Conducting case study research and combining it with expert and external knowledge and input represented a valuable contribution to the research area of industrial AI, providing a broad, as well as concrete field to shed light on the issues and challenges a suggested solution should address. However, the given set-up also represents a limited perspective and cannot fully guarantee being generalizable to fit every use case in any related domain.

10.2 Main Arguments

The following section summarizes each chapter of the thesis and the related arguments, findings and results in a short statement. It does not only provide a condensed overview of the most important aspects of each chapter, but also serves as a basis for further investigation and discussion.

Part I. Foundations
Design is influenced by technological advancement and therefore technology shapes design practice; in this regard AI and ML are a new design material. Based on the assumption that design can and should add value to the development of AI infused solutions, and that this in turn affects current practices, methods and tools for designers, two hypotheses to serve as a foundation for the scope of the research could be drafted.

Part II. Framing
State of the Art Research in the context of the boundary objects, design, AI/ML and industrial domain reveal that current developments in AI and ML as well as in design call for new paradigms; both being related to a human-focus. The given research endeavor is related to scientific stances and technology, but it is also concerned with people, practice and socio-cultural issues. This calls for an appropriate and flexible methodological set up with methods and tools that address and combine a broad spectrum of concepts and worldviews. Design outcome related pragmatism and aspects from technology as mediation from postphenomenology, later adding concepts from Design Science

Research approaches provide a novel examination of the paradigms that suit the given research requirements.

Part III. Problem Space
The convergent section provides a view on overall pitfalls and challenges in the development of AI agents in the industrial domain based on case study research. 17 themes were discovered, related to issues that are a) AI related, b) project specific and c) HCD/UX specific.
The divergent section represents a focus on design relevant issues by adding the expert perspective. Issues such as HCD/UX professionals lacking AI/ML-expertise, human-centered and data-centered approaches are not aligned, and a need for new methods and tools, as well as best practice sharing emerged. This angle provided the scope of the Solution Space.

Part IV. Solution Space
The convergent section presents a systematic guide - AI process modules - which foster the collaboration of design, data (science) and business, as well as providing a starting point. The solution is flexible and modular to support different project patterns, but at the same time, proposes concrete activities and related action items. The process modules contribute to filling the research gaps found in Problem Space.
The divergent section represented by the AI project framework supports the collecting and documenting of concrete use case exemplars to foster best practice sharing and at the same time, supplements the process modules with actual context.

10.3 Conclusion and Discussion

This work aims to contribute to the emerging field of design and AI by helping the design community embrace this new design material. Case study research and the literature review revealed that Human-Centered-Design activities can play an important role in the development of AI agents, as stated in the first hypothesis, but also, that more work, activities and initiatives are needed to fully embrace the potential assumed by the second hypothesis. It gives guidance with a systematic approach based on the process modules, related activities and dependent features to include design, data (science) and business perspectives in the overall development, as discussed in Chapters 8.3 and 8.4. This is supplemented with a framework for collecting AI infused project exemplars to provide a concrete background for the development steps and foster best practice sharing by creative practitioners (see Chapter 9), in accordance with the hypothesis that the successful integration of Human-Centered-Design implies the need for new methods and tools.

While this work is based on a limited number of case studies from the industrial AI domain, making the findings and the outcome transferable to other domains was always a requirement, so external input and feedback were brought in as soon as possible, like the expert interviews (see Chapter 6.2.2), structured literature review (see Chapter 6.3.2), a conference workshop with a broad spectrum of practitioners and researchers (see Chapter 9.2 and 9.3), as well as mapping the solution with an external case study from the public sector (see Chapter 8.5). However, the context of the case studies cannot be denied and represents some bias. The influence of Siemens AG's roots in German culture with its engineering driven heritage and workforce, data regulation and privacy issues that are only relevant for German-based companies, are reflected in the research findings so have indirectly influenced the final artifacts.

To next step it to detect research gaps and further evaluate the validity of the results by collecting more case studies and mapping them to the process modules. The same goes for the AI project framework. While the solutions complement each other, additional value will be created when they are actually applied by practitioners in various roles, areas, and different settings. As discussed in Chapters 3.5 and 3.6, the missing examples that are relevant for practice and design specific material and notational forms have been addressed by this thesis. It therefore contributes and extends the current status of research in design and AI. This research area is immature and lives on new ideas and concepts that will continue to evolve and develop over time as will their use in practice. The purpose of this work was to present results that indicate the basic directions and fundamental principles to provide a starting point for further investigation within international discourse. This field is evolving, and this work's purpose is to take part in actively shaping it, now and in the future.

It was also shown that the selected set-up of methods offered a valuable framework to reveal both insights and findings from the intersection of AI and design in the industrial domain, as well as derive related action procedures to address the challenges uncovered. The solutions introduced in Chapters 8 and 9 represent only two proposed artifacts that could be derived amongst many other possible outcomes.

10.4 Outlook

To make the findings and results of this thesis accessible to the UX/HCI/HCD community, lastly and consequently, a decision about the right format and publishing media needs to be taken. It should be flexible enough to incorporate pictures, interactive content and other sources, in addition to text. A digital open-source solution is therefore preferable, to potentially supplement the analogue thesis and make it available to the broader community, integrate changes easily, and add more content and use cases. Since in the given domain of AI and design, many sources and links are available online, so the Solution Space should be approachable digitally, at least. The digital version would use different language and be without academic guidelines, to address a target audience outside the scientific domain. A web address for this has already been reserved: design-intelligence.net.

Collaboration with institutes and companies that work on similar issues, such as IBM, Microsoft and Google, as shown in Chapter 3.3.4, is also a way forward. Google researchers have started to document Machine Learning models, and introduced so-called 'Model Cards'[308], with information about their performance, metrics, training and evaluation data and intended use cases.[309] The 'Model Cards' and the 'AI use case framework' could benefit from information exchange about each other, so providing very comprehensive explanations and documentation of best practice sharing, ensuring more transparency and information about potential pitfalls are available to a large group of stakeholders. Furthermore, the European Union is currently developing the 'Artificial Intelligence Act' (AIA)[310], a law to regulate AI activities, related to three risk categories. This shows that the output of AI/ML systems is the subject of regulatory activities, confirming the need for more transparency and the tendency to put more focus on how such systems are developed, providing advantageous conditions to place a Human-Centered-Design approach on the market.

308. Model Cards. Retrieved from https://modelcards.withgoogle.com/about. (Accessed on 2022-11-21)
309. Mitchell, Margaret, et al., "Model Cards for Model Reporting", FAT* ,19: Proceedings of the Conference on Fairness, Accountability, and Transparency, pp. 220-229, 2019.

310. Artificial Intelligence Act. Retrieved from https://artificialintelligenceact.eu. (Accessed on 2022-11-21)

Furthermore, besides the focus on making the findings available and transferable to broader industrial and commercial contexts, it also became clear that teaching material and design education play a fundamental role. The process modules can serve as a foundation to teach design and business professionals, as well as students, about AI/ML development in practice. The knowledge gathered can serve as additional material to create training material and content and provide designers with a starting point from which to enhance their skills. The insights and findings gained from the research also indicate research gaps that can be further explored by the design science and research community.

This work has clearly shown that design is currently lagging behind the technological development of AI/ML systems, but also, that it can provide valuable input with the potential to improve the current situation and challenges faced by AI technology. In order to stay relevant in the age of AI, the design profession needs to embrace this new design material and speed up the process to bridge their knowledge and skill gaps.

Glossary

A

(Agile) Scrum

Scrum is a framework that supports a specific type of project management. It is characterized by lean processes, step-by-step development - so called sprints - and regular feedback loops. It was originally used in software development but is now used in many other domains and industries where an iterative approach is valuable.[311]

311. Home of Scrum. Retrieved from https://scrum.org. (Accessed on 2022-11-21)

Algorithms

An algorithm can be defined as a precise step by step guide for a system to identify which problem to solve. ML algorithms differ from regular heuristic-based algorithms since the data itself creates the model. Much of the system's final behavior, the actual way to solve the problem, emerges through learning from data and experience over time. The choice of algorithm depends primarily on the type of problem and type of input data, and second, on the choice of accuracy and performance levels.

Artificial Neural Network Algorithms

Artificial neural networks are models that mimic the structure and/or function of biological neural networks. They use layers of interconnected units to learn and derive weights based on observed data. As data input changes, neural networks are able to adjust and learn new weights, suitable for unstructured and unlabeled data. There are hundreds of algorithms and variations for all types of problems.

Association Rule Learning Algorithms

Association rule learning methods extract rules from large multidimensional datasets. These rules observe the relationships between variables in data and discover important associations.

Automated ML

AutoML solutions provide ML methods and tools for non-experts[312]. These systems often support the data handling process by providing tools for data preparation and cleaning. These systems also provide pretrained models with the possibility to adjust settings to control the output. However, the problem for non-experts is the untransparent nature of these systems, often referred to as a 'black box', and lack of knowledge about how to overcome failure or understand the error messages provided by the system.

312. autoML. Retrieved from https://automl.org/automl. (Accessed on 2022-11-21)

B

Black Box

In computer science and engineering, a black box refers to a system where it is impossible to understand and explain its internal mechanisms, how the output is related to the input. Artificial neural networks are often referred to as black box systems, since it is not obvious how the neural net reaches its conclusions. The opposite concept of a black box is often referred to as a white or glass box.

C

Classification and Classification Algorithms[313]

When a Machine Learning model identifies an object it performs a classification. The simplest classification is binary, meaning 'black' or 'white'. Multiple classification algorithms are able to sort input into several groups.

313. Classification refers to a class of algorithms, but also to a group of problems and related outcomes.

314. Clustering refers to a class of algorithms, but also to a group of problems and related outcomes.

Clustering and Clustering Algorithms[314]

Clustering refers to a technique where the algorithm interprets the parameters of the data, objects with similar parameters and features are grouped in a cluster. All methods are concerned with using the structures inherent in the data, which is not labeled, to best organize the data into groups with the most features in common.

Context Errors

When the AI/ML system produces an error that does not make sense in the given context of the user, these are so called context errors. The systems' output is perceived as awkward or irrelevant from the user's perspective.

Confidence Score/Level

In ML, confidence scores or levels are used to illustrate how confident the underlying algorithm is that it has derived the correct value. It is meant to provide more transparency about the model's decisions and output.

D

315. Ridsdale, Chantel, et al., "Strategies and Best Practices for Data Literacy Education Knowledge Synthesis Report", Dalhousie University, 2015.
316. Bell, Gordon, "Foreword: The Fourth Paradigm - Data Intensive Scientific Discovery", edited by Tony Hey, Stewart Tansley, and Kristin Tolle, Published by Microsoft Research, 2009.

Data Literacy

Data literacy refers to a skill, the ability to collect, understand, and prepare different types of data and evaluate and use this data in a critical manner[315]. Since AI/ML depend on data, the ability to infer meaning from data and act based on that meaning is a crucial need for working in that area[316].

Deep Learning Algorithms

A deep neural network contains several connected (and hidden) layers. It is an update of artificial neural networks. Deep Learning algorithms are suitable for interpreting unstructured data such as images, audio, and text to help the system make near real-time decisions. Particular algorithms in that category are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs)[317]. The latter are used for several image generating applications.

317. editGAN. Retrieved from https://nv-tlabs.github.io/editGAN. (Accessed on 2022-11-21)

Dimensional Reduction

Dimensional reduction is a method that discovers and exploits the features inherent in data. With this it is possible to simplify and reduce a large dataset and eliminate irrelevant data points.

E

Error Metrics

Error metrics are a way of measuring the error of an ML model prediction, to make a statement about its accuracy, either to compare competing models or to compare against the current status. Different types of error metrics are related to different statistical techniques (e.g. Mean Squared Error (MSE), Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE))

Explainable AI (XAI)

The purpose of XAI is to provide a set of ML techniques that foster transparency and explanation of AI and ML models and their behavior and outcomes for humans to understand AI output and build trust, improve model performance on the one hand, but also support humans in effectively developing reliable and equitable ML solutions.

H

Heuristic

Hard coded, rule-based software that is based on static if-then-else functions, is called heuristic-based. The output of this software is always the same.

Human-Centered-AI (HCAI)

HCAI is an emerging discipline with the purpose of creating and developing AI and ML systems that foster Human-AI collaboration and co-creation. It includes aspects and methods from HCD, while also responding to the new challenges the technology implies, such as preserving human control, aligning with human needs, operating transparently, delivering ethical outcomes, and respecting data privacy.

Human-Centered-Design (HCD)

HCD describes an approach for solving problems and providing solutions in process, product, service and system design, management, and engineering. It provides frameworks, design principles and activities that create solutions to problems that come from considering and integrating the human perspective into all the steps of the development process. Human-Centered-Design contains methods and concepts from numerous fields such as engineering, psychology, anthropology and the arts.[318]

318. Human-Centered-Design Society. Retrieved from https://human-centered-design.org. (Accessed on 2022-11-21)

Human-Computer-Interaction (HCI)

Human-Computer-Interaction is related to research and design that focuses on the interfaces between humans and computers. HCI practitioners observe humans and how they interact with computers and as a result, design technological solutions that allow humans to interact with computers in intuitive and, at the same time, innovative ways. It is situated at the intersection of computer science, behavioral sciences, design, media studies, and several other fields of research.

I

interactive Machine Learning (iML)

interactive Machine Learning (iML) refers to the development of ML models in collaboration with a human, incorporating their feedback during the model training process. The aim is to derive more efficient and accurate ML models that also improve the interaction between humans and machines.[319]

319. Interactive Machine Learning lab. Retrieved from https://iml.dfki.de. (Accessed on 2022-11-21)

Intelligent Augmentation (IA)

Intelligence Augmentation is an alternative conceptualization of Artificial Intelligence. It focuses on the assistive and supportive roles of AI with emphasis on the fact that it is supposed to enhance and augment humans rather than replace them.

P

Probabilistic

Situations with multiple possible outcomes are probabilistic. Each outcome has a varying degree of certainty of it happening.

R

Regression and Regression Algorithms[320]

320. Regression refers to a class of algorithms, but also to a group of problems and related outcomes.

Regression algorithms model relationships between data points that are iteratively refined using a measure of error within the predictions made by the model. Predicting future values based on historic values is one useful application of regression analysis. Regression methods are used for statistical analysis and have been co-opted by Machine Learning.

Reward Function

A reward function's goal is to reinforce a certain learning behavior of an algorithm by specifying a desirable result. A reward function provides a numerical score to represent the desired state.

T

Technology Assessment (TA)

Technology Assessment describes a process that aims to identify and measure the eventual impacts of aspects of technology early on in its development cycle. It is intended to inform public, political and general decision-making. It examines the short and long term consequences of the application of technology. The assessment is related to societal, economic, ethical and legal issues.[321]

321. Institute for Technology Assessment and Systems Analysis (ITAS). Retrieved from https://itas.kit.edu/english/index.php. (Accessed on 2022-11-21)

Time Series Forecasting

Time series forecasting is based on historic data points for making predictions about the future development of the given data set. Algorithms that are related to this kind of problem-solving use observations from the past as a basis for making a prognosis in the future to drive decision-making.

U

User Experience (UX) Design

UX design describes the process of defining all the aspects of the experience of a user when interacting with a digital product or service. Decisions in UX design are driven by research, data analysis, testing and evaluation. UX design includes aspects, such as usability, usefulness, desirability, performance and overall interaction with a company.

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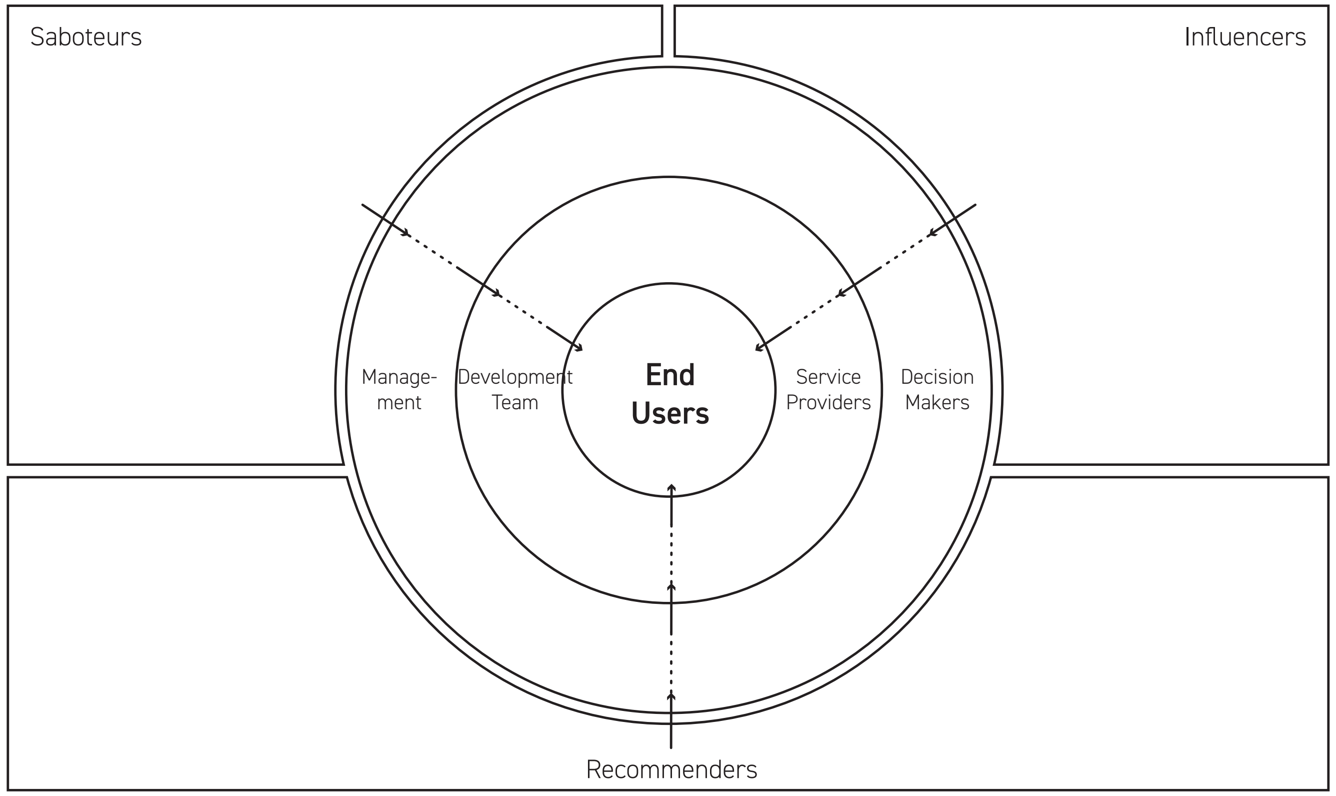
Appendix

I. List of Figures and Tables

II. Tools and Canvases

AI is a possible solution	AI is NOT a good solution
Overall, AI is suited for dynamic, personalized content, that allows for unpredictable behaviour.	Overall, static, simple and rule based solutions are not weel suited for AI.
Customized recommendations, different content for different users, such as recommender systems for movies. Predicting the future, forecasting of events, such as weather forecast or price development for houses. Personalized products and services, combined with automation features, such as smart home applications. Natural language interactions, speech recognition, text classification, such as personal assistanst, chat bots, dictation sofware. Classification and recognition of a large amount of data, an entire class of entities, where heuristic methods are too limited to get every possible solution and combination, such as photo tagging Anomaly and outlier detection, detection of events that occure in an unfrequent manner, such as fraud. Automated help desks, service support, that follow domain specific requirements, such as AI agents or chatbots for hotel bookings. Reducting tedious tasks that are unpleasent to get solved by people.	Predictable behaviour is necessary, appearance and user input need to be the same regardless of context and different users. The cost of errors is very high and outweighs the benefits of a small increase in success rate, such as banking apps. Transparency of the system and understanding of each step and decision the system makes is necessary. Speed to optimize for low cost is more important than anything else. Data access is critical due to ethical reasons, or privacy issues. Highly valuable tasks and problems people like to solve by themselves.

- AI or not AI checklist -

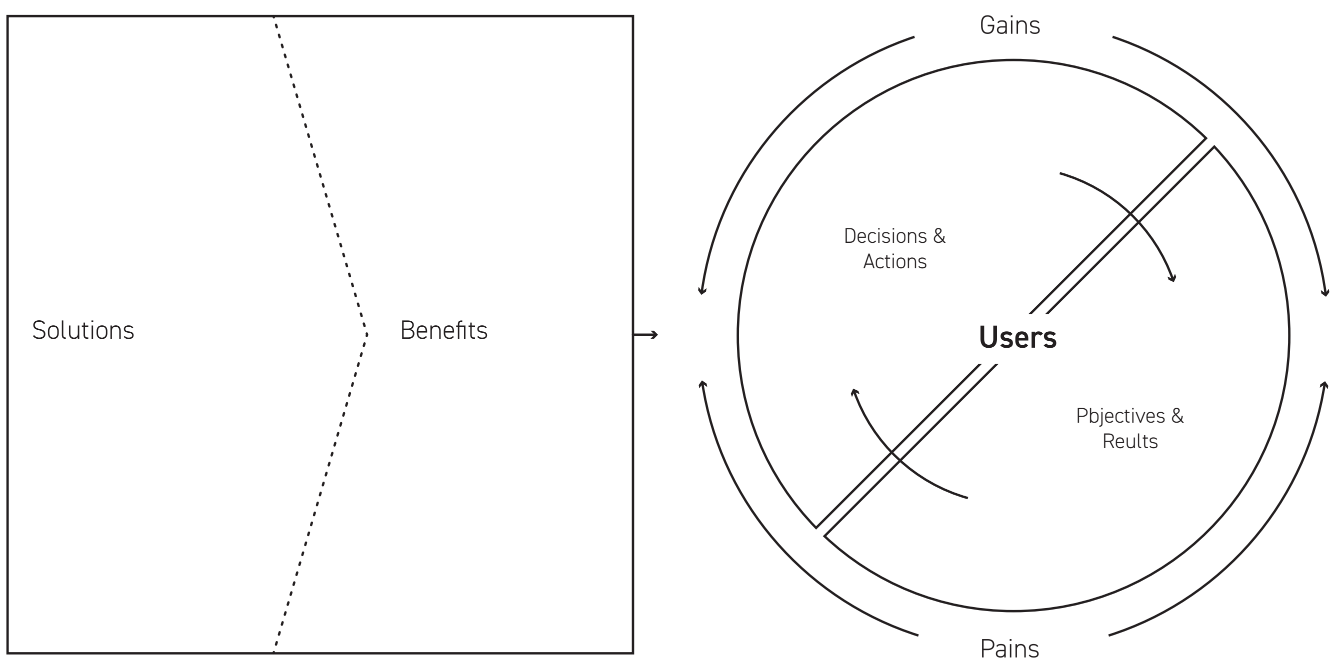


- Stakeholder Analysis Canvas -

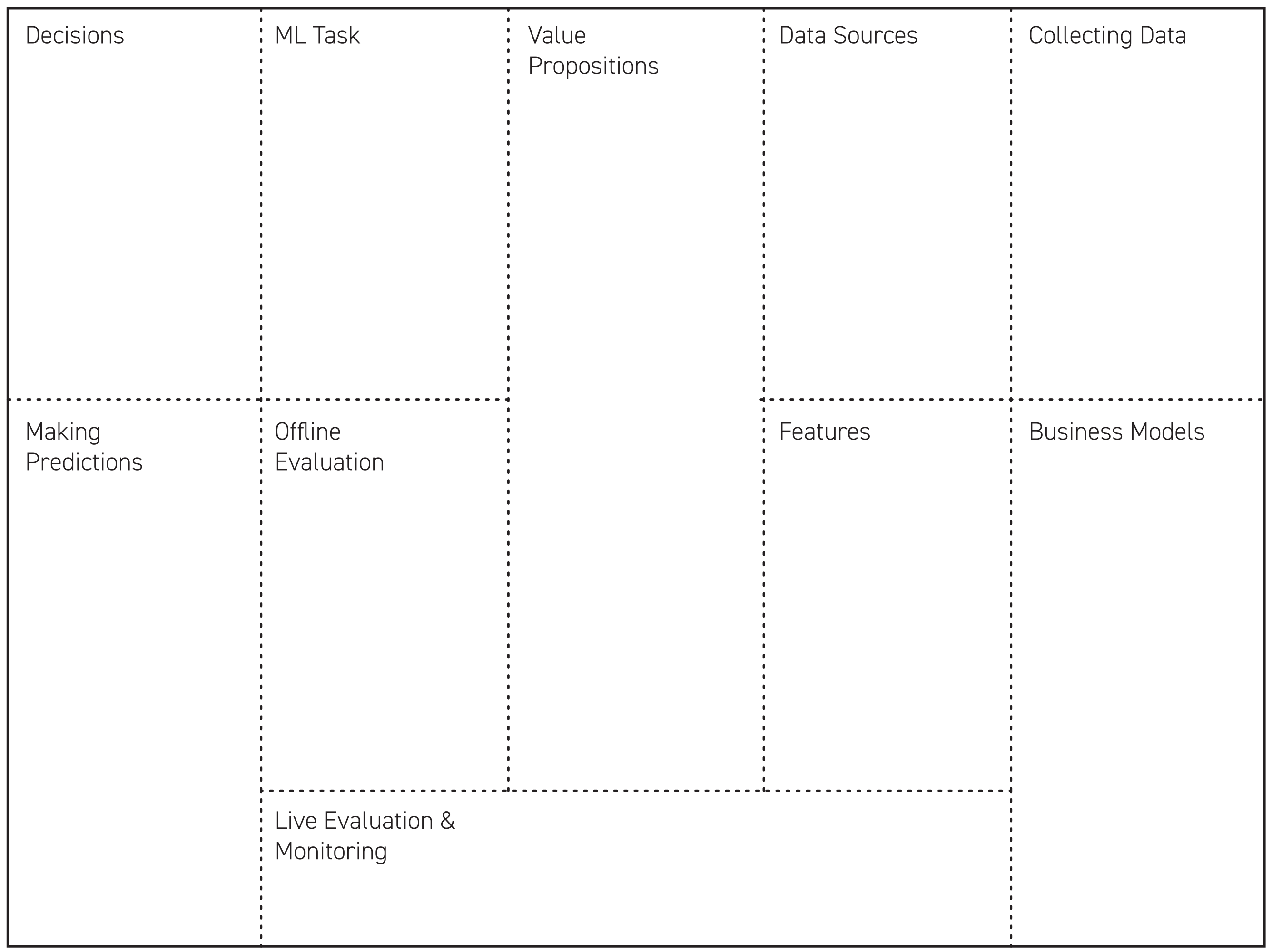
Machine Output

Reference	positive	negative
positive	True positive The system makes a correct prediction	False negative The system makes a wrong prediction
negative	False positive The system makes a wrong prediction	True negative The system makes a correct prediction

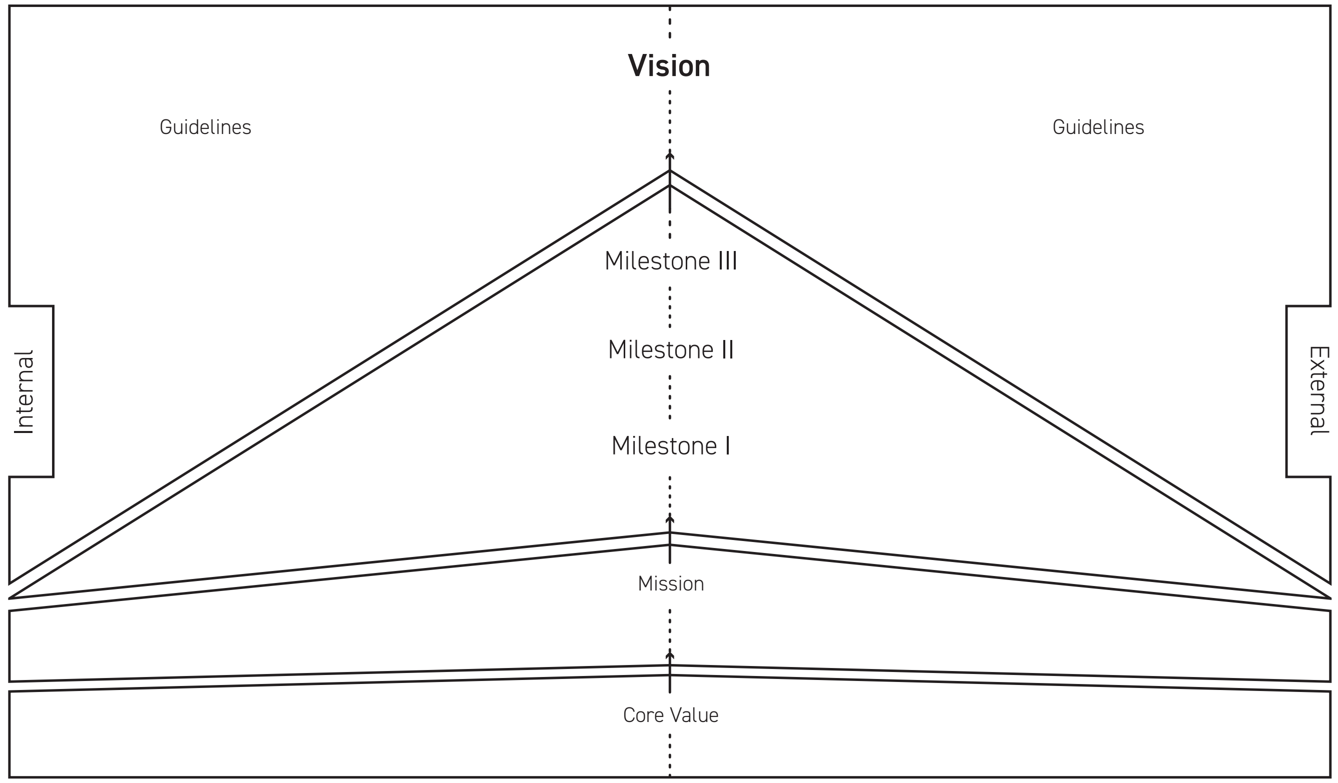
- Confusion Matrix Canvas -



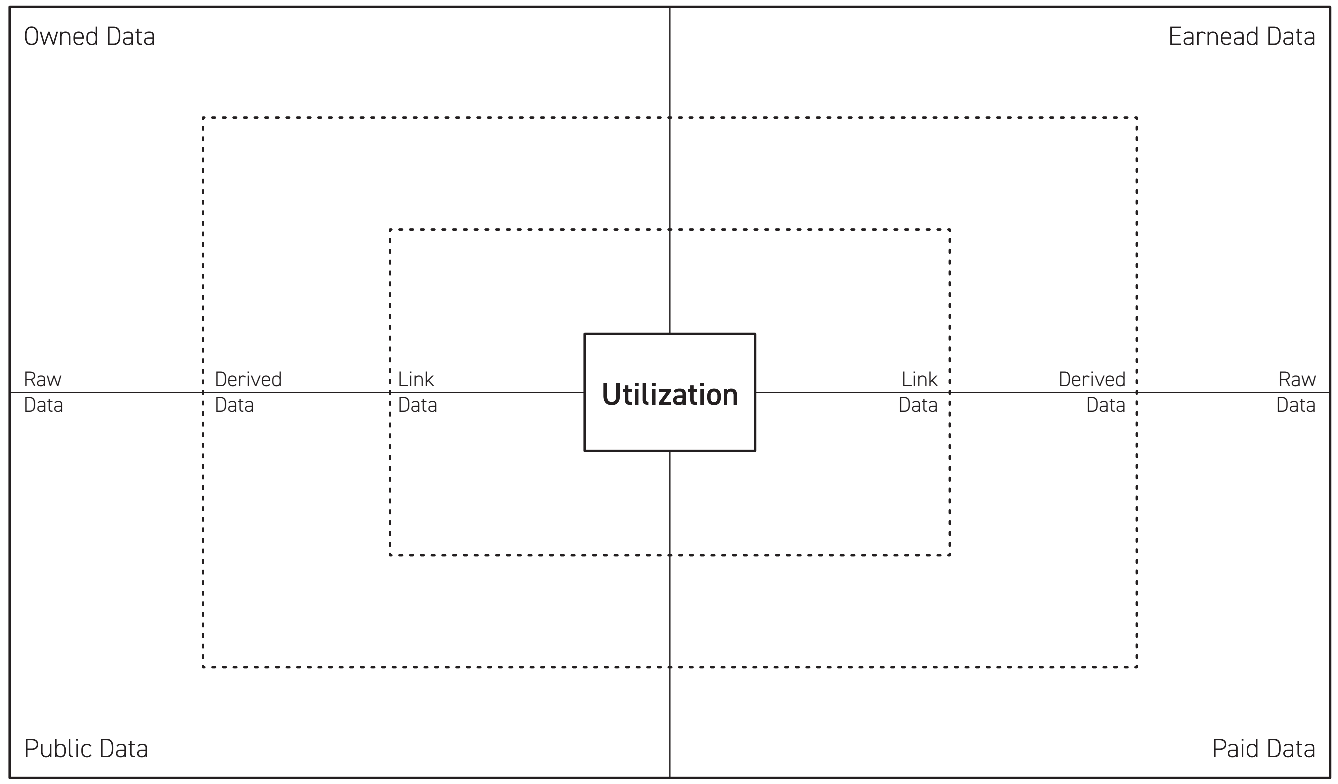
- Analytics Use Case Canvas -



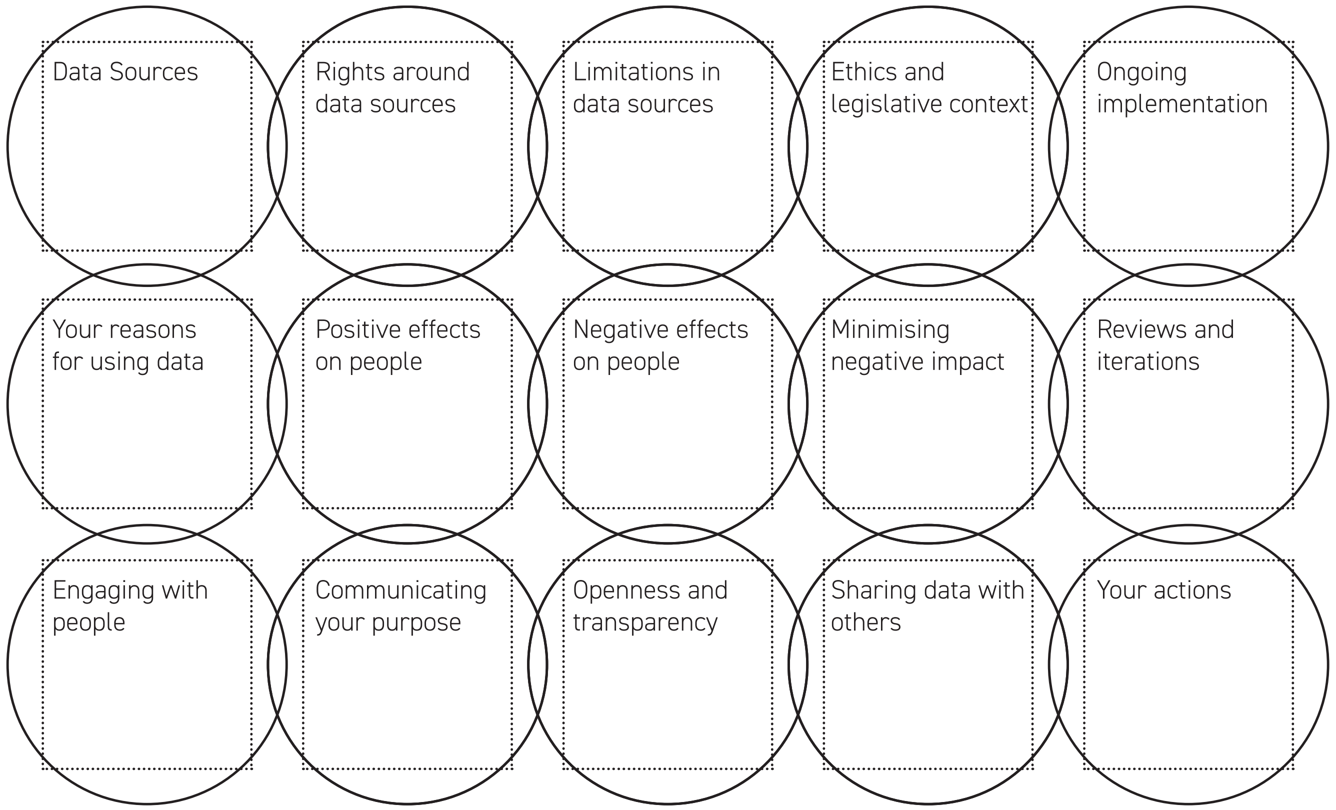
- ML Canvas -



- Strategy Pyramid Canvas -



- Data Landscape Canvas -



- ODI data ethics canvas -

III. Overview of ML tools used

This thesis made use of available ML tools, firstly, to support the process of writing and layout along the way, but secondly, also to gain more knowledge and experience with those 'little helpers', and also to evaluate their usefulness.

This work is based on German, as well as English data and information sources. For the final result, the German input needed to be translated into English. 'DeepL'[322] was used as a translator since it is the most precise and differentiated ML-based solution currently on the market.

322. DeepL: Translator. Retrieved from https://deepl.com/translator. (Accessed on 2022-11-21)

The ML-based transcription software 'trint'[323] was used to transcribe the interview audio files. This worked well for English, not so well for German interviews. Checking the final outcome was necessary in both cases.

323. Trint: transcribe video and audio to text. Retrieved from https://trint.com. (Accessed on 2022-11-21)

'Fontjoy'[324] was used as inspiration for the choice of fonts. DIN 2014 has been used as the main typeface for headings and running text, whereas lora medium italic has been used for special headlines and to highlight text.

324. Fontjoy: generate font pairings in one click. Retrieved from https://fontjoy.com. (Accessed on 2022-11-21)

Each chapter and its related graphics has its distinct color code. The color palette was created with 'colormind'[325]. It provides a database of color schemes that a Deep Learning algorithm together with other users had already created, or a user can create their palette themselves as in this case.

325. Colormind: the AI powered color palette generator. Retrieved from http://colormind.io. (Accessed on 2022-11-21)

The mood board for Chapter 8.2.1 was generated with an AI experiment from Google called 'Mood Board Search'[239]. This tool uses mood boards as the search query input to generate an exploratory image collection. Instead of words, the algorithm is trained on pictures and looks for similar features and patterns in other images. Human input compromises pictures related to Information Theory, DFD'S, layers, pcb's, Claude Shannon, thesaurus maze, process flow, network structures.

The cover design is inspired by using the image generating bot from 'Midjourney'[104]. The initial set of prompts were related to design and AI collaboration but did not produce any meaningful results. The next attempt used artificial neurons, human brain, creativity and intelligence as prompts, which generated more suitable variations that came close to the final result.

'GPT3'[3] is a language model that uses deep learning to produce human-like text. Unfortunately, it is not 'advanced' enough to produce an entire thesis, however, the idea was to use it to experiment with generating an alternative abstract for this thesis.

GPT3 prompt

Write an article based on the following input:

>> Starting point - This study deals with Design for AI/ML systems, in the industrial AI context based on case studies
>> Concept 1 - Human-Centered-Design (HCD), User Experience (UX) and Human Computer Interaction (HCI)
>> Concept 2 - Artificial Intelligence (AI), Machine Learning (ML) and the impact of technology
>> Requirement - The final outcomes should be transferable to a wider spectrum of domains
>> Goal - Examine the role of designers in the age of AI
>> Hypothesis - Current AI/ML development lacks the human perspective
>> Research 1 - Initial literature review revealed that AI/ML are perceived as a new design material
>> Research 2 - From qualitative case study research 17 themes emerged
>> Insight - Designers need new processes, methods, and tools in the age of AI/ML
>> Result 1 - Seven process modules for design, data science and business collaboration with related activities and dependencies
>> Result 2 - A unified framework for collecting use case exemplars

IV. Extracts of Interview Transcripts

In total 19 interviews were conducted for this thesis. The initial Meta-Sample interviews lasted for an average of 90 minutes. The Beta-Sample interviews were between 30 to 60 minutes, the expert interviews, 60 minutes. This produced a lot of material and information. Plotting the entire interview transcripts would result in 200+ pages, which would exceed the size of this document. The decision was made to include extracts of the interview transcript in this section - those which support the insights and findings derived from the data analysis and synthesis - the entire interview transcripts can be accessed digitally in the cloud using this link: https://bit.ly/3CY3sE3.

P1: Scrum Master

(in person, MUC)
Date: 01. August 2019
Time: 11:30 - 13:00
Language: German

[00:09:58] ... das Management... die natürlich auch manchmal so Ziele haben wie, besonders angesagte oder populäre Technologie einzusetzen.

[00:15:17] Durchsetzen, dass die Planer... wie sage ich das denn richtig... dass die Planer sagen, was es ihnen nützt und das sie deswegen auch mehr Einfluss haben auf die Lösung. Ich muss dazu direkt kritisch anmerken... Was da echt schwierig war, ist die Beurteilung was ist eine gute Prediction. Im Moment sind wir, nach langem damit auseinander setzen dabei das sowohl die line charts zur Beurteilung dienen, die Volatilität widerspiegeln und vielleicht auch das Niveau von Nachfrage für ein Produkt, als auch Fehlerkennzahlen. Und bei den Fehlerkennzahlen, das war auch ein längerer Prozess, brauchen wir eine normalisierte Fehlergröße NrMSI, brauchen wir eine relative Fehlergröße Mape und dann brauchen wir eine absolute Fehlergröße. Und alle drei Kennzahlen haben ihre Berechtigung und sind in der ein oder anderen Situation aussagekräftig oder nicht, je nachdem wie viel von so nem Produkt nachgefragt werden mit welchen anderen Produkten man es vergleichen kann, ob man es vergleichen will... und so weiter.
Es braucht aber aus meiner Sicht eine handhabbare Beurteilungsgröße damit ich relativ schnell sagen kann, ja der Forecast passt, oder nein der passt nicht ich muss nochmal neu trainieren oder ich spar mir, ich nutzt für dieses Produkt keinen Forecast aus der Maschine. Genau. .. Ich glaube, dass wir immer noch keine handhabbare Größe haben, vielleicht gibt es die auch nicht und man muss sich das verschiedenartig anschauen... und das den Planern alleine zu überlassen funktioniert aus meiner Sicht nicht, denn jeder Planer hat anders charakterisierte Produkte, jeder Planer hat einen anderen Erfahrungshintergrund, jeder Planer hat abhängig von seinem Material andere, wie sag ich's, Restriktionen. Also haben wir z.B. gelernt, das ein Material so groß ist, ein einziges Stück, in ner Würfelform werden die geliefert das man davon gar nicht besonders viele auf Lager halten kann, weil man den Platz dafür nicht hat, oder nicht bereitstellen kann. Das weiß natürlich das neuronale Netz überhaupt nicht; ist ja klar. Aber deswegen hat dieser Planer ein ganz anderes Interesse zu viel oder nicht zu viel in stock zu haben. Wieder andere Materialien sind so teuer, dass man die nicht groß in stock halten will. Und bei wieder anderen gibt es unterschiedliche Beziehungen zum Lieferanten. D.h. manche Lieferanten liefern genauso wie gewünscht wird und bei wieder anderen weiß Siemens da müssen wir Monate im Voraus bestellen damit wir es überhaupt kriegen. Da gibt es eine Reihe von anderen Einflussfaktoren, die nicht für jeden Planer gleich sind.

[00:21:21] Ich fand's total wertvolle, diese beiden produktiv Phasen zu haben. Und wir alleine hätte da nichts draus erkannt, wenn die Planer uns nicht dazu ihr Feedback gegeben hätten. Vielleicht hätten wir mehr von solchen Phasen haben sollen. Also immer mal wieder angeschaltet ausgeschaltet. Oder sie auf eine andere Art und Weise dazu kriegen, dass sie die Forecasts anschauen müssen. Und dann sagen, das nützt mir nix oder das nützt mir x oder es nützt mir sehr viel. Dieser Feedback-Loop, was haben die Planer wirklich davon, der hat entweder spärlich stattgefunden... ja nicht zu spät, aber immer früher wäre noch besser gewesen, na klar. Und was wir unterschätzt haben, dass die Planer da so skeptisch sind. Also das wurde natürlich dann schon klar und da muss ich sagen da hat der Product Owner viel Arbeit geleistet sie zu überzeugen. Wie bei jeder Vertrauensfrage, das entsteht nicht auf Knopfdruck, sondern über die Zeit. ... wenn uns das früher bewusst gewesen wäre, hätten wir vielleicht ein besseres Expectations-Management gemacht.

[00:29:55] Die erste Test-Produktiv-Phase, da gab es zwei davon, die im August war total wertvoll, weil wir da drauf kamen es braucht so ne Art Post-Processing. Wir können nicht alleine mit den Prognosen was anfangen.

[00:31:16] Dann war das schon ne gute Methode dafür, weil so viel neue Perspektiven und Anforderungen reinkommen, das wär krachend gescheitert, wenn man zum Zeitpunkt x im Sommer letzten Jahres zum Beispiel Anforderungen festgezurrt hätte. Da hätte so viel gefehlt. ... Das wichtige ist diese timegeboxte, diese 2 oder 3 Wochen Sprints.

[01:02:13] Für mich war, bevor ich dich kennengelernt habe Design Gestalten und zwar in irgend ner Form schick. Gestalten dass es pleasing to the eye ist und langfristig gedacht. Genau. Quality first. Mit so ner Klarheit. Und dann habe ich dich kennen gelernt und deine Arbeit, auch in diesem Projekt und habe eigentlich erst gelernt, dass das ganz viel damit zu tun hat welche Anforderungen werden erfüllt. Wer kann denn überhaupt Anforderungen stellen oder reinkippen, wem muss den geholfen werden oder was hilft dem denn. Genau. Und jetzt von meiner alten Design Definition personifizierst Du für mich diese Denke... Du hast immer ne slightly andere Perspektive mit reingebracht. Und deswegen will ich dem Design credit geben... ja... weil es auch immer mal wieder aus deiner Sicht nen Fokus setzt, und versucht was ist denn da der Kern, was liegt denn da dahinter, warum soll das denn so sein und nicht anders. Also ich glaube diese andere Perspektive und dieses Fokussieren wäre hilfreich gewesen. Und grundsätzlich je früher du eine Anforderung kennst und weißt die muss ich irgendwann berücksichtigen, umso leichter habe ich es dann.

[01:05:37] Wenn Design nur Requirements reinkippen will, ja... wenn Design dazu beiträgt, dass man eine Sache nicht tut und dafür eine andere Sache tut, dann wäre es wertvoll.

P2: ML Engineer

(in person, MUC)
Date: 01. August 2019
Time: 14:00 - 15:30
Language: German

[00:04:18] Also, ich hatte das Gefühl, dass die Erwartungshaltung in Erlangen zu hoch war, dass da einfach dieses Gefühl gar nicht da war.

[00:10:57] Gute Frage. Der wurde abgefragt auch schon relativ schnell. Danach haben wir im April angefangen, uns nochmal mit den Planern zu unterhalten überlegen und eigentlich schon recht klassisch versucht, den Prozess weiter zu durchleuchten und zu verstehen. Da war ich gar nicht so wahnsinnig selber beteiligt und habe nicht so viel Zeit investiert. Mein Eindruck ist, dass wir das fast noch nicht genug verstanden haben, um alle Fragen, alles nachvollziehen zu können. Also auch die Fragen der Planer nachvollziehen zu können. Da is immer noch ne Diskrepanz... wie wir das sehen und wie es tatsächlich läuft, glaube ich.

[00:28:59] Da gab es die Situation, dass wir davon ausgegangen sind, das ist schon viel besser, dass die Akzeptanz bei den Planern viel größer ist und dann rauskam, dass ist sie nicht. [...] Noch eine Sache, die man sicherlich hätte anders machen müssen, war dieses Ding, dass wir am Anfang haben wir Resultate gezeigt, mit einer Technologie und einem Ansatz, den wir aber so in der Form nicht wirklich operationalisieren konnten. Das war eben so verrückt, dass es so viele Probleme verursacht hat, weil jeder denkt dann in genau in diesen Fehler Metrics. Wir hatten genaue Vorstellung, was diese bisherigen Modelle und Fehler ergeben und jetzt nur durch diesen Technologieaustausch sind die eben ein bisschen schlechter. Und dann hat man ein Riesenproblem. Wir hatten es dann erst mal ganz schwer zu rechtfertigen.

[00:32:48] Hätte man das vermeiden können?

[00:32:57] Ja, auf jeden Fall. Was man daraus lernen kann, glaube ich, dass man auf der einen Seite war es gedachtes als so ein prototypische Ansatz. Das Problem ist sozusagen, wenn die Resultate des Prototypen zu gut sind. Das is der Grund, warum man in der UI Entwicklung lieber sketchy Prototypen zeigt. Weil man nicht nicht diese Erwartung liefern. Im Prinzip ist sowas ähnliches passiert. Man hat sozusagen einen Prototypen gehabt, den man, aber man wusste, den kann man gar nicht so verwenden. Oder vielleicht wusste man es auch nicht. Gerade wenn man schon so genau Werte liefert, ist das dann auch skalierbar.

[00:38:25] Das ist eine gute Frage. Ganz ehrlich, es ist schwierig das ganz konventionell zu machen. Was ich meine, es ist natürlich ganz wichtig die Erkenntnis, dass du iterativ vorgehen musst. Es hat sich natürlich wieder herausgestellt, du kannst dir noch so noch so viel Gedanken machen über die nächsten sechs Monate. Vergiss es. Du kannst ja nicht planen über die nächsten sechs Monate. Du wirst immer von fast Unerwartetem heimgesucht, und je weniger du es erwartest, desto mehr wirst du heimgesucht. Das ist einfach so, und das war schon wichtig. Was jetzt agile Methoden angeht, ja mei es war halt wieder so selbst gestrickt. Wir haben nicht genug Zeit, in die Anforderungen in den Backlog, in die User Storys gesteckt. Das hätte man noch mehr machen müssen oder können. Das heißt ja gut, das hätte halt doch mehr Aufwand bedeutet. Aber das wäre gut gewesen. Da haben wir auch dazu gelernt. Das ist eigentlich ein Riesenthema.

[00:41:00] Zum Beispiel das Timeboxing hätte man so viel besser machen können. Da haben wir dann auch immer wieder versucht das zu verbessern. Aber das war so eine Erfahrung. Wahrscheinlich ist das eine große Herausforderung. Das mit dem Timeboxen, weil man im Machine Learning doch immer wieder diese Komponenten hat, wo alles offen ist. Und es auch immer neu ist und du nicht weißt was dabei raus kommt. Und das ist ja eine riesen Herausforderung. Bei so Projektarten.

[00:46:01] Es wäre schon gut noch Jemanden zu haben mit mehr Zeit und dieser PO Rolle und vielleicht ein bissl mehr Erfahrung. Ansonsten glaube ich ja. Ich glaube schon, dass wenn wir die Möglichkeit gehabt hätten, hätten wir die Planer besser und mehr integriert. Und das ist auch sicherlich ne gute Idee. Man müsste vielleicht von vornherein ein paar mehr Sachen abklären, mehr darauf beharren, dass wir von den Stakeholdern oder von unseren Partnern, dann diejenigen, die es benutzen, noch mehr, dass man noch mehr daran arbeitet, die Vorstellungen und die klaren Ziele zu schärfen. Auch dass man die vielleicht auch noch mehr auf der einen Seite unterstützt, dann vielleicht auch so ein bisschen fast zwingt dazu, noch genauere, noch genauer zu definieren, was zum Beispiel wie gut ist denn gut genug. Das war ein Riesenthema. Und es ist jetzt immer noch nicht komplett klar. Und noch nicht jeder hat da die gleiche Sicht drauf.

[00:52:08] Ganz viel zentriert vor allen Dingen darauf, die Forecasts zeigen und interessanterweise ist das auch gar nicht so ohne, weil es ist ein Riesenthema, welche Fehler-Metrics trägt dazu bei, wie Du die Forecasts bewertest. Welche ist da richtig und aussagekräftig? Das ist es überhaupt nicht leicht. Und man ist ganz schnell geneigt, die Dinge dann zu positiv zu präsentieren. In jeder Situation hast du verschiedene Möglichkeiten. Und je nachdem, welche du wählst, kannst du Dinge durchaus noch positiver oder negative darstellen. Das ist ein richtiges Problem. Wir sind da einfach nicht zu einem Entschluss gekommen.

[01:12:31] Ich hab echt ein Problem mit dem Projekt mit ähnlich hohen Erwartungen. Das verwundert mich immer noch. [...] Also lessons learned, Forecasting ist schon ne einfach echt schwieriges Feld. Ich glaube vor allen Dingen, die Erwartungen müssten noch besser gemanaged werden.

[01:18:17] Ich hab ne Idee. Doch ich kann mir vorstellen, was mich interessiert hätte, wäre es nicht doch möglich gewesen, vielmehr auch den Planer oder deren Prozess vielleicht auch mehr umzugestalten? Wobei ich vielleicht gar nicht den Planungsprozess an sich meine. Ich glaube den so genau zu verstehen, wäre für uns fast nicht möglich gewesen. Aber zum Beispiel die Frage warum nicht doch die einfach arbeiten mit so nem Dashboard? Da bin ich mir nicht sicher. Es wäre doch sehr interessant. Ich glaube, es ist schon verdammt schwierig, mit so einer Ablehnung noch was rauszuholen und ist es dann so Human-Centric, wenn man erst mal so eine Mauer durchbrechen muss. Aber manchmal, das habe auch schon als Consultant in der Vergangenheit erlebt, ist es auch manchmal richtig gut. Und das haben wir gezielt ab und zu gemacht und du hast den Nachteil, dass manche Leute total happy sind und manche eben nicht. Und die Leute werden dann vielleicht entlassen. Aber das geht schon manchmal. Ich weiß nicht ganz sicher, ob es wahrscheinlich wäre es auch wieder an der Kapazität gescheitert. Dass die Leute zu sehr unter Druck stehen. Veränderungen muss das Backup des Management haben. Hatte es in dem Fall auch zu wenig. Und was passiert? Genau die gleichen Fehler sind passiert, die in jedem agilen Transformationsprozess, dass von oben gesagt wird, ja, ihr macht da jetzt mal Plan 2.0, aber bitte doch in genau dem Modus den ihr vorher auch gemacht habt. Und das funktioniert halt nicht. Du hättest zumindest einen der Leute, hätte du quasi freistellen müssen, vielleicht nicht für die ganze Zeit. Und wenn du das nicht machst dann siehst du aber… da kann man nur sehr, sehr bedingt Erfolge verbuchen.. Was hätten die denn auch machen können?

P3: Project Manager/Stakeholder/Supervisor

(in person, MUC)
Date: 07. August 2019
Time: 10:00 - 11:30
Language: German

[00:03:47] P5 hat damals, aber auch als hier das Team nach und nach zusammen kam, wurde damals für eine gewisse Stichprobe ein Modell entwickelt, was sich dann einfach sukzessive erweitert hat. Und die Stichprobe dann irgendwann immer klarer wurde. Damals war die Stichprobe so etwas wahllos gezogen, und irgendwann hat man mal angefangen ein bisschen mehr Gehirnschmalz reinzustecken, welche Produkte denn auch tatsächlich Sinn machen, weil die Resultate so vielversprechend waren. Daraufhin hat man dann angefangen zu evaluieren, okay, wie kann ich jetzt mit einer sinnvollen Stichprobe mein breites Produktspektrum so gut wie möglich darstellen, um auch nochmal die Performance der Modelle zu überprüfen?

[00:05:54] Total rudimentär ehrlich gesagt, wenn du dich noch an unserem Workshop bei IBM erinnerst. Das war so ein Einstieg in das Thema, wo wir mal versucht haben darzulegen, wie eigentlich der Stand heute ist mit den Planern und mit den jeweiligen Sales Kollegen und UPM. Wie die miteinander agieren? War ein Design Thinking Workshop. Es war das erste Mal, dass wir dezidiert versucht haben zu veranschaulichen, wie der Prozess heute läuft und wo es Schwierigkeiten gibt.

[00:09:35] Ich glaube die Problemstellung ist halt ne andere. Du hast da nicht etwas, was du auf einer grünen Wiese hinstellt und sozusagen neu erschaffst, wo vorher nichts gewesen ist, sondern es hat sehr viel mit Veränderung zu tun. Und natürlich dadurch, dass es ein KI Thema ist viel mit Vertrauen. Das heißt, die Problemstellung und die Komplexität der einzelnen Themen, mit denen wir uns auseinandersetzen sollen und müssen, um das zu erreichen, noch mal was anderes als bei einer Neuanlage.

[00:12:47] Ich glaube, es wird die Kappa teilweise auch, was machbar ist. Da zu gucken, ist es denn auch sinnvoll, für jedes einzelne Produkt ein Modell anzuwenden? Wenn ich eigentlich schon weiß, dass ich in meinen Produkten xyz Anzahl an Produkten habe, die einfach nicht predictable sind. Dann muss ich einfach sinnvoll meine Stichprobe oder meine Daten entsprechend schon so vorbereiten, aber das erfordert natürlich auf Kundenseite auch sehr viel Zeit, das entsprechend zu machen. Und so sind wir oft diejenigen, die das machen, indem wir einfach alles machen.

[00:13:36] Wir haben natürlich die technologische Expertise, ich nenne sie jetzt mal Data Scientist oder ML Engineer, die zum einen wichtig ist, was die Modell-Konfiguration anbelangt. Und zum anderen auch die ganze Prozessautomatisierung, die dahinter steckt. Im Sinne von welche Infrastruktur, im Rahmen einer Cloud kann ich dann den Prozess so abfahren, dass ich diesen manuell Daten -Up und Download wöchentlich nicht mehr habe. Das ganze Thema auch was in deine Richtung geht, wenn wir Interviews mit den jeweiligen Nutzern gemacht haben. Ich glaube, da erfordert es ein gewisses Talent, die richtigen Fragen zu stellen oder auch richtig zuzuhören, um auch tatsächlich die Pains zu erfahren und nicht die, die wir hören wollen.

[00:19:08] Ich glaube weil wir dann doch oft durch äußere Umstände in irgendeine Not gekommen sind, was darzulegen oder weil wir es an irgendeinem Thema hing, was dann so viel Kappa gefressen hat über einen längeren Zeitraum, den wir nicht vorhergesehen haben, oder so nicht abgeschätzt haben und dann priorisiert wurde. Das ist doch zwei, dreimal passiert, glaube ich, dass der komplette technologische Aspekt und die Modellgenerierung im Fokus stand. Dass wir das Thema Nutzer wieder so ein bisschen aus der Perspektive gelassen haben.

[00:21:49] Weil wir sonst eine technologische Lösung bauen, die mega techy ist und super fancy, aber von keinem benutzt wird. Und was ich auch glaube, was ich noch hätte besser machen können. Da hätte ich mich vielleicht auch einen anderen Meeting noch mehr mit einbringen müssen und mehr Zeit investieren müssen. Gefühlt ist aber meine Wahrnehmung… weil wenn du dir überlegst wir sind seit Ende 2017 mit dem Thema beschäftigt, wir haben jetzt Mitte 2019. Wir haben bald zweijähriges bei dem Thema, und ich glaube, wir haben unendlich viele Schleifen gedreht, am Anfang was ist die richtige Stichprobe, wie kriegen wir es sicher, dass das ganze Thema Dateninput konsistent ist? Da haben wir unglaublich viel Zeit verloren. Und da wirklich vehement sagen das Thema kommt von euch, das prüft ihr, ihr macht den Qualitätscheck und wir haben trotzdem immer nochmal doppelt gemacht getestet, was auf der einen Seite gut war, weil man viele Fehler entdeckt haben.

[00:31:20] Ich glaube, die Modellierung ist sehr schwierig, weil wir ein sehr diverses Portfolio haben und wird auch viel Zeit in Anspruch nehmen. Ist aus Kundensicht auch der gefühlt wichtigere, weils immer Performance getrieben ist. Aber auch das Thema Implementierung ist nicht trivial. Was das ganze Daten Handling anbelangt. Ich glaube, der wird uns nicht ganz so viel Zeit kosten, aber fast genauso viel Zeit kosten wie das Thema Modellierungen. Und was wir nebenbei konsequent begleiten müssen, ist das ganze Thema Prozess Veränderungen. Wie wollt ihr mit den neuen Modellen arbeiten? Was macht ihr anders als bisher? Könnt ihr das auch sicherstellen. Oder auch diesen Denkprozess überhaupt anzuregen. Hat aber nicht so viel Zeit gekostet, bzw. haben wir uns bis dato noch nicht so viel Zeit dafür genommen, wie für das andere. Jetzt muss man auch sagen das ist eine schwierige Situation aus PO Sicht gewesen, weil für diese anderen Themen immer sehr weit im Fokus standen.

[00:37:57] Weil es uns gar nicht so bewusst war. Ganz am Anfang war es mir persönlich auch nicht so bewusst, wie wichtig UX doch ist. Weil wir uns so in diesem, ja ich muss ja jetzt erstmal technologisch überprüfen, ist das denn überhaupt technologisch machbar können, verloren haben. Und wir meinten das schauen wir uns später an.

[00:41:31] Und ich würde mit unglaublich viel Lessons Learned von genau diesem Projekt ankommen, gerade was dieses Thema Nutzer anbelangt. Ich würde mit unglaublich viel Lessons Learned, wie brauchen wir die Daten. Und mit welcher Menge von Daten fangen wir an? Und was ist Minimum Requirement, damit so ein Modell überhaupt sinnvoll ist, überhaupt in ein Machine Learning Modell gepackt zu werden? Wenn ich jetzt zwölf Datenpunkte habe, dann kann ich auch gleich den Mittelwert ausrechnen. Da habe ich mehr davon, als wenn mich jetzt mit einem neuronalen Netz totschlagen. Das bringt nämlich gar nix. Und ich glaube auch klare Requirements von unserer Seite am Anfang darlegen, genau, an den Kunden. Was brauchen wir, damit wir euch bestmöglichst unterstützen und ohne das können wir gewisse andere Sachen eben einfach auch nicht tun, was auch so ein bisschen ins Erwartungs-Management geht.

[00:49:02] Sie geben schon Feedback. Aber ich glaube, Kollege x koordiniert das vor Ort in Kontakt, damit wir nicht mit allen Fünfen in Kontakt treten müssen. Ich glaube der tut sich ungeheuer schwer. Zeitnah, von alle, weil es natürlich auch unglaublich viele Daten sind, muss man auch sagen, das Feedback zu bekommen und was er mit dem Feedback anfängt, wenn jemand sagt, passt oder passt nicht, weil… dass jeder aus einem ganz anderen Argument heraus entschieden hat.

[00:59:41] Das wäre für mich jetzt eine Sparte, sozusagen. Also Sparte, aber ein Bereich eben, weil er sehr breit ist hinter den einzelnen Funktionen und darunter verstehe ich wie wir den Mensch in den Mittelpunkt als Nutzer setzen und auf Basis dessen, was seine Schwierigkeiten sind, versuchen, ich will jetzt nicht nur sagen ein Design zu entwickeln, weil ich glaube, es hat für mich auch etwas mit Prozess zu tun, nicht nur mit Applikationen, sondern auch Prozess, zu entwickeln, die dem gerecht wird.

[01:01:34] Absolut hat es einen Mehrwert. Es ist ja, glaube ich, das was wir heute feststellen, dass wir hier und da nicht gut gemacht haben. Ich glaube, viele verstehen es immer nur unter der Applikation hübsch machen. Sehe ich jetzt nur als einen gewissen Teil hier und da. Und hübsch machen heißt ja auch nicht immer, dass es dem Nutzer entsprechend gerecht wird mit dem, was er für seine tägliche Arbeit braucht. Und ich glaube, dass wir viel stärker auch dieses Bewusstsein brauchen. Das ist eigentlich genau diese Frage. Was verstehen wir darunter und wenn wir es auch unter dem Sinne breiter verstehen, und das tue ich auch im Bereich des Prozesses, dann geht es ja darum, dass wir uns überlegen, wann macht es Sinn? So wie du auch gefragt hast. Und es macht von vornherein zu Beginn sinn, nämlich anzugucken wie ist der Prozess heute. Und was sind die Bedürfnisse des Nutzers? Wo hat der Nutzer heute Schwierigkeiten? Basierend auf einer technologischen Lösung, die wir geben können, was ändert sich für den Nutzer? Und was sind Parameter, die man überdenken muss, indem wie er heute arbeitet, versus wie er zukünftig damit arbeiten muss und das dann natürlich auch irgendwie in eine nette Applikation oder Interface zu packen, die auch genau das ermöglicht, ist ja wieder ein anderer Baustein. Aber das ist halt nicht nur, sondern für mich ist es auch der Prozess, der damit hinter steht. Das kann man auch gar nicht losgelöst voneinander betrachten. Sollte man überhaupt nicht losgelöst voneinander betrachten, weil das eine geht ohne das andere nicht. Aber ich glaube, wir haben halt oft immer bei Design das Thema, ich mache jetzt mal vom Layout her hübsch.

[01:06:23] Ich glaube immer, wir wollen Dinge oftmals nur so halb, indem wir irgendwas cooles, technologisches reinbauen, um zu zeigen, wie toll wir sind. Das ist jetzt nicht blöd gemeint. Aber wir vergessen eigentlich die Zielsetzungen manchmal dahinter. Was wir damit erreichen wollen. Mit Zielsetzung gehört für mich dazu, ich will morgen anders arbeiten, als wie ich heute arbeite. Und wenn anders arbeiten, hat für mich etwas damit zu tun, wie die Leute damit arbeiten. Auch eine technische Lösungen anbelangt und nicht die technische Lösung an und für sich selber, dann habe ich nur irgendein blödes neues Tool. Es ist ganz oft diese Tool-Denke, was ich auch echt bald nicht mehr hören kann. Ich hab ein neues Tool und damit kann ich das und das machen. Alles wird eigentlich auf das Tool fokussiert, was das Tool alles macht, alles kann und es wird parallel gar nicht geschaut, was ich denn eigentlich mit vielleicht viel einfacheren Sachen machen könnte, indem ich einfach gewisse Sachen in meinem Prozess ändere oder Rollen ändere, das ist teilweise viel wichtiger.

P4: Data Scientist
(in person, MUC)
Date: 08. August 2019
Time: 11:00 - 12:30
Language: English

[00:04:14] For the set of 25. But this came later when we realized, like, what's going on here? So, yeah, so they put in some work to try to get a representative sample of the entire production line.

[00:09:49] Um, yeah, so I guess. I view it as trying to make some forecasts. Of customer demand based on historical, I guess, customer demand. I think the goal was to help the factory planners figure out how many products to make. So not necessarily telling them exactly what to do, but to give them a suggestions, more in the lines of decision support. And for the ones where I would say if the estimation was like stable and somewhat robust I would imagine then they're manual efforts is reduced. So I think one of the goals was to reduce the manual efforts, the others to kind of give more unbiased estimate of what the demand forecast would look like just because between the different inputs they would get from the sales guys. The factory planner kind of added to that, like some sort of weighting of what they believed from the sales guys because there will be like sales guy A is optimistic sales guy B is pessimistic. And then they kind of had this kind of subjective view on what that true value is. And I think that the demand planning from the machine learning algorithm would give less subjective, or at least less emotional estimate of what the demand patterns will look like. So I think it's more like to bring a little bit more neutrality to this estimation if that makes sense or a more non subjective estimate. But to me, it was never the goal to replace them, but rather to help their job. Yeah, help their performance.

[00:17:33] But the thing is, like, even from a non domain expert, if you look at the formula you're like, that's kind of nonsense. That's respectively like not doing what you would want and adding noise to the estimate. But then it's more like okay, like, well, why did they come up with this formula? It's because they want to incorporate this kind of concept in the post processing. So it was more like trying to group what they want, but express it in a, like, properly said, like formal mathematical formula that made sense. But not relying on them to say like, like not 100% relying on them. I think it's somehow a goal in between, like, you're trying to, like, listen to them, but then translate this into something that is computable.

[00:18:54] Yeah. And in what way. So some sort of like translator, but not like, literally in language per se. Well, maybe it is natural language to mathematical language. So, I mean, I think that's common though, like, sometimes they like, oh, why don't we just do this and you're like, well, if you do that, then this will mean a lot of like, inefficiency in computing something or whatever. And you kind of just need to guide them in the right way.

[00:26:56] And some of the questions where we would ask her like, oh, could you define what is a useful KPI for you was like completely challenging. But we couldn't really define that for her. So I think the customer needs some sort of technical like competency. Okay, like I think we somehow managed. I think it would have been good if the factory planner somehow was also in like process with colleagues x, y and z. We would have a lot of meetings with these three. We've very rarely had a meeting with the factory planners. And if they had a role there like a, I mean, they had a role but just in a different subspace of roles.

[00:33:46] I mean if that project didn't exist, and it was a different task as a classification task, like completely different models that couldn't apply to this use case anyways. I mean, I think there was also still things to look into. I mean, a product grouping. This was something that was always like, no, we won't do it. Or maybe we'll do it. No, we won't do it and now it looks really well. I feel like the requirements kept shifting. I think it would have been much more efficient if we spent more time to fix this. And then we just did it.

[00:34:55] Yeah, yeah, I mean, I think like anyone on the team had the power to be like, no let's look at that list of requirements. Is it on there? If not, then we're not doing it or something like that. Or we vote on it. Somehow I think we were, like, super eager to please the customer. And so we kind of gave the customer like the like. Yeah, no crown to say. Yeah. So, no, that was I think, probably took some hit in productivity. I remember we did one week of this product group concept, but for nothing like there was no follow up or anything until now, which is debatable whether or not that was dependent on the experiments.

[00:41:18] I think the feedback probably. The feedback loop when they said, uhm I can't use this. And then us refining the method I mean I guess if we didn't do that, and they're just like, we can't use it, you don't use it. Everything with the feedback loop.

[00:41:58] Yeah. I think that was one thing, like, the forecasts, in the beginning would sometimes give negative numbers especially if it's like something that had very low demand and like 000 demand and then like three pieces, and you know, this kind of thing. And so the algorithm itself didn't know it was forecasting something that could only be positive, though technically we could have taken care of that, but we didn't. And so in the beginning, P7 would be like, there is a negative number there's negative one why is there a negative one? Or one thing that was kind of interesting to me was I remember I did one of my first file exports, it'd be like 1.2 or something. And the planners were like I can't make point two. Are you serious? Like, make 1. So I think that was one thing that was really surprising. For I think both me and P5 are like, are you kidding me? Like, like, it's a suggestion, right? Like, don't take it so seriously. Or like, you just have to do some sort of interpretation. Like I think that was one thing that was like, I mean, it was supernatural for us, but maybe it was like completely like, oh, no, the machine learning algorithms like completely shit is giving like nonsense numbers. Right. So I think there was a gap there and trying to like, relate to like, what they're expecting. Yeah, I think that was one thing. I think it was really hard in the beginning because they would say like all but like last year, it would be like more like in these numbers or something like that. But, like you're suggesting something much lower and stuff like that. But then like a few months later, they like how did you know it would be less? Like, we're just, you know, trying to use historical patterns. Like, it's not like we told them to be more pessimistic. I was just kind of like. I think it would be these kind of comments that we get as feedback. I mean, some we can address. Yeah.

[00:44:54] … sometimes like the people who are more in the project manager role, maybe they didn't have this AI experience so like, there was a little bit like a bit of a gap there where you're like, okay, like, well, when I say why this doesn't make sense, or why it's not efficient, like, we actually need to kind of share some information. They're like, why? But that means not a main issue. I don't think like, it's just more like, okay, I noticed that was a little bit different with other project managers who kind of like are used to the language and everything.

[00:48:06] I think so. I think if the factory planners didn't have maybe a feeling of insecure, job insecurity, they would have been more cooperative. I mean, it's just judging from other projects. So like, I remember talking to one of these guys from another department and he was one of, I think, maybe a data citizen or something like that. And he was saying how other colleagues in his group were, like, amazed that he was actually participating in this data citizen stuff, because they're like, aren't you scared, you're like going to be replaced and that the machine can do your job better and blah, blah. And he was like, no, because I feel like this is going to help me work more efficiently. Like, I don't wanne do this nasty stuff, but I can actually do the more complex stuff and perform better overall. So I think it's like the perspective is, like super important. And if the if there's members on the team that are not really like motivated to try this, they will just act as friction or cause some sort of friction to the momentum of the project. So I think if they didn't have those feelings of insecurity, they would have maybe been more helpful.

[00:50:13] Yeah, I mean, I think the shitty thing was we got the interview done after we had set some requirements. Like, oh, maybe we should have done that first.

[00:50:35] And I think maybe we could have been more sympathetic, knowing that perhaps this could be a touchy subject for them that like, oh, look how well the machine learning algorithm performs, right? It's kind of like a jab like we did last year and look what we did this year. So I think maybe we could have been a little bit more sensitive to that right? Like, okay, like, maybe be more balanced or like, seems like for these cases we perform better. These ones not so much. What would have been better like or what, how can we improve like, what do you look at to improve your estimations like, you know, try to be a little bit more sensitive to perhaps this insecurity might have been better? Yeah.

[00:52:07] I mean, I think even how we presented the results, like, you know. Instead of just be like, look how good we perform compared to last year, like we never even really set up the problem like, you know, this is a hard task. The, you know, the factory planners, they have a lot on their minds, and there's all these different things, components, moving components that they need to consider. How can we make their jobs easier, like, you know, like, try to make them feel like they're important this whole occasion and that we're trying to help them like, I don't think we really did that. We're just kind of like, look how good we can do. I felt like maybe in hindsight, we could have been more sensitive and show that we did respect their domain knowledge. Yeah.

[00:54:55] So I think it's just because AI could seem so cold. Like as the Data Scientist who somewhat delivers the AI we need to kind of show there's a human aspect to it, I think, or at least I feel like you could get people who maybe are not in the right mindset, and if we approach it the wrong way, we just keep them in the wrong mindset.

[00:57:21] Yeah, I mean, I think we shouldn't have relied on them to manipulate the numbers themselves. Like, I think we should make this as, like, trustworthy as possible in all the different ways that they can but say do sanity checks. I think this is important. And if they do even raise this question, of course, the post processing that we did is more sophisticated now than just taking the max and making sure it's positive. Like we actually went in, did some experiments and developed something that was, you know, a little bit more sophisticated. So I think, it is good that they made a point and we improved the solution. But on the other hand, I think they also need to make some changes and how do they work. Right? So, okay, it's a different column now in their system, and they have to look at this. But, like, I think somehow they need to kind of, like, change their way of working. It's not just like, you could just put in this number, and now I don't think or whatever, like you said, to do a little bit of work, right? Like, you know, there's a big order coming, like, have the expectation the model doesn't know it is. So you know, and also the capacity so, you know, you probably want to spread that large order over the week. So, like, I guess, yeah, you still have to kind of work with it is not just magic. So I think it's on both hands, but I think as a Data Scientist, we should make sure that the solution is as kind of comfortable to use as possible, given the resources that we have of course.

P5: Sr. Data Scientist
(remote)
Date: 13. August 2019
Time: 13:30 - 15:00
Language: German

[00:15:04] Ich bin so ein bisschen am Überlegen, ob mir teilweise der Input, den wir von den Kollegen aus Erlangen bekommen haben, und von der Einbindung des Kunden selber, ob ich den eng genug fand. Und im Hinblick auf den Product Owner war er das, aber im Hinblick auf die Leute, die später damit arbeiten, also wirklich die Planer, da hatte ich manchmal den Eindruck, dass die zu sehr an der Seitenlinie standen und auch zu viel mit ihrem Alltagsgeschäft vertraut oder betraut waren. Also hättest du da wirklich einen Planer komplett freigestellt von seinen Aufgaben und hättest du ihn quasi – genötigt würde ich jetzt nicht sagen, aber hättest du sozusagen dafür gesorgt, dass er quasi aktiv in dem Projekt seine Rolle da auslebt, dann hätte, dann wäre vielleicht die eine oder andere Iteration uns erspart geblieben.

[00:20:06] Also wir haben es ja letztendlich versucht, in einem agilen Scrum-Prozess dann entsprechend zu fahren, und ich glaube, dieses, dass man hier versucht hat, immer in kleinen Sprints Arbeitsergebnisse vorab zu definieren und die dann zu erreichen, das war auch schon ein Schlüssel, dass man sich bei solchen Sachen nicht verzettelt und auch der Kunde immer schnell sieht: Wo stehen wir denn da gerade? Also was ist denn der Vorteil auch der – wo sieht man sozusagen die Weiterentwicklung? Und so weiter und so fort. Ja

[00:20:46] Wichtig, weil es ein sehr abstraktes Thema ist, auch erst mal was so die Begriffsbildung angeht. Also das, wenn ich sage, ich habe einen, ich mache einen – also ich unterscheide in Prognose und Planung. Und viele von den Kollegen, wenn die planen, ist für die Plan gleich Prognose. Und auch da erst mal überhaupt zu gucken: Worüber reden wir? Was ist sozusagen der – also was ist sozusagen da auch vom Sprachgebrauch her das Richtige? Und was meinen die Leute eigentlich? Und dann ihnen zu zeigen, was diese Prognosemodelle können und was sie nicht können, weil letztendlich hast du historische Daten. Was in diesen historischen Daten drin ist, kann reproduziert werden und, was da nicht drin ist, halt nicht.

[00:24:28] Ja. Also erstaunlicherweise, obwohl die Daten eigentlich aus einer gepflegten Datenhaltung stammten, also aus einem SAP-System, war da einiges erforderlich, um die Daten dann auch irgendwie so aufzubereiten, dann entsprechend für Datenkonsistenz zu sorgen, Doppelbuchungen oder irgendwelche Ausgleichsbuchungen, also das erst mal klarzukriegen, hat P2, glaube ich, sehr viel Zeit und Nerven gekostet. Und das ist halt auch so eine der Botschaften, also generell würde man sagen, man sollte gerade den Bereich der Datenaufbereitung/-konsolidierung nicht unterschätzen im Hinblick auf die Zeit und den Aufwand, den man da hat.

[00:27:16] Ist, war ein recht langes Thema. Also ich meine, wir hatten – also man kann halt irgendwo gucken, gerade wenn du prozentuale Fehler anschaust. Also du hast halt, das ist, weil – das ist das typische Beispiel: Du hast einen High-Roller, da gehen, sagen wir mal, in einer Woche 1.000 Einheiten werden produziert. Und du machst eine Prognose von 1.050 zu 1.000, dann hast du halt irgendwie 5% Fehler. Und wenn du, ich sage mal, ein Small- oder ein wenig nachgefragtes Produkt hast, da werden also zwei Einheiten nachgefragt und du sagst sieben, dann hast du auf einmal einen Fehler von ein paar Hundert Prozent. Und trotzdem hast du dich nur um ein paar Stück geirrt. Also dass man das da überhaupt mal ein gewisses Verständnis zu haben: Was ist ein gutes Performancemaß? Ist das ein prozentualer Fehler? Ist das ein Fehler in Stück? Und vor allen Dingen auch: Wie bewertest du die Güte eines Absatzplanes? Also auch im Hinblick auf: Wie stabil ist der über die Zeit? Also du willst ja auch nicht von Woche zu Woche immer deine komplette Planung umschmeißen. Ich glaube, das ist, dabei war auch ein Lernerlebnis, dass es nicht die Performancekennzahl gibt, sondern letztendlich nur Vorschläge, die mehr oder weniger Nachteile haben, und es sich dann auch vielleicht lohnt, nicht nur eine Kennzahl anzugucken, sondern auch vielleicht auch zwei oder drei Kennzahlen.

[00:31:05] Ja. Die Frage ist halt immer: Wann fasse ich ein Modell an? Und man kann natürlich sagen, gut, du trainierst, versuchst ständig nachzutrainieren, auch von Woche zu Woche. Aber ich meine, statistisch gesehen ist – also der Wunsch ist natürlich verständlich, die Modelle immer auf aktuellster Informationsgrundlage zu haben. Wobei es, wenn du anguckst, wir arbeiten mit Wochendaten und die Modelle haben so meistens, ich sage mal, 200 Datenpunkte, also was ja ungefähr drei, vier Jahren entspricht. Und wenn du da jetzt irgendwie einen Datenpunkt noch dazubekommst, ist das nicht so viel in Anführungszeichen. Also das heißt, da hast du auch im Hinblick darauf, wenn du es zwar alles machst, also Rechenleistung gegen dann wirklich den Effekt und Mehrwert, ist das eher vernachlässigbar und insoweit hin, dann auch zu sagen, ja, Modelle, die auch gut laufen, muss ich erst mal gar nicht anfassen und da kann ich natürlich auch viele Ressourcen dann sparen, so ein bisschen so auch so ein Diskussionsprozess gewesen und natürlich auch so ein bisschen ein Prozess, wo man dann auch testen kann oder konnte. Also wann lohnt es sich, dann entsprechend nachzutrainieren, und wann nicht?

[00:40:41] Also das ist – also jetzt für Data Analytics Projekte gesprochen, ist es eine Funktion, die eine Brücke baut zwischen einer Fachdisziplin oder einer Domäne von Modellwelt oder Mathematik, die für die meisten Leute erst mal komplett neu sind oder sehr mystisch sind, und die sozusagen hilft, dass die Anwender dann auch in gewisser Weise ein Vertrauen in eine derartige Lösung und in derartige Algorithmen aufbauen, nämlich dahingehend, dass sie auf der einen Seite die Chance haben oder die Möglichkeit haben, die Anforderungen zu spezifizieren, zu spezifizieren, was erwarten sie von einer solchen Lösung, dann aber auch in gewisser Weise auch aufgezeigt zu bekommen, was es da nicht kann. Also das ist auch ein bisschen so Erwartungsmanagement da mit rein. Ich meine, du kannst ja als User, du kannst ja alles Mögliche definieren, denke ich, aber dann aber auch gleichzeitig zu sagen: „Nee, das wahrscheinlich nicht" oder „Das eher, das bleibt dann schon noch bei euch als Funktionalität hängen." Und da denke ich auch, zu moderieren und auch genau zu identifizieren „Was ist denn da eigentlich dann, was ist da sozusagen der Need?" und das herauszuarbeiten, ist ganz zentral.

[00:45:00] Ich denke, dass... Also auf der einen Seite glaube ich, dass das Kunden unterschätzen, was sie irgendwie selber machen, sie irgendwie eine ganz klare Vorstellung haben von dem, was das Problem ist, aber die Übersetzung dann in eine Data Analytics Lösung oder Entscheidungsunterstützung, da gibt es durchaus ein Mismatch. Und den muss man erst mal identifizieren oder da halt auch dann eben gucken: Was kann man sozusagen da machen? Und wie kann man helfen und wo kann man nicht helfen? Und das sozusagen für die einzelnen Rollen dann auch zu spiegeln, ist zentral. Und die Erkenntnis halt auch, dass Data Analytics jetzt nicht nur irgendwie Datenquälen ist, sondern dass da immer ein Geschäftsprozess mit dazugehört mit entsprechenden Anforderungen und mit entsprechenden Notwendigkeiten. Und ich habe halt auch den Eindruck, also, wie gesagt, dass halt viele Softwareanbieter oder, sagen wir, viele Lösungsanbieter, die kommen klassisch aus der Informatik und sehen so was erst mal nicht. Oder du hast halt Leute, die kommen eher aus dem Business, also so wie SAP, aber die sehen, die greifen dann halt bei der Informatik zu kurz, also bei den Modellen. Und das irgendwie unter einen Hut zu bringen, ich denke, da ist dann, da ist sozusagen Design Thinking oder User Experience ein Punkt, um insbesondere die Kundenseite da einzubeziehen und dem Nachdruck zu verleihen.

P6: Data Analyst

(in person, MUC)
Date: 17. September 2019
Time: 12:30 - 14:00
Language: German

[00:04:28] Dadurch dass ich mehr den Teil der Visualisierung gemacht hab, war das schon gut zu verstehen, was die Data Scientist brauchen aus deren Sicht, aber auch die Planer und unsere Kunden, wie sie die Daten sehen. Und es war ganz gut eben diese Schnittstelle zu haben, dass man nicht zu technisch ist und einfach beide Seiten verstehen kann. Der eine der nur mit den Algorithmen kommt und der der nur die wöchentlichen Zahlen sieht.

[00:05:25] Man hat ja gesehen, dass die Planung schlechter waren als die Zahlen, die wir geliefert haben. Aber trotzdem haben sie dem Algorithmus nicht zugetraut, weil die Kurven einfach anders ausgesehen haben. Sie haben sehr optisch die Zahlen bewertet.

[00:06:41] Ich glaube, es liegt daran, dass das Verständnis nicht da ist, auch wenn man jetzt von Algorithmen spricht, weil wir sagen, wir haben es ja ansatzweise schon erklären, auch was der Algorithmus macht. Aber einfach das Verständnis zu haben, wie man mit historischen Zahlen zu diesem Ergebnis kommt, das zu haben und es zu akzeptieren, dass es oder auch historisch gesehen, die hatten diese Kurven gar nicht vorher. Sie haben auch ihre Planung nie gegenübergestellt. Sie haben ja gesagt, ja, ich finde das, so sieht es aktuell aus. Meine manuelle Planung sieht so aus, es driftet auseinander und ich akzeptiere das, dieses Bild haben sie bisher nie gehabt. Und jetzt? Die Erwartungshaltung von KI ist ja, dass es perfekt wird. Also gefühlt, sagt er, wird immer besser. Das muss ja besser werden, wenn ich erst dann erst mal diesen Vergleich habe. Er sagt, nein, das driftet ja hier genauso auseinander.

[00:12:57] Also im Endeffekt hat man versucht, die Visualisierung besser zu machen und eigentlich nicht den Inputgeber von der Visualisierung? Habe ich das richtig verstanden?

[00:13:09] Genau so. Man hat sich halt sehr viel erhofft, dann noch mehr Inputs, also noch mehr rauszuholen und vielleicht auch darzustellen, dass es so passt. Also das es für deren Zweck halt gepasst hat. Genau.

[00:13:36] Ich glaube schon, dass es für die Datenanalyse, also für den ersten Schritt, was eigentlich wesentlich ist, und in dem Projekt finde ich noch zu kurz gekommen. Man hat halt sehr früh mit Predictions gestartet und auch mit vielen Themen hat man halt parallel gestartet. Und das was man halt ein bisschen ausgeblendet hat, ist halt die Datenanalyse um den Input ein bisschen mehr zu evaluieren. Das haben wir mit P7 angefangen, ansatzweise das, was er da so gesehen hat, man muss einfach auch erstmal konsequente Daten, also konsistente Daten bekommen, um überhaupt sowas auf zu setzen. Man hat darauf reagiert und hat nicht jetzt gesagt vom Prozess her. Ich soll mir vielleicht mehr Zeit nehmen, um meine Daten anzuschauen. Was ist überhaupt möglich, was ist da? Kann ich das hernehmen als Basis oder muss ich es anreichern? Wie kann ich das anreichern? Ich glaube, diese Thematik haben wir sehr oberflächlich gemacht.

[00:18:30] Ich glaube ja, ehrlich gesagt, die Planer hat man nicht gefragt, es war das Management dass es wollte und das Management hat das Ganze auch getrieben. Wir waren ja auch immer in dem Druck etwas zu liefern. Was das Management möchte.

[00:21:56] Stakeholder hätten man wahrscheinlich auch rausfinden können, Daten sicher, also Dateninput, das auf jeden Fall und in dem Zuge halt auch Prozess, weil das haben wir auch nicht sauber und komplett gemacht. Ja, haben wir sehr, zu kurz gemacht.

[00:23:05] Ich glaube, das ist aber bei beidem drin, sowohl bei der Datenanalyse, als auch in der Implementierung. Ich muss ja am Schluss Alle abholen. Das ist ja ein Werkzeug dafür, dass man alle abholen kann und sagen kann, okay, sind wir auch noch 'on the same page', oder haben wir ein anderes Verständnis?

[00:26:17] Also teilweise haben wir ja gesagt, teilweise war das ja nicht faktenbasiert, weil natürlich der Mensch das Ganze bewertet. Und die Planer, die das Tool nutzen oder diese Prediction nutzen sollten, die wurden halt nicht am Anfang integriert. Das heißt, die grundsätzliche Haltung der Planer war ja auch ausschlaggebend. Die waren nicht am Anfang Teil des Teams und mussten aber mit einem Ergebnis leben, das aus dem Projekt entsteht. Das war schwierig. Da hätte an auf jeden Fall noch mehr darauf fokussieren können.

[00:27:46] Also ich würde mich tatsächlich mehr auf den Anfang konzentrieren. Genau, dass wir uns einfach Zeit nehmen, und uns nicht dauernd unter Druck gesetzt fühlen, weiter machen zu müssen. Das 'Definition of Done' das ist total wichtig. Wann hat das Erfolg oder wann macht es Sinn überhaupt dieses Projekt zu planen? Die Daten passen nicht, dann wäre das tatsächlich ein ‚To Do' zurück ans Business. Wir würden euch gern helfen, aber Stand heute macht es keinen Sinn, dass wir auch tatsächlich sagen, jetzt machen wir erstmal nen Cut und kommen gerne wieder zurück, wenn diese Themen geklärt sind. Auch da müssen wir das Coaching machen, weil dann kommt vielleicht auch das Verständnis rein, wann macht eine Prediction Sinn. Manchmal macht es keinen Sinn. Liegt es an den Daten? Liegt es an den Prozessen, liegt es irgendwo, bevor man jetzt auf Teufel komm raus eine Prediction macht, die im Endeffekt schon wieder besser ist, aber trotzdem nichts was den Prozess angeht. Genau.

[00:47:26] Also wenn man jetzt über ein konkretes Produkt spricht, dann spielt UX da auch eine Rolle mit. Aber ich würde es wahrscheinlich nicht bei jedem Sprint sehen, sondern erst dann, wenn tatsächlich die Anforderung da ist, wie ich dieses Produkt nutzen. Wie ich als Planer in dem Fall, dann kommt die Rolle ins Spiel, aber nicht in jeder Phase, wenn ich zum Beispiel bei den Algorithmen, das sehe ich zum Beispiel nicht. Genau.

P7: Product Owner

(in person, ERL)
Date: 19. September 2019
Time: 10:45 - 12:15
Language: German

[00:01:22] Und im Juli, Mitte Juli gab es diese Data Analytics and Artificial Intelligence Konferenz und da haben sie eben diesen Forecasting Core vorgestellt, also ein Projekt davon. Und der Kontakt über den P5 kam dann so zustande. Und dann haben wir gesagt: „Okay. Wenn die eh schon Forecasting machen, dann geben wir ihnen einfach mal unsere Daten und würden" – heute sage ich mal – „schauen mal einfach, was dabei rauskommt." Also das war wirklich, wir haben Ansätze gesucht und das war so das Erste, wo wir gesagt haben, das passt oder das könnte klappen. Wir haben P5 unsere Daten gegeben. P5 hat was uns zurückgegeben, ich glaube, im September, Oktober 2017 war das dann. Und wir waren sehr überrascht, positiv überrascht von dem, was da rauskam, und haben wirklich gesagt: „Wie jetzt? Echt?" Und das waren ja für die Vergangenheit dann immer nur Daten, weil du ja für die Vergangenheit nur Ist-Zahlen hast und du vergleichst ja immer zum Ist. Und das war so gut, dass wir gesagt haben: „Okay. Wir machen genau an dieser Stelle weiter mit P5."

[00:06:39] Die anderen... Nee, nee, nee. Die anderen gibt es noch und da wird einfach der Forecast angezeigt im APO, unser Planungstool heute, und die Planer übernehmen aber die KI-Planung nicht. Also die Planer, die setzen, die können wählen und die machen ja im Prinzip eine manuelle Planung und können aus verschiedenen Inputfaktoren wählen, also einmal UPM-Planung oder KI-Planung und was sie dann noch darüber hinaus machen können.

[00:07:23] Was wir jetzt als kleines Hindernis sehen, momentan diktiert unsere Werksleitung, was wir für einen Umsatzplan machen sollen, also das ist im Prinzip, da spielt weder UPM noch KI eine Rolle. Und das ist eben für die nächsten vier Monate, sodass, wenn wir jetzt zweiten, dritten, vierten Monat die Zahlen drin haben, spielen sie jetzt eigentlich keine Rolle, weil die werden überschrieben. Und das ist jetzt momentan, der momentane Stand.

[00:09:53] Mittlerweile haben wir ganz gute Einblicke, was eine KI kann und was nicht, Grenzen, was möglich ist und was nicht. Und eben jetzt würde ich eben tatsächlich einschätzen 7, sage ich mal, für mich persönlich.

[00:10:30] Nicht nur die Expertise, sondern, ich sage mal, so Projektleitungsskills, also solche Digitalisierungsprojekte oder KI-Projekte. Also es gibt ja den CRISP-DM-Prozess. Wenn du den kennst? Okay. Cross Industry Standard Mining... Cross Industry Standard Process for Data Mining. CRISP-DM heißt der. Und da ist im Prinzip das Vorgehen beschrieben, wie du in solchen, bei solchen Digitalisierungsprojekten oder halt so KI-Projekten unter anderem dann auch vorgehen sollst. Und an den Prozess haben wir uns im Prinzip gehalten. Das ist ein genereller Standardprozess. Und da steht zum Beispiel, zuerst Data Understanding und Business Understanding und dass du eben zuerst deine Daten verstehst und dass du zuerst deinen Businessbereich verstehst. Also heute ist es tatsächlich so, sage ich mal, ihr habt das mathematische Verständnis und was wir nicht haben, und ihr habt aber nicht das Prozessverständnis oder das Planungsverständnis, was wir aber haben. Und dann dieses Planungsverständnis in Mathematik zu übersetzen, das ist halt wirklich, das war viel, wo wir uns anfangs auch, glaube ich, sehr viel Zeit gebraucht haben, um uns da zu verständigen. Also, wenn du nur aus deiner Planungsperspektive siehst und keine Ahnung von Mathematik oder von der KI-Mathematik die dahinter steht und da überhaupt nicht weißt, wie das funktioniert, redest du anders, als wenn du jetzt, als wenn ich jetzt wissen würde – ich habe jetzt ein besseres Verständnis von dem, was ihr braucht in dem Sinne. Das hatte ich damals nicht. Und genau so wenig hattet ihr aber damals, glaube ich, auch keinen Plan davon, wie wir planen. Das habt ihr heute aber. Also heute würden wir – anfangs haben wir damit, glaube ich, viel, von der Kommunikation her viel Zeit verloren, da wir uns, dass wir uns da abstimmen mussten oder es dann immer wieder Rückfragen gab oder: „Wie und warum muss ich jetzt noch mal das machen?" oder „Warum, wofür gehört jetzt nochmal das?" und „Wieso wollt ihr jetzt plötzlich das?" Also da gab es, glaube ich, viel. Und, genau, also von daher im Zeitverlauf die Lernkurve ist enorm. (Lacht)

[00:13:22] Und was ich sehr, sehr gut fand, ist wirklich diese Sprint-Logik, weil da hast du wirklich definierte, kleine definierte Bausteine, die zu, wo du capable bist, diese zu erledigen auch, also wo du sagst: „Okay. Das ist überschaubar und das schaffe ich bis dann und dann."

[00:20:27] Meine Rolle im Projekt war Projektleiter beziehungsweise Product Owner dann, also in der Scrum-Methode dann der Product Owner. Und ich war Mädchen für alles. (Lacht) Ja, also Ansprechpartner Nummer eins. Und was mir anfangs wirklich schwer fiel oder was uns allen, glaube ich, schwer fiel: Wohin wird das führen? Also wirklich dieses erste halbe Jahr, wo ich mir gedacht habe: „Wo kommen wir denn hin? Wo kommen wir denn da raus?" Und wo ich jetzt aber eigentlich sehr, sehr guter Dinge bin, wo wir sagen: „Okay. Wir haben unseren Automatismus, der unsere Werksplanung erstellt." Ja, und für welche Einsatzgebiete sind in Definition noch, definieren wir noch, wo wir es einsetzen, aber da haben, eben das kann ich nicht bestimmen in dem Sinne, also kann ich nicht vorgeben. Da habe ich einfach nicht die Weisungsbefugnis dann dazu. Und aber von anfänglicher oder von – also sage ich mal, dass von anfänglich wirklich Misstrauen in solche Zahlen und ich sage mal so, meine anfängliche Aufgabe war ja überspitzt gesagt: „Rationalisiere die Planer weg." Und da kann ich nur zu gut verstehen, dass die Planer da nicht mitmachen wollen. Ja. Und das war schon eine heftige Aufgabe eigentlich, als ich damit angefangen habe, ich ersetze jetzt, ich erfinde was, um die Planer zu ersetzen. Und das ist schon recht heftig, wo ich mir auch denke: „Ja, da würde ich als Planer auch nicht mitmachen." Und nach einer Zeit dann aber – also es war wirklich schwierig teilweise, dieses Change Management, und mit der Zeit sind dann aber wirklich, sind die Prognosen auch besser geworden und wo du sagst, wo die Planer auch gesagt haben: „Ja, die Zahlen, mit den Zahlen kann ich arbeiten." Und also wirklich dieses langsame Change Management, dieses Überzeugen, miteinander Reden, Kommunizieren, wo du dann sagst: „Okay. Ja, jetzt sind wir an einem Punkt, wo die Planer mitziehen." – zumindest einer zieht immer mit. (Lacht)

[00:30:32] Ich hätte halt – also laut dem CRISP-DM-Prozess wäre so eine User Experience ganz, ganz vorne halt gestanden und du kamst, glaube ich, relativ spät mit rein. Und das war, glaube ich, das, wo uns am Anfang über solche User-Experience-Sachen komplett das Know-how gefehlt hat, komplett, was du nun eigentlich machst, was deine Aufgabe ist und so weiter. Und, also sage ich mal, auch das Verständnis, das habe ich erst seit, ja, seit diesem Jahr, sage ich mal, wie das ganze Zusammenspiel in dem Sinne.

[00:38:23] Das war – wie soll ich das beschreiben? Ich sage mal, ich habe mir das schon so gedacht also, weil ich ja die Arbeit der Planer kenne, und dann war es niedergeschrieben. Und was die im Prinzip Auswirkung auf das Projekt? Ich glaube, an der Stelle relativ wenig, weil es eben, glaube ich, hätte zu Anfang mit einfließen müssen und am Anfang hätte es dann, glaube ich, eine Richtung auch vorgeben können. Also wir hatten da schon irgendwie an der Zeit oder zu der Zeit eine Richtung eingeschlagen, wo es, na ja, nicht schwierig war, die Richtung zu ändern, aber es hätte früher kommen müssen dann einfach, um das weiter mitberücksichtigen zu können.

[00:48:44] (Lacht) Was noch? Wir haben zwar viele Daten, aber die kann man auch nicht unbedingte so gleich verwenden, sondern man muss noch viel die herumrühren und noch mal schütteln und noch mal (Lacht) da was und da was daran machen, ehe man sie tatsächlich, ehe man auch gute Ergebnisse mit den Daten bekommt. Dann, genau, diese Zusammenarbeit zwischen Fachbereich und Data Science. Also das ist, glaube ich, noch ein extrem wichtiger Teil, dass du da dieses Verständnis hast: „Okay. Was braucht denn der Data Scientist? Und andersherum eben: Was braucht denn die Data-Science-Seite aus dem Fachbereich?"

[00:55:39] Ja, genau. Und ich glaube halt, das ist dieses Verzetteln, wenn du: „Ah, jetzt will ich aber noch das. Und, ah, jetzt will ich aber noch das." Und ja, aber das brauchen wir doch eigentlich gar nicht. Und das stellst du halt dann eben erst hinterher fest, dass du das ja vielleicht doch gar nicht gebraucht hättest, aber dann Zeit damit verschwendet hast dann eben so. Und wenn du von Anfang an so einen Rahmen feststecken kannst – und das hat uns, glaube ich, auch so ein bisschen gefehlt aber, weil eben keiner weiß, wie es weitergeht oder wo es eigentlich hingeht. Deswegen haben wir da, waren wir, haben wir da uns teilweise auch verzettelt dann, weil es diesen Rahmen einfach nicht gab. Und das war dann, wenn du das tatsächlich am Anfang machst, dann ist das, glaube ich, schon eine große Hilfe.

P8: Planner

(in person, ERL)
Date: 19. September 2019
Time: 12:30 - 14:00
Language: German

[00:05:17] Es gibt da eine Präsentation, dass in der Siemens AG, die Planer reduziert werden sollen.

[00:07:13] Im Moment noch nicht, ne. Sobald die nicht eins zu eins überspielt werden können die Zahlen ist es nicht einfacher für uns. Aktuell!

[00:07:34] Heut saßen wir ja zusammen. Da müssen dann noch einige Hebel angesetzt werden, einfach um, wenn wir solche Zahlen, eins zu eins in die Fertigung kippen würden, dann wären da Schwankungen drin, die die Fertigung nicht abfangen kann. Drum muss das nivellierter in die Fertigung einfließen, damit wir sagen können immer, jeden Tag, dieselben Stückzahlen, da gibt es Schwankungen mit drin, die auch die Fertigung mit abfangen kann. Aber das muss nivelliert in die Fertigung runter gegeben werden.

[00:09:29] Wenn ich die Zahlen von der KI nehme und die einspiele, dann stehen die so drin, und dementsprechend wird materialisiert. Und dementsprechend würde sich dann auch die Fertigungen aufstellen. Aber das würde ja bedeuten Mitarbeiter in den Kühlschrank. Und wenn ich sie brauch, hole ich sie mir raus und die nächste Woche stelle ich sie wieder rein in den Kühlschrank. Drum braucht man den zweiten Schritt, wie du jetzt gesagt hast beim Post-Processing, damit man dann nivelliert, das Ganze. Ist jetzt nicht die Aufgabe von der KI, sondern von dem ganzen Prozess, der dahinter steckt.

[00:12:07] Doch ich war schon Mitglied. Ja. Allerdings war es neu. Du weißt nicht, wo die Reise hingeht und was auf dich zukommt in diesem Fall.

[00:16:03] Ich denke immer mir fehlt ja das Wissen dazu.

[00:37:23] Ich kann das nachvollziehen, weil der Algorithmus rechnet sich das ja aus Vergangenheitswerten aus und spielt uns das so ein. Es gibt ja neue Programme bei uns, die das dann Richtung Fertigung dann leisten können. Somit können wir dann in naher Zukunft die Fertigung Aussteuer mit beiden Programmen mit KI und dem neuen Programm. Alle Großaufträge wird eine KI nie erkennen können.

[00:39:35] Ja, es ist natürlich schwierig von außen, den Prozess zu erkennen oder zu kennen. Wenn man sich das vor Ort häufiger einmal anschaut hätte vielleicht, oder mal zwei, drei Tage mitgelaufen wär. Dann hätte man sich mit Sicherheit einige Diskussionen erspart. Kann ich mir gut vorstellen.

[00:41:07] Wobei du ja auch sagst, es gehören zwei dazu. Du weißt ja auch, dass du vom Algorithmus nicht alles verlangen kannst, und es ist ja dann allen irgendwann klar geworden, leider werdet ihr manuell immer noch irgendwas machen müssen. Und genau, hoffentlich kommt dann irgendwann der Punkt, wo dann aber der Algorithmus wenigstens das unterstützt, was bis jetzt sozusagen gelaufen ist.

[00:49:43] Nein. Weil ich Richtung Fertigung gehe und sage ich brauche 100 Geräte und nicht, schau dir die Kurven ordentlich an, ich brauche da ein paar mehr. Und wenn ich das in Tabellenform hab, oder als Liste, dann sehe ich jawohl KI sagt 80, Kundenwunsch ist 100, Differenz 20. Dann kann ich etwas damit anfangen und nicht da mit Kurven. Es ist schön, ich weiß. (Lacht)

P9: Product Owner/Management Planners

(remote)
Date: 25. October 2019
Time: 10:00 - 11:00
Language: German

[00:06:27] Und weil das halt mit der Lieferzeit schwierig war, die Bauteilbeschaffung und die Planung passen nicht, das war der Handlungsbedarf zu sagen: „Hey, wir können Eskalationen vermeiden, wir können Kosten senken in Richtung Beschaffungsprozess, wenn wir das etwas besser hinkriegen von der Planung." Und dann war die Frage: Warum nimmt man nicht ein System mit Algorithmen und die Statistikmethoden dann im Bauch haben, und lässt die Systeme prädiktieren und unterstützt dann praktisch den Planer? Das war letztendlich dann der Handlungsbedarf zu sagen, wir schauen uns auf dem Markt um und schauen: Was gibt es da? Und dann kam halt das Thema mit der Beratungsfirma, wo wir dann einen Proof of Concept gefahren sind mit unseren Planpositionen. Das Ergebnis war, dass das System besser prädiktiert als der Planer in einer Vielzahl von Planpositionen und das hat uns dann dazu bewogen, dieses Thema, diesen Proof of Concept letztendlich dann produktiv einsetzen als Planungsunterstützung.

[00:12:56] Genau. Wenn das nicht zu breit ist, dann hast du natürlich den Vorteil wieder, dass sich manches ausgleicht, dass du einfach viele, viele Mehrfachverwender hast in deinen Bauteilen. Aber, gut, letztendlich haben wir dann jetzt eine Softwareplattform, wo wir vergangene Sachen reinschieben und über Statistikmodelle Prädiktionen kriegen. Und da sind wir jetzt gerade am Analysieren: Wo schlägt das System gut an, wo schlecht? Um da, sage ich mal, zu sehen: Wo hilft uns die Prädiktion? Wo müssen wir noch nachschärfen? Mit welchen Themen müssen wir nachschärfen? Also da stehen wir noch ganz am Anfang auf der einen Seite im Output, auf der anderen Seite brauchen wir ja eine Prozessänderung. Wir brauchen ein Change Management, weil der Planer hat heute seine Planungstabellen und hat eine eigene Methodik, um die Planzahlen vorzuschreiben. Da haben wir jetzt im ersten Schritt es geschafft, die Prädiktionsinformationen, also die Daten, die aus dem Tool rauskommen, die so in seine Welt reinzubringen, dass er in seiner Excel-Tabelle dann eine Sonderzeile hat.

[00:16:21] Nein. Das Change Management ist noch im Kleinen gedacht, dass der Planer jetzt eine neue Information kriegt vom Tool und dass er jetzt irgendwie erkennen muss, ob er diesen Informationen Vertrauen schenken kann oder ob er sagt: „Nee. Da passt es nicht, weil das System nicht das Wissen hat, wie ich es habe, weil da so Sondereinflüsse sind, die nur ich im Kopf habe, die noch nicht digital irgendwo im Datenstrom drin sind." Also die Idee ist ja, dass über unser Tool er eine Entlastung kriegt und er manchen Positionen Vertrauen schenken kann, sagen: „Ja, das übernehme ich." Und bei anderen sagt er: „Nee, übernehme ich nicht, weil da muss ich noch daran arbeiten." Aber wie greife ich das ab? Wo erkenne ich, ich kann Vertrauen schenken oder ich muss was machen? Das ist für uns noch das Thema. Jetzt fangen wir mal an, erst mal Daten zu zeigen, um in die Diskussion zu gehen, in den Dialog mit dem Planer, um dann einen Modus zu finden: Welche Informationen braucht er denn von dem Tool? Damit er sieht: „Ja, das hat schon die letzten, sagen wir mal, die letzten drei Quartale super performt, die Methodik, und das kann ich jetzt übernehmen." Wie kriegt man das hin?

[00:17:57] Das ist ein Standardtool, das wir aber nicht in der SOP-Welt haben, also das ist letztendlich

dann auch ein Drittanbieter, aber es ist ein Standardtool. Eines mit einer Lösung von einer Beratungsfirma.

[00:29:31] Also ich muss sagen über den, über die Consulting haben wir da wirklich viel erschlagen, weil das, das hätten wir nicht selber machen können. Also das, was die da hingelegt haben, das wäre undenkbar. Da bräuchte man Spezialisten. Also ich kann zwar in ein paar, also sagen wir mal, in einer Woche lernen, das Tool zu verstehen, wie ich damit umgehe, aber Entwicklungen und dann wirklich mächtige… Das ist Modellierung auf der einen Seite, aber auf der anderen Seite ist auch das Thema Datenvorbereitung. Die müssen ja schon so vorbereitet sein, dass das Modell dann passt und…

E1: Solution Expert / Process Consultant

(remote)
Date: 10. March 2020
Time: 10:00 - 11:05
Language: German

[00:04:50] Genau. Also Visualisierung im Allgemeinen, KPIs erzeugen, Sachen so darstellen, dass sie in einen Bericht kommen und für das Management als auch für einen IT-Menschen dann entsprechend aufbereitet werden, weil die Art der Darstellung beeinflusst ja schon, wie ich es verstehe oder wie ich es aufnehme. Und auch bei so etwas wie Machine Learning, also die Ergebnisse, die ich im Bereich Machine Learning darstelle, können ja so oder so interpretiert werden. Also alleine von der Güte eines Forecast-Modells habe ich ja unterschiedliche Möglichkeiten, das zu quantifizieren beziehungsweise visualisieren. Ein Data Scientist oder ein IT-Mensch möchte sich eher eine ROC Curve angucken, also eine spezielle Visualisierung einer Qualität eines Forecast-Modells. Einen Manager interessiert vielleicht ein ROI oder eine relative Abweichung oder wie viel da am Ende plus/minus rauskommt. Es gibt halt unterschiedliche Arten und Weisen, so ein Erzeugnis, was wir innerhalb unserer Projekte ja generieren darzustellen. Deswegen finde ich es wichtig zu wissen: Welche Möglichkeiten der Darstellung habe ich und wie mache ich das? […] Wir haben natürlich auch bei uns Experten, die im Bereich Machine Learning, einfach was Deep Learning beziehungsweise einige sehr spezialisierte Bereiche des Themas Machine Learning angeht, auch weiter oder spezialisierter sind als ich. Das sehe ich als Vorteil an im Sinne von, ich habe die Rolle eines Konzeptionisten, eines Generalisten, und es gibt bei uns Personen im Team, die, wenn es nachher zur Implementierung kommt beziehungsweise zur spezifischen Verbesserung des Forecast-Modells, dann noch mal die zusätzlichen 20% rausholen können beziehungsweise dann entsprechende Möglichkeiten noch aufwerfen, und wir so dann noch weiterkommen. Also es geht mir nicht darum, in einer Person die 100% Kompetenz in den jeweiligen Bereichen zu bündeln, sondern das schon sozusagen kollaborativ im Team zu machen, dass es einen starken Spezialisten im Bereich Machine Learning gibt, einen starken Spezialisten vielleicht auch bezogen auf eine Technologie im Bereich Reporting und dann aber auch Generalisten zu haben, die mit dem Kunden kommunizieren, die das Gesamtbild sehen, die zielorientiert arbeiten beziehungsweise das Projekt als solches oder das Projektvorgehen dann auch entwerfen und das den Implementierern sozusagen mitgeben beziehungsweise das dann auch überwachen. Genau. Und in der Rolle, letzteres, sehe ich mich dann auch entsprechend.

[00:17:56] Dass wir sozusagen als Enabler dienen für Unternehmen, diesen Teil der Digitalisierung, Machine Learning ins Unternehmen zu bringen und das ganze nachhaltig mit dem Fachbereich. Und zwar wollen wir oder unsere Herangehensweise ist nicht, dass wir sagen, „Gebt uns Daten, wir liefern euch Ergebnisse", sondern dass wir überhaupt keinen Black-Box-Ansatz fahren. Also jedes Projekt, was wir bis jetzt machen beziehungsweise gemacht haben, machen wir so, dass wir sozusagen am Anfang des Projektes -- und das war auch bei Siemens zum Beispiel der Fall in Karlsruhe, dass wir uns mit dem Fachbereich zusammengesetzt haben und das Thema Predictive Analytics beziehungsweise Machine Learning erst mal erläutert haben und im Vorhinein auch schon mal Daten gefordert haben, dass wir für diesen Workshoptermin, den einen Tagestermin, schon mal ein Szenario aufbauen konnten, wo Machine Learning auf die eigenen Daten angewendet werden konnte, angewendet wurde, damit die Kollegen sozusagen einen praktischen Eindruck bekommen, wie läuft das Ganze ab, was steckt dahinter, und auch in einem gewohnten Umfeld das Ganze erleben. Das ist sozusagen der Aufgalopp, dass wir beim ersten Schritt schon den Fachbereich mit reinholen, das Thema erläutern, sehr viel Transparenz mit reinbringen und diesen theoretischen Part dann auch mit einem praktischen Part verbinden im Umfeld beziehungsweise mit den eigenen Daten, dass da schon mal sozusagen Vertrauen geschaffen wird. Der nächste Schritt ist dann, dass wir coachen, das heißt, wir haben immer so ein Initialprojekt, so ein Minimum Viable Product, was dann daraus entsteht, wenn man jetzt hier dieses Buzzword benutzen möchte, oder einen Proof of Concept. So was starten wir dann halt mit dem Fachbereich zusammen. Das heißt, wir waren dann vor Ort bei Siemens, haben uns einen Datentopf beziehungsweise einen Teil des Ganzen sozusagen rausgesucht und schauen. Die Machine-Learning-Algorithmen, die wir darauf anwenden, beziehungsweise die Datenaufbereitung, die wir machen, die führt zu dem Erfolg, den wir uns am Anfang gesetzt haben. Und das machen wir dann auch mit dem Fachbereich zusammen. Das heißt, die gucken uns über die Schulter. Also wir installieren bei denen auch die entsprechenden Tools, mit denen wir arbeiten, und geben dann gegebenenfalls auch schon Teilarbeitsschritte in diesem PoC an den Kunden ab, damit er einfach involviert wird. Und wenn das PoC-Projekt dann abgeschlossen ist, geht es halt darum: Möchten wir das produktiv setzen oder nicht? Haben wir die Erfolgskriterien erreicht oder nicht? Und wenn der Fall vorhanden ist, dass wir Erfolgskriterien erreicht haben, dann würden wir halt auch zusammen die Produktivsetzung planen. Und bei der Produktivsetzung arbeiten wir dann wieder genauso wie im PoC, das heißt zusammen. Wir machen… Parallel haben wir sozusagen einen Strang Projektarbeit und den anderen Strang Coaching. Und das generelle Ziel ist, den Fachbereich dazu zu bringen, dass er erstens versteht von Anfang an, zweitens mitarbeitet und dass der nachher aber auch selber bedienen kann beziehungsweise selbst implementieren kann und selbst warten kann. Und so war das jetzt auch bei Siemens in Karlsruhe, dass wir genau die Schritte gegangen sind, beim initialen Workshop mit dem Kunden zusammenzuarbeiten, beim PoC mit dem Kunden zusammenzuarbeiten, bei der Produktivsetzung und immer parallel Projektarbeit vor Ort mit dem Kunden zusammen und Coaching vor Ort mit dem Kunden zusammen zu machen. Das heißt, Coaching im Sinne von: Wir lehren: Was ist Predicitive Analytics? Wie mache ich Datenaufbereitung beziehungsweise Feature Engineering? Wie gehe ich allgemein mit den Daten um? Wie wende ich Algorithmen an? Was bedeutet Automatisierung eines Prozesses? Wie programmiere ich entsprechend, dass am Anfang des Monats Analysen ausgeführt werden, dass die auf bestimmte Daten zugreifen, dass das Ergebnis irgendwo abgelegt wird, dass ich ein selbstlernendes System implementiere? So was gehen wir in spezifischen Schulungen durch, sodass wir am Ende sozusagen ein fertiges System, ein produktives System da stehen haben, was wir implementiert haben schon in Zusammenarbeit mit dem Fachbereich, aber wo wir sozusagen die Schirmherrschaft hatten, zu konzeptionieren, das Vorgehen festzulegen und die Verantwortung für die Plattform am Ende zu haben, aber trotzdem den Fachbereich jetzt involviert haben, dass er permanent halt sieht, wie entwickelt sich die Plattform, und wenn sie dann am Ende da steht, schon nachvollziehen zu können: Wie ist sie entstanden? Wie bediene ich sie beziehungsweise wie warte ich sie, damit sie zumindest gut funktioniert? Das ist sozusagen die Vision beziehungsweise die Strategie von Firma x, den Fachbereich mitzunehmen beziehungsweise den Fachbereich dahingehend zu trainieren, dass er das Ganze versteht und selbstständig betreiben kann. Genau.

[00:35:14] Deswegen auf die Frage hin wegen Human-Centred Design: Alles oder unsere ganze Projektvorgehensweise richtet sich schon danach, nach dem Fachbereich. Das heißt: Welche Qualifikationen hat er? Möchte er mitarbeiten? Wie stellen die sich den Prozess vor? Über so was diskutieren wir da immer. Und wenn der Fachbereich nicht programmieren kann, müssen wir halt schauen, dass wir ein Tool mitreinbringen, was wir beibringen, was so visuell einen Datenfluss beziehungsweise einen Analyse-Workflow implementiert. Oder es sind halt IT-Leute da, die dann auch entsprechend programmieren können. Oder die Abteilung hat gar keinen Bock, etwas zu implementieren, sondern möchte nur anwenden. Das heißt, sie möchten schon eine standardisierte Lösung da herbekommen, wo es dann eher in den Bereich Automated AI geht, halt nur noch anzuwenden und Daten abzulegen und dann auf ein Ergebnis zu schauen. Über so was müssen wir da halt dann sprechen und fassen das Ganze dann zusammen für die Zielsetzung des Projektes beziehungsweise komprimiert das Ganze: Wie ist die aktuelle Situation? Mit entsprechender Notwendigkeit, Dimensionen der Zielerreichung, Vorschläge zur Behebung und der Umsetzung. Beziehungsweise: Wie soll das Ergebnis aussehen? Und das gucken wir uns dann oder das ist sozusagen unsere Marschrichtung für… Das ist sozusagen unser Aufhängepunkt während des Projektes, immer gegenüber tracken, ob wir das dann erreicht haben beziehungsweise wo wir lang hinwollen, was wir einsetzen, und gucken dann auch wieder am Ende des Projektes darauf. Zusätzlich gibt es halt beim, geht es halt bei diesem initialen Workshop darum, das geschäftliche Problem in ein Data-Mining-Problem zu übersetzen. Das heißt, wir machen erst mal eine fachliche Diskussion, wie du es eben gesehen hast, fachliche Anforderungen und technische Anforderungen, fassen das ganze komprimiert zusammen und übersetzen das Ganze dann in ein Data-Mining-Problem, das heißt, noch mal zusammenfassen, wo das Defizit der aktuellen Planungssituation besteht. Was sind die KPIs der Teilnehmer beziehungsweise der Abteilung, an denen Erfolg gemessen wird? Das heißt, das ist ja auch etwas, an dem wir uns messen wollen. Kann das Ganze quantifiziert werden, dieser Erfolg? Ist es gegenüber einem manuellen Forecast nachher oder einer Qualitätsgrenze von einer durchschnittlichen Abweichung von 5%? Welcher analytische Output wird erwartet der Treibermodelle beziehungsweise Muster oder nur Prognosen in Form von Klassifikationen oder Regressionen? Welche Datenquellen sind mit der Analyseentität assoziierbar? Also die Analyseentität ist zum Beispiel ein Produkt oder eine Produktgruppe je nachdem, auf welcher Ebene ich nachher forecasten möchte. Und was habe ich alles für Daten im Unternehmen, das mit dieser Analyseentität assoziierbar ist? Das sind halt so Leitfragen für uns, um dieses geschäftliche Problem dann in eine Vorgehensweise für unser Data-Mining-Projekt oder Machine-Learning-Projekt zu übersetzen.

[00:42:30] Genau. Also Fragestellungen, die uns nachher helfen, unser Machine-Learning-Projekt zu strukturieren, beziehungsweise auch dem Implementierer, also in der Rolle „Ich implementiere das Projekt nachher", solche Sachen mitgeben zu können wie: Was ist die Analyseentität? Was ist eine Zielvariable? Wie weit soll prognostiziert werden? Was für Daten sind mit der Entität assoziierbar? Wo bekomme ich

die Daten her? Wie kann ich richtig aufbereiten, dass ich da keinen Fehler mache? Das heißt, das ist ja eine technische Kommunikation, die ich dann, ich sozusagen als Vermittler, als Projektleiter, mit meinem Implementierer führe. Dazu muss ich dann halt fähig sein. Das heißt, wir haben einmal den Fachbereich, mit dem unterhalte ich mich, um das Geschäftsverständnis aufzubauen, um das Problem zu erfasse beziehungsweise das Ziel, und ich bin dann derjenige, der das Ganze in ein Data-Mining-Problem übersetzt, die Kommunikation vorbereitet zu dem Implementierer.

[00:47:43] Also die größten Herausforderungen bei Siemens waren, dass wir einfach die Mitarbeiter motivieren mussten, mitzuarbeiten beziehungsweise sich auch Zeit dafür zu nehmen. Das ist verständlich, dass man oder dass jeder Fachbereich jetzt nicht komplett freigestellt wird, sondern auch sein operatives Geschäft hat, aber damit muss man immer kämpfen -- und das hört sich jetzt auch ein bisschen überspitzt an -- kämpfen nicht wirklich, aber überzeugen, dafür einzutreten beziehungsweise einzustehen auch gegenüber seinem Vorgesetzten, mehr Zeit in das Thema zu investieren, weil es bezogen auf die Nachhaltigkeit besser ist. Ich verstehe, also wenn ich mir mehr Zeit für das Thema nehme, verstehe ich das Thema besser. Hintenraus, wenn das produktiv gesetzt wird, spare ich sowieso sehr viel operative Zeit ein. Deswegen ist es gut, dass ich mich jetzt schon damit beschäftige. Und ich brenne dann irgendwann für das Thema beziehungsweise stehe dahinter und überzeuge auch meine Chefs davon, dass es dann produktiv gesetzt wird, weil das einen Mehrwert schafft. Dass der Mehrwert da ist, das haben sie gar nicht diskutiert beziehungsweise das haben sie auch gesehen, aber zwischen verstehen und „Ich treibe etwas selber" ist halt noch ein Unterschied beziehungsweise eine Hürde. Also ich will nicht sagen, dass das was Besonderes beim Kunden Siemens ist, sondern dass wir das Problem allgemein haben, immer den Fachbereich sozusagen dazu zu treiben, mehr mitzuarbeiten beziehungsweise sich dem Thema mehr zu widmen. Genau. Und wenn man das initial dann mal geschafft hat, dann fällt es einem auch peu à peu immer leichter, weil, wenn man zum Beispiel mal so ein Coaching gemacht hat oder den Fachbereich in der Projektarbeit tatsächlich involviert, dann leckt er sozusagen Blut und hat wirklich auch Spaß daran. Und diese Hürde erst mal zu überwinden, dass mitgearbeitet wird, das ist, glaube ich, das größte Problem oder die größte Herausforderung sozusagen.

[00:52:21] Was ich im Nachhinein noch zusätzlich ändern würde, wir hatten zwei Meetings mit den Controllern zusammen [...], mit den Controllern hätte ich gerne noch direkteren Kontakt gehabt. Das versuchen wir immer am Anfang zu forcieren. Wir hatten zwei Meetings, wie gesagt, wo wir uns mit denen zusammen getroffen hatten und einen aktuellen Stand gegeben haben beziehungsweise so unterschiedliche Fragen gestellt haben, die unseren Prozess dann oder in dem Prozess einen Mehrwert gegeben haben. Aber noch direkter mit denen zu sprechen beziehungsweise nicht eine Zwischenperson zu haben, das kann man halt im Nachhinein noch besser machen beziehungsweise mehr forcieren, dass das so, dass ein permanenter Austausch mit dem Controlling einfach Mehrwert bietet und nicht nur zwei Meetings stattfinden beziehungsweise einfach die Möglichkeit haben oder die Kontrolle zu haben, mit dem Fachbereich zu kommunizieren. Genau.

[00:54:25] Nee. Also das haben wir -- wir sind bei anderen Firmen auch im Einsatz. Das ist immer so, dass ein wenig Angst gezeigt wird, die Kommunikation mit dem Controlling aufzubauen so, dass man das Risiko minimieren möchte und eine Zwischenperson da dazwischensetzt, zwischen externen Beratern sozusagen und dem konkreten Fachbereich oder denjenigen, die nachher damit arbeiten sollen. Aber wir wissen ja alle, dass, wenn wir irgendwelche Zwischenpersonen haben, die vielleicht Fragen anders auffassen beziehungsweise Sachverhalte anders auffassen und dann entsprechend runterkommunizieren, dass das manchmal nicht zum richtigen Ziel führt. Ja. Also einfach eine Person dazwischen zu haben, kostet mehr Zeit beziehungsweise mehr Aufwand als eine direkte Kommunikation. Und deswegen bin ich ein Fan davon, direkt mit dem Fachbereich da zu sprechen beziehungsweise diese Rolle einzunehmen als Koordinator zwischen Projektleitung, Fachbereich und dem externen Unternehmen, aber dann auch eine Person da zu haben, die sich in der Domäne beziehungsweise in solchen Projekten halt gut auskennt und die richtigen Fragen stellt beziehungsweise dann direkt kommuniziert, weil diejenigen, die nachher am Ende damit umgehen sollen beziehungsweise deren Prozess ich umgestalte -- oder ich gestalte es nicht um, aber die neue Disziplin oder die neue Technologie hat irgendeine Auswirkung auf den Fachbereich später. Da finde ich es noch wichtiger, mit denen direkt und permanent zu sprechen als mit der Projektleitung beziehungsweise den technischen Mitarbeitern, sage ich mal, die auch eine Rolle haben bei der Implementierung des Systems. Genau. Also da kann ich nur dafür plädieren beziehungsweise bei jedem Projekt versuchen wir, das halt zu forcieren. Und im Nachhinein betrachtet, beim Siemens-Projekt hätte man an der einen oder anderen Stelle auf jeden Fall noch mal mehr Druck machen können, auch auf anderen Ebenen direkter mit dem Fachbereich oder den Controllern zu sprechen.

[01:02:57] Ja, also ich sehe einfach in der Frequenz -- also in Bezug auf Software- oder Planungsprojekte sehe ich einfach die Besonderheit, erstens die Zusammenarbeit mit dem Kunden, damit es von Erfolg gekrönt ist, und dass, sage ich mal, eine permanente Kommunikation und auch die Entwicklungszyklen einfach kürzer sind. Weil wir merken, wenn wir jetzt tatsächlich im Machine-Learning-Bereich angekommen sind im Projekt, dass wir relativ schnell Ergebnisse sehen und, wenn Ergebnisse noch nicht zufriedenstellend sind, dass dann wieder, man unterhält sich wieder mit dem Kunden beziehungsweise geht wieder in den Bereich Geschäftsverständnis und schaut: Hat man alles richtig aufbereitet? Hat man die Daten richtig verwendet? Gibt es zusätzliche Daten? Könnt ihr nicht doch vielleicht euer Expertenwissen, was ihr auch zusätzlich nutzt, mit in den Prozess mit reinbringen, um den Forecast zu verbessern? Das heißt, diese Schleifen, die man dreht, sind, finde ich, häufiger als in DWH-Projekten beziehungsweise in Reporting-Projekten oder auch in anderen Projekten, einfach weil dieses klassische Wasserfallmodell, dass wir am Anfang irgendwas definieren, festlegen und danach dann gearbeitet wird und am Ende irgendwas präsentiert wird, das war also nahelegend noch nie der Fall. Also man hat zwar ein Gerüst am Anfang, aber trotzdem wird, weil diese Datengrundlage oder das Thema an sich schon eine gewisse Komplexität hat, werden Schleifen iterativ wiederholt, um das Bild, was man am Anfang hatte, zu schärfen beziehungsweise abzuändern. So was passiert häufiger als bei anderen Projekten, finde ich. Ja. Und deswegen ist es einfach wichtig, regelmäßig solche Termine einzustellen, dass man sich abstimmt, also mindestens wöchentlich so einen Status gibt, an welcher Stelle man ist, welche Probleme aufgetreten sind und ob man nicht noch mal ein Meeting mit dem Fachbereich macht oder mit denjenigen, die das Branchenwissen haben, um eine Anpassung zu machen. Genau.

P10: Management

(in person, BLN)
Date: 19. November 2019
Time: 14:05 - 14:55
Language: German

[00:11:23] Ein Thema war dieses Thema Predictive Demand Planning. Warum? Weil wir eigentlich nie einen Forecast bekommen haben so richtig, schon gar nicht auf Produktebene. Und das ist eigentlich immer noch so. Wenn ich heute den Vertrieb frage: „Sage mir doch mal: Wie viel Umsatz soll ich denn einplanen, Kapazität? Was glaubst du, wie viel du reinholst für wie viel Umsatz?" Ich kriege eine AE-Zahl, aber die sagen mir nicht, wann der AE zu liefern ist. Und mit P14 kam dann jemand rein, der sich mit diesem Thema auseinandergesetzt hat, und dann haben wir also ein Predictive Demand Planning aufgebaut halt erst mal für das Thema SIPROTEC 5. Warum? Ganz einfach, weil wir ja da auch besser werden. Wir können – es hat ja noch andere Auswirkungen. Wenn ich heute eine gewisse Forecast-Genauigkeit habe, weiß ich, na klar, welche Materialien ich bestellen muss, wie viel ich auf Lager haben muss, ich kann aber auch danach eine Kapazitätsplanung machen. Das heißt: Muss ich ALGs reinholen? Muss ich nicht ALGs reinholen? Das hat dann P14 da aufgebaut, zuerst mal nur für unsere SIP 5, für die Highrunner. Und das wird jetzt ausgerollt. Das Problem, was immer noch bestand und noch besteht, ist, dass wir ein – ich nenne es mal hart – Akzeptanzproblem haben bei gewissen Kreisen.

[00:42:37] Wenn Sie heute noch in andere Werke von Siemens gehen, finden Sie da Heerscharen – also Heerscharen nicht, aber finden Sie, sage ich mal, eine zweistellige Anzahl von Leuten, die sich nur um Arbeitspläne kümmern, die die aufbauen, machen. In Karlsruhe machen sie, haben sie ein Tool entwickelt, die automatisiert zu machen. Da arbeiten wir daran. Wir hatten anderthalb Leute für das Thema Arbeitspläne, weil jemand mal vor meiner Zeit, weit vor meiner Zeit entschieden hat, Arbeitspläne brauchen wir, das kostet bloß Geld. Darunter leiden wir jetzt, weil Sie in einem Simulationstool eben nicht das abbilden können, weil wenn Sie fünfmal den gleichen Arbeitsschritt drin haben, dann fragt er sich: „Was macht der jetzt da?" Weil unsere Arbeitspläne das nicht hergeben, ja, oder auch veraltet sind. Das ist auch so ein Thema, wo man: Bullshit in, Bullshit out. Wenn ich die Daten nicht habe und die Daten nicht sauber sind oder – um jetzt nochmals auf diese Prediction zu kommen – ich jahrelang die Leute trainiert habe: 22, 24, 26, 28. So wurde auch unsere Umsatzplanung gemacht.

P11: Developer

(in person, BLN)
Date: 19. November 2019
Time: 15:00 - 15:25
Language: German

[00:02:12] Dann bin ich letzten September nach meinem Studium nun quasi als Vollzeitkraft angefangen und ich war auch während meiner Werkstudentenzeit mit P14 zusammen in dem Predictive Demand Planning tätig. Das heißt, ich habe auch tatsächlich den Code mitgeschrieben und auch an Verfahren mitgearbeitet. Und daraus hat sich dann irgendwann mal ergeben, dass ich die Rolle des Planers übernommen habe, die P14 früher hatte. Dementsprechend war es für mich eher quasi andersrum. Ich musste mich nicht von dem Prozess überzeugen, sondern ich habe es quasi, eher vom Tool aus schon verstanden, wie

quasi unsere Prozesse gegebenenfalls angepasst werden sollten, weil das Tool teilweise schon gewisse alteingesessene Prozesse so ein bisschen verändert hat.

[00:07:34] Zum einen in unserem kleinen Team hatten wir das Problem mit dem Change Management und Akzeptanz eher nicht. Früher war Planungsprozess ein bisschen anders aufgestellt. Das heißt, wir haben auch die sogenannten Product Owner. Das sind so die Produktmanager, die für gewisse Produktgruppen zuständig sind oder für mehrere Produktgruppen zuständig sind. Und früher war die Planung eher so, dass der jeweilige PLM dadurch, dass er dann die Informationen über der Markt hatte, und manchmal auch mit den Kunden tatsächlich in direkten Gesprächen ist, die Planung vorgegeben hat. Und der Planer aus dem Werk hatte sich eher erst gemeldet, wenn irgendwas drastisch nicht gepasst hat. Und mit dem PDP haben wir natürlich auch ein Tool, welches eine Prognose in einer bis zwei Minuten rausbringt und die PLM's, wenn man sich vorstellt, man hat PLM's die setzen sich teilweise hin, versuchen sich da irgendwas zusammen zu rechnen, das entsprechend noch herunterzubrechen auf das Monats-Ebene. Das war ein sehr langwieriger Prozess mit sehr vielem manuellen Aufwand. Nichtsdestotrotz hatten wir mit dem PDP Tool natürlich auch von der Seite etwas Skepsis bekommen, denn der PLM der das jahrelang gemacht hat und natürlich auch weiß, wie viel Kraft es ihn oder Kenntnisse es ihn gekostet hat, nicht sofort daran geglaubt hat, dass irgendein Tool jetzt in zwei Minuten irgendwie bessere Ergebnisse ausliefern kann als er, ohne dass seine Expertise mit einfließt. Das war ein Thema. Nichtsdestotrotz hatten wir dann irgendwann mal gesagt, dass wir quasi die Teile, die Produktgruppen so ein bisschen aufteilen. Die Produktgruppen, die quasi mit dem Tool auch eine gewisse Accuracy erreicht haben, die lassen wir auch so, und wenn wir dann längerfristig sehen, es gibt Schwankungen pro Anlauf, Auslauf, Planung, solche Themen, da sind wir nach wie vor im direkten Kontakt mit den PLM's und beraten uns, inwiefern das, was das Tool aussagt, tatsächlich auch in der Realität zu erwarten wäre.

[00:09:54] ...zum Beispiel die Fälle, wenn wir ein ganz neues Produkt bekommen, dann kann keine Zeitreihe, kein neuronales Netz irgendwas ausrechnen, weil keine Historie vorhanden ist. Und da fangen wir tatsächlich an, einem mit einer Annahme von PLM. Danach können wir auch noch mal gucken, inwiefern also in den ersten Monaten gucken wir ein bisschen verstärkt drauf, inwiefern diese Annahme tatsächlich dann eintrifft und ab einem gewissen Moment können wir dann auch noch mal PDP dazu schalten. Oder wenn wir auch die Information bekommen, dass die gewisse neue Produktgruppe dann entsprechend die und die und die Produktgruppen ersetzen sollte oder teilweise ersetzen sollte, dann versuchen wir da zum Beispiel an unserem Regressions Modell, was auch drin ist, ein bisschen das anzupassen. Aber gerade in solchen Fällen neue Produkte oder Ausläufer ist der Input von PLM immer noch interessant. Und natürlich auch Großprojekte.

[00:21:16] Wir hatten auch öfters mal Erfahrungsaustausch mit den anderen Business Units und da kam es auch immer wieder mal dazu, dass wir ein Prototyping angeboten hatten von unserem Tool. Und gerade da sind wir auch teilweise auf solche Themen gestoßen. Das aus unserer Sicht zum Beispiel Planungsprozess in erster Linie etwas angepasst werden sollte. Oder dass gewisse Sachen... oder dass gewisses Feedback, was danach kam, schwer umzusetzen war, weil gerade aus unserer Sicht das Prozess von Anfang an nicht komplett optimal aufgestellt worden ist.

P12: Planner Procurement

(in person, BLN)
Date: 19. November 2019
Time: 15:30 - 16:00
Language: German

[00:11:03] Genau das ist dann immer nur schwer zu beurteilen, weil sind da jetzt weniger Stückzahlen kommen, weil auf einmal die Nachfrage eingebrochen ist oder weil der Forecast da zu unterdimensioniert hat. Aber man braucht natürlich immer eine gewisses Grundvertrauen in den Algorithmus. Ich glaube, das ist schon so. Traut man dem Ganzen also vom Grund her, oder ist man dem eher skeptisch gegenüber? Ich traue dem eher, weil ich die Personen dahinter kennen, die es entwickelt haben und auch wahrscheinlich auch mit der Zeit, wie lange man es schon nutzt. Dass da die Akzeptanz am Anfang vielleicht noch geringer ist, als wenn man jetzt sagt: Okay, das läuft hier seit 2, 3 Jahren und wir haben die und die Genauigkeiten bestätigt schwarz auf weiß. Das hilft immer. Also wenn ich jetzt ein Projekt selber machen würde, dann hätte man, müsste man sich auch die Lernzeit selber auch nehmen, bevor man das jetzt ausrollt, bevor man da jetzt das ganze kommuniziert.

[00:29:49] Absolut. Also das ist auch jetzt so... mein Ziel ist auch, dass das erst mal mit meinen Daten, wo ich mich noch ein bisschen besser auskenne, das auch mal zu sehen, wie da dieser Transfer so ist. Absolut. Das ist die Hoffnung, dass ich da was mitnehmen kann für mich.

P13: Team Lead/Project Manager

(remote)
Date: 02. December 2019
Time: 14:30 - 15:00
Language: German

[00:03:30] Ich hatte eine Stelle, die ich ausgeschrieben habe und habe mir dann, ich sag mal sehr spezifisches Know how reingeholt, weil ich halt jemanden haben wollte, der sehr stark aus der analytischen, mathematischen und statistischen Schiene kommt. Und hab mir dann die Person quasi reingeholt. [...] Und ja und dann haben wir angefangen mit der ersten Produktgruppe, die zu predicten. Das war dann Ende Januar 2017.

[00:07:14] Wir waren eigentlich immer schlecht. Wir lagen irgendwie bei 50, 55%, Forecast Genauigkeit. Unsere Bestände waren, sind immer gestiegen, gestiegen, gestiegen wie das Material z.B.. Die Bestände wuchsen an und wir hatten immer das Falsche da, was so ein bisschen das Schlimmste ist, was du kannst in der Logistik Planungs Perspektive. Und daraufhin haben wir dann, habe ich dann quasi auch mit verändertem Personal, hatte ich dann wieder die Kapazitäten, um das Ganze dann wirklich mal, ich sage jetzt mal statistisch fundiert und auf der Basis von Zahlen anzugehen. Und dann haben P14 und ich entsprechend, ich sag mal die erste Produktgruppe predicted haben uns das angeguckt und dann wurde das relativ schnell agil, dass das mehr und mehr wurden. So haben wir halt damit angefangen, vor fast drei Jahren.

[00:14:12] Wir wussten, dass wir besser sind. Wir haben es dann im Schatten mitlaufen lassen und haben dann nur noch das, was uns der Product Owner gesagt hat, zur Kenntnis genommen, würde ich jetzt mal ganz fies sagen. Für's Budget wurde es berücksichtigt, für das Thema Materialplanung nicht mehr.

[00:26:23] Wir sind ja die User. Wir sind die User und Designer, wenn du so willst.

P14: Planner/Data Scientist

(remote)
Date: 04. December 2019
Time: 15:00 - 15:20 and 16:05 - 16:40
Language: German

[00:07:04] Und es ist aber unglaublich schwierig, da jemanden zu finden, der auch eine Affinität dann auch zum Coden hat und trotzdem auch das Business auch versteht.

[00:08:49] Und das ist auch genau das, was fehlt, quasi so eine Schnittstelle zu einem anderen Business zu finden. Einerseits ein Change Manager, der sich auch mit den Prozessen beschäftigt, mit den Leuten, die da arbeiten, wie man die Ergebnisse aus so einem Tool überhaupt verstehen kann. Plus jemanden, der dann auch die Technologie in einer anderen Einheit, ich sage mal einfach, zum Laufen bringt. Also ist die Cloud für eine SILP die richtige Lösung oder sollten sie es über eine Datenbank machen? Sollten sie es lokal über Excel machen? Wie gucken sie sich die Ergebnisse an? Welche KPIs sind wichtig für das Business? Das sind alles Fragen, die muss man prozessual beantworten und die sind losgelöst jetzt von dem Planungsmodell, was sicher toll ist, aber die kommen da gleichzeitig mit auf. Und das fehlt meiner Meinung nach noch.

[00:04:37] Ja, technologisch ist es eigentlich schwierig. Das müssen vielleicht auch andere beurteilen. Mit der Lösung an sich bin ich zufrieden. Auch, dass die jetzt auf der Cloud läuft. Nicht alles funktioniert beim ersten Mal, ja, aber da ist jetzt was lauffähiges da und die Logik, die da implementiert wird, die ist schon echt gut. Vielleicht, was Lessons Learned sind, – das geht aber schon echt ins Detail – es gibt so falsche und echte Nullen, da konnte man sich echt daran verschlucken. Das war so ein Datenthema, da saß ich auch ein paar Tage dran, bis ich das dann gelöst habe. Aber, gut, das lernt man eben auch dabei.

E2: AI Consultant/Sr.Data Scientist

(in person, MUC)
Date: 24. October 2019
Time: 11:00 - 12:00
Language: English

[00:05:50] Exactly. (both laughing) So this AI consultant role is in between the data scientist and data strategist.

[00:07:35] I mean, there's this problem of pilot status that large corporates think: Right, we need to get in data science and AI, MVP is a fairly low risk way of doing it. But then you just get activities that don't add up to anything. And the initial enthusiasm goes away and executives are saying: Okay, that's it?

[00:08:06] I mean, I think, it's an absolutely, it's a big problem. But I think there's kind of two ways to come at it. One side is the kind of the culture of the technical work and how that... you know, what you're trying to achieve in a proof of concept is not what's required for a production like system. So there's a technical question there. But then there's also this kind of what McKinsey called the data, translator role. And their job is really to understand what's the business problem and to be able to translate that to the technical people. And so it's this kind of go between where you can say: Okay, yeah, I understand what the methods are capable of, and the technologies, but equally, I know that actually, these are the whatever, these are the processes and these are the personalities, and these are the politics going on. And so yeah, that's a simple POC and we can do it, but it might not get traction beyond that PoC for reasons x, y and z. So this kind of translator role comes out a bit more from the, from the business side.

[00:10:21] So I think, I mean if we're talking technical expertise, there's always the split in the AI world between like machine learning, and statistics. And my expertise is much more one the statistics side, so I can do the basic machine learning stuff. But my interest in backwards which ones statistics, so it's thinking about the processes that are actually generating the data, making predictions, yes, but caring how those predictions were made. So in other words, being able to make inferences of the models that are predicting them. Not just making the prediction. And I can give you an example, actually from a current case I'm working on right now. So we're looking at basically predicting a fraud event. And you have a lot of, if you take all the people, for example, that might have this event, most of them don't have it. So you have a whole bunch of zeros. And then you have a bunch of discrete counts of events that happen if this sort of threshold is met, and some one does commit this type of fraud. And so if you think about it as a machine learning problem, that maybe you've got a labeled data set, nicely, this is fraud, this is not fraud, you get some features and a black box and you get your predictions out. But it's not telling you really what's going on under the hood and why these features are leading to that prediction, and there's the explainable AI thing that's sort of a different discussion. In this case, you know, what we're really interested in is understanding those parameters. So like, what is the probability that someone commits this fraud? And then once they have committed it, how large is it? And so for that actually statistical models are really useful, because you want to be able to draw an inference. But what it means in a change of probability or what factors are contributing to that probability.

[00:15:21] Yeah. So I mean, we would do stakeholder interviews and try and get an understanding of, if they had competing use cases, what would be their criteria? What would be their motivation for testing the different ones. I think. If you think about sort of design skills, one of the important ones would be this sort of empathy piece. So the organization was undergoing a lot of change. So introducing technical changes, technical improvements, efficiency improvements through technology, we're very quickly interpreted as I'm going to lose my job if this works. And so then it's a a thing about: Okay, so what is the value that you add in this process? How does this technology fit into the overall test development process? Something like that. So that, you know, maybe the first round is an assistive technology, you're not pitching it as a replacement, but you're saying: Well look, you're really overworked and this particular company has had actually run this in the past for a regulators, and the regulators have said: We want to go and do an audit and understand how this test was developed. And they just didn't have the documentation to support the audit. So say: Right, you know, okay, we improve this process with the assistance of technology. When the auditor comes back next time, you're going to have everything lined up, ready to go and that way, they're much more supportive.

[00:20:51] So, as I say, people that come from the technical side, have a sort of standard data science workflow. You think you kind of know what the use cases, and you've got some data. And so away you go.

[00:23:37] But you know, you're basically trying to understand, kind of define the problem, I think empathy is in it, empathy, define, ideate, prototype, test, that sort of cycle. So the, the empathy and the define that those we will involve technical people in those processes, but that will be led by the strategists typically, the ideate again, we do that almost always with workshops with the clients. And it's very rare, in my experience it's pretty rare that at that stage we would actually have any sort of technical solution to show it will just be whiteboards.

[00:30:55] Exactly. The KPI's of the sales people. And so if the KPI's that... you've got a model that now you put the KPI in and you get a prediction out. But if the KPI going in is like a six sigma outlier, you know that historically, it's always been one plus or minus point five. And all of a sudden now it's five, the value going in, you know, do you have something in place that flags up: Oh wait a minute, this was not within the range of historic data at all, when we made the prediction. So there's that kind of thing of understanding, technically, how is your model working? And what was the range of inputs that it saw when it made these predictions? But as I said, there's the white elephant thing of: Okay, we've got these factors that are quantitatively in the model, but what are the qualitative features that we think might be relevant to this problem? That we may be identified but weren't able to quantify and therefore couldn't model, or maybe, you know, we couldn't think of a way to quantify it, but we think it's still relevant.

[00:32:37] I had some colleagues in a previous role and they were doing similar things. They're doing logistics and sort of stock management problems and material planning. And they had always used these two different models for sort of stock planning. And I forget the names of them. But basically it's the fundamental philosophy for how you manage your stock. And they were sort of looking at the problem. And they suggested totally changing it. And they said: You know, you've used this approach for years. But you know, we really think this one is better and look quantitatively, it'll give you this savings. And so there was kind of an agreement that: Yes, we should move to that new approach. But culturally wasn't there. So the prediction as a prediction was being made, but then the stock managers are saying: Okay, yeah, times two. Because you know, that's more familiar to them, based on what they've done previously.

[00:33:58] I mean, I think one thing that's really worth mentioning, as well, which is kind of related to that use cases robustness, right? So you've got a model that makes a prediction, and you feed it blindly into your process. And it's wrong by whatever. And it's one above. And it should be, you know, one below is a total disaster, but one below is totally fine, that sort of situation. So if the overall process is that vulnerable, then you need to be quite careful.

[00:42:28] Which is, I think, is absolutely the thing with KPI's that, you as the technologist, you need to measure stuff. And even better, you need to optimize stuff. And so you press someone for a number and they say for example: Okay, yeah, I don't know, like, widgets per person per hour, great. Anywhere you go, and then you realize that maximizing widgets per person per hour creates all sorts of problems in addition to the thing about like, people might cheat for widgets per person per hour to look better. So I think, you know, that's, that's actually a really good example of this sort of thing that you're trying to link these two sides, there's always going to be something that is unable to be quantified and you need to be sensitive to that.

[00:45:24] So I think, you know, having a designer and a data scientist working together with a designer says: Okay, data scientist, you've come up with this, and you've got your coefficients and standard errors, and you want to plot them as box and whisker plots. No one's gonna understand what that means, you know, what if we did it this way? Would that still capture the technical essence, but in a way that's more accessible?

E3: Sr. Data Scientist

(in person, MUC)
Date: 22. November 2019
Time: 10:30 - 11:30
Language: German

[00:14:44] Und der Kollege x, der vor allem die Transitionen zwischen PoC zur Skalierung fokussieren soll, weil das eine der digitalen Sollbruchstellen ist: Wie macht man eine Pre Acceleration, also wie kommt man von einer Orientierung zu einer Acceleration? Und wie schafft man es, die nächsten Schritte einfädeln? So gesehen.

[00:28:11] Ja. Also das eine ist ja "Das kann es und das nicht" und: Was heißt Training? Was heißt eine Trainingsplattform? Sozusagen so ein bisschen einen kurzen, zwei Level hinter die Grundkonzepte schauen: Was funktioniert und warum funktioniert es nicht? Das ist elementar. Und auch wenn die meisten sagen, "Nee, du brauchst mir jetzt nicht eine Stunde lang erzählen, was KI kann und was nicht", wir machen es trotzdem, weil wir gelernt haben, die Erwartung an eine bestimmte Technologie ist manchmal sehr divers. Und obwohl Leute vielleicht sagen, sie wissen genau, was eine Technologie kann oder nicht, ist es trotzdem sehr nährend und wir machen es einfach in einem Kurzsprint und wiederholen dort die grundlegenden Sachen kurz: Was heißt überwachtes Lernen? Was heißt datengetrieben? Was sind die Probleme in Komplexität? Was heißt Feature Engineering? Was heißt Netzlernen? Was heißt unüberwachtes Lernen? Was heißt Reinforcement Learning? Solche Grundkonzepte werden dann in einer Stunde einfach noch mal kurz durchterpediert und dann im gegebenen Kontext, wo er ist, seine Technologien rein. Bei HR sind das Aspekte, da habe ich gesagt: "Na ja, ihr beschäftigt euch mit HR, also lasst uns mal anschauen: Wie funktioniert bei LinkedIn das Ranking? Wie funktioniert bei LinkedIn die InMail Success Rates? Was ist daran Machine Learning?" Solche Aspekte greifen wir dann aus dem Kontext raus und das versuchen wir so.

[00:48:50] Na ja, okay. Also wir haben die zwei, also zweierlei zu unserer Idee. Wir haben die Industrialisierung, also Effizienzsteigerung, Produktivitätssteigerung, und du hast die Consumer, B2C-Bereich, das auf Predictive Behaviour, Attention und vielleicht so ein bisschen auch Manipulation geht. Wir nennen das Personalisierung so. Bis dato haben wir...

[00:49:15] (Lacht) Das hast du jetzt aber sehr diplomatisch ausgedrückt. (Lacht)

[00:49:20] Das heißt, du hast, an sich erst mal kann man jetzt natürlich sagen: "Na ja, die Industrial AI fokussiert sich eher auf die Industrialisierung, das heißt Effizienzsteigerung, Produktivitätssteigerung, Efficiency Gains. Und wir sind nicht, keine Ad Company. Wir sind nicht die Big Tech Companies, soziale Netzwerke, Ad Business - centric, Interaktions-Prediction und -Manipulation. Genau. Das Spiel wird derzeit gespielt, aber ich sehe, dass, um Fortschritt zu erlangen, wir die Welt des Predictive-Behaviours-Aspekts in die Industrialisierung reinziehen müssen. Wir müssen wissen, wie Leute ihre Systeme verwenden. Wir müssen wissen, welche Energielasten auf Netzen sind. Wir müssen wissen, wie ein Automative – welche Pains und Gains sie haben. Und wir müssen das relativ nah an Sensoring wissen. Wir müssen wissen, wo Autos fahren und wie sie Autos fahren. Ja, das heißt, diese zwei Welten, die wir an sich erst mal gerne trennen würden, weil wir sagen, wir wollen nicht in das auch durchaus fragwürdige Anwendungsverhalten Transparent Work, was wir nennen sozusagen Profilbildung, Überwachung, dass wir das in der Industrialisierung nicht haben. Wir haben es. Wir müssen sie haben. Wir müssen näher an den Kunden ran. Personalisierung ist per se jetzt kein schlechtes Wort, sondern einfach, wir müssen näher ran. Und das wird momentan noch sehr getrennt.

E4: Sr. User Researcher/ML Designer

(remote)
Date: 24. October 2019
Time: 18:00 - 18:45
Language: English

[00:04:52] But while I was there, I was like, I can't be the only one that's interested in studying this. I can't be the only one interested in practicing this. And I found a bunch of other folks kind of interested in not only just like machine learning, but like policy applications, all the stuff, too. At the beginning It was a very small community of skilled ML designers. So I decided, you know, I'm just going to start maybe a 30 person monthly pizza party kind of thing and start really small. I think our third event at Autodesk, we had like 200 people show up and we're like, Oh no, this is too many people interested in this feature. So we've been really fortunate. So we started it about two years ago and it's all volunteer sponsored. So venues sponsor or volunteer their space and sponsor food and speakers and all that stuff too. But we've really had no sort of speakers or anything either, which has been awesome. So yeah, so originally founded to like just because I was interested in the field. But it's very clear and apparent that like a lot of other folks are interested in doing really cool stuff in this space too.

[00:06:47] Yeah. So what we're trying to do is create a collaborative space for anyone interested in machine learning, AI data science as well as like UX design research, anyone really in between to come together, share those best practices, create a community around this too, because we really don't have it's always like this is a new and emerging technology and we're really excited about the future of that. So really just by hosting regular events where we all get to meet each other, meet the actual faces behind the cool products that are coming out is really important. We're very lucky that in the Bay Area there's a lot of that, although I know up in Seattle there's a lot of that too. So really our goal is to just host a space for folks to come together and for us to learn from each other, really learning from those best practices with our speakers and all that stuff too.

[00:07:48] When I first got started and I would tell people like, Oh, I'm interested in ML and UX, people would kind of like look at me like if you're interested in both, you must not be able to do either very well. Like I don't those are two separate job categories, HCD/UX professionals and data scientists work in different departments. Like all this stuff which now sounds like silly to say because we see a rise in these types of jobs and everything too. So yeah, just in the two years that we've like founded it, we've seen a huge rise in like jobs, as I mentioned. Business understood that we can contribute to the lack of human focus and luckily, some companies already understood the demand for Human-Centered-AI. They are hiring for this kind of combined skills. But what I actually mean by jobs is like the role of like machine learning prototype is something that's really interesting to me. So like this idea that how do you make a low fidelity machine learning model to just run research on that? So IDEO has a data science practice that's kind of around this right now, too. We've also seen the role of like UX designer focus on bridging the disciplines of design and ML/AI practices, which is super exciting to see a lot more of like more systems style design too. So like, what does it mean to make a modular style system that is something that can work really well with machine learning. So like what does it mean to have everything kind of be powered by almost like confidence intervals, like, oh, how, how confident are you in this type of content? And it's modular, so it can easily change shape and everything too, as well as allow for feedback for these systems and everything. So that's why systems designers are kind of interesting because it's like, well, how do we make sure the system from the beginning allows and invites feedback because machine learning is probabilistic, so it won't always work as you'd expect. So like treat that is like a graceful failure and be like cool. Like how could we improve for the future and make it very clear to your end user, like the value of giving feedback to the system, not just for like you know them immediately but also like long term, like how can this help them get better content that they want, all that stuff too.

[00:10:05] Yeah. Yeah, for sure. And like the other thing that's been really interesting too is that, you know, it can sometimes feel like it. At first it felt like a lot of chat bots and AI systems, but actually the more that, you know, we continue and showcase some really great examples, it's very clear that like ML and UX is so much more than just chat bots in like Alexas and whatever it, it really is. Like a lot of the experiences that we have are algorithmically driven. So like how do we make sure that that like is apparent to the end user? Like where that data is coming from and it doesn't feel like AI is just something that happens to them, but they actually have control of the system. And it's been really cool because like the audience is pretty much evenly split between machine learning analysts, data science folks and UX practitioners. So it's nice to kind of like keep that consistent over the years and everything too, and also showcase those voices and the speakers that we invite to speak.

[00:11:14] Oh yeah. I mean, so many. So I feel like I mentioned, because machine learning is probabilistic and dynamic. Ah, in the UX field, if you're not familiar, we typically have design pattern style guides, red lines that are very static and they don't really show kind of the dynamic nature of machine learning. So like that's something that instead of like a problem, I think it's an exciting opportunity of like we have not solved that at all. And like, what is that going to look like?

[00:15:54] Oh, my gosh. I'm so happy that you asked. Just a couple weeks ago, I finally took my reading list that I have been keeping in a long running Google doc and like made it into a cleaned up medium article. So I finally have like, like drill down into like, you know, what have I seen cool companies doing? Like, of course Google is doing some really interesting stuff, like the people in AI guidebook. Microsoft's also doing some really cool things, too. They have like their human centered AI interaction cards and misquoting them, but like they have some really cool stuff. Spotify is doing some really cool things around. Like, Hey, how you triangulate between like quantitative like data science research as well as qualitative, like what happens when the quant and the call don't line up that kind of stuff. So there's like individual case studies as well as like other resources and best practices and like those kinds of things that I've seen too. And you can find those a bit like MLUX resources. It's just like a long running medium post, but yeah.

[00:17:31] So when we're developing like these materials for the students, we really are thinking about like, hey, let's think about the future of these models and examples and everything a little bit different than traditional UX classes where we already assume the students have had some design thinking so they understand how to problem solve with like the 'Capital D' design thinking methodology. We also really value interdisciplinary classes too. So our class is actually half technical and half non-technical. So like people from Apple Computer Vision Interns or Google Brain interns or all those folks too, as well as like people who are like have a medical degree and like our doctor or like getting their Ph.D. in education or law and policy or agriculture, business, even architecture, those types of discipline. And we bring them together. To kind of think through like, what would the future look like if we were to co-create the future of machine learning and AI for all of these disciplines? So like this is not the class to take. If you want to be a data scientist, like we're not going to teach you like nitty gritty, like how to code and be a data scientist, but it is the class if you want to think about, hey, what would machine learning, I mean, for my discipline and how can I apply it to a different field and think about how can I get people to actually use this rather than, you know, how do I make the best model? I realized that design professionals lack the skills and deep knowledge about AI/ML capabilities and this class is meant to solve that issue, too.

E5: Sr. UX Designer

(in person, MUC)
Date: 29. November 2019
Time: 14:00 - 15:00
Language: German

[00:11:14] Ja, absolut. Und was das Thema GANs angeht, gibt es so viele interessante Künstler wie Helena Ceron, glaube ich, ist eine. Und Gene Kogan, der coole Sachen mit GANs macht. Ich weiß, dass ich immer wieder von Leuten aus dem Designbereich angesprochen werde, die sagen, oh mein Gott, KI wird uns die Arbeit wegnehmen, weil sie sehen, was mit GANs passiert. Und ich denke mir, wie kann man das so sehen, wenn man sagt, dass die KI mir die Arbeit wegnehmen wird? Ich sehe eher, dass die KI mehr kreative Designprobleme aufwirft, auf die ich nun meine Design Praxis auf coole, neue kreative Weise anwenden muss. Vielen Designern ist nicht bewusst, dass KI/ML ein neuartiges Designmaterial ist. Ich denke, dass Autodesk hier wirklich gute Arbeit leistet, indem sie GANs für neue generatives Design einsetzen. Im Grunde generieren sie Tausende von neuen Modellen, aber ein Designer muss sich immer noch fragen: Okay, aber welche davon sind für die Menschen wirklich sinnvoll? Ja, ich glaube, es wird immer noch eine von Menschenhand geschaffene Note dabei sein, und das finde ich cool. Aber ja.

[00:20:54] Ja, auf jeden Fall. Und wenn man Systeme gemeinsam mit verschiedenen Disziplinen entwickelt, dann sind die Dinge, die von allen entwickelt werden, auch für alle da. Wie bringen wir also andere Leute in den Raum, die normalerweise nicht über die Zukunft dieser KI-Modelle für maschinelles Lernen nachdenken würden, und geben ihnen die Möglichkeit zu sagen: Hey, was bedeutet das eigentlich für mich? Designer wissen nicht, was sie zu ML-Entwicklungsprojekten beitragen können. Sie sollten darüber nachdenken, was das für ihre Praxis bedeuten könnte. Wenn sie dann zur Entwicklung beitragen, können sie sich wirklich dafür einsetzen und verstehen, dass es eines gemeinsamen Vokabulars bedarf, wie man über diese Dinge spricht und so weiter. So können sie wirklich die besten Lösungen für die Nutzer und ihre Disziplinen entwickeln.

[00:34:38] Ja, ich glaube, das ist so wichtig, weil ich so oft mit UX-Designern oder Produktdesignern gesprochen habe, die sagten: „Muss das ML-Modellsystem nicht erst einmal gebaut werden, bevor man es testen oder das Interface gestalten kann? Aber ich bin der festen Überzeugung und das ist auch Teil meiner Praxis, dass man die Erfahrung des Modells testen kann, bevor man das Modell überhaupt baut. Sonst kommen die UX-Designer erst viel spät in den Entwicklungsprozess. Also setzt man sich mit den Experten des maschinellen Lernens zusammen, um zu verstehen, was die Inputs und Outputs der Beispiele sind. Und wie sieht das Modell aus, das wir erstellen werden? Legen wir die Karten auf den Tisch und evaluieren wir, ob es wirklich Sinn macht. Bauen wir die richtige Art von User Experience auf, bevor wir all das Geld, die Zeit und die Energie in den Aufbau des ML-Modells und alles andere investieren? Und selbst wenn man ganz am Anfang anfängt, bevor man überhaupt ein Konzept hat, wie man es verstehen kann, weil maschinelles Lernen den Menschen eine Menge Möglichkeiten eröffnet, so wie generative Forschungsmethoden wie 'Trip Tech' ein großartiges Beispiel dafür sind, wie Menschen, wenn sie ein Gespräch mit einem anderen Menschen darüber führen würden, wie würden sie versuchen, dieses Problem zu lösen?