Multi-disciplinary Learning and Innovation for Professional Design of AI-Powered Services

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Abstract. Companies face several challenges when adopting Artificial Intelligence (AI) technologies in their service and product offerings. Adaptive behavior that changes over time, such as personalization, affects end-user experiences in sometimes unpredictable ways, making designing for AI-powered experiences difficult to prototype and evaluate. To fully make use of AI technologies, companies need new tools, methods, and knowledge that relate to their specific design context. This includes learning how to adapt design and development processes to fit AI-powered services, communication in cross-functional teams, and continuous competency development strategies. This paper reports on an innovation and learning program called AI.m that facilitates practical learning about how to use emerging AI technologies for human-centered design. The program has been executed for 15 companies and evaluated using interviews with researchers, design practitioners, and company representatives that have worked within the learning program. This study suggests and verifies a productive and efficient learning environment and process where companies, university research departments, and design agencies collaborate to produce AI-powered services and at the same time develop their competency in AI and human-centered design. The qualitative analysis provides a set of categories of learning implications organized as a framework of prompts to help organizations develop AI and design capabilities.

Keywords: AI · Design · Learning environments · Innovation · Digitalization

1 Introduction

The field of Artificial Intelligence (AI) has provided companies and organizations with new opportunities for creating personalized, adaptive, and autonomous service and product experiences. However, AI-powered services impact the end-user experience in complex and interconnected ways, rendering it difficult for organizations to keep a connected and holistic overview when designing service interactions [1]. The recent rise of data availability, access to powerful Machine Learning (ML) algorithms, and processing power have created new possibilities in assistive and agentive interfaces and automation of services [2]. AI is indeed claimed to be one of the most transformative technologies of our time [3]. Designers, developers, economists, researchers, and managers in all sectors

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need tools and practical know-how to support them in creating and evaluating designs that address the challenges and opportunities this new technology presents to society.

At the same time, AI is a heterogeneous collection of techniques and application areas and is therefore hard to define and learn to apply in practice. AI can make specific processes – such as searching, mining, and prediction based on big data – more efficient, and more advanced AI can be implemented to make services agentive – i.e., take the initiative and act on users' behalf. This affects how tasks and work are carried out and has substantial implications for how organizations orchestrate their workforce and what skillsets are prioritized [4].

There are multiple toolkits for *developing* and *applying* AI technologies from a technical point of view available. Google, Facebook, IBM, OpenAI, and other organizations have made ambitious AI-based development platforms available for developers to access algorithms and data sets. However, fewer support tools are available for helping designers and managers *understand* how designing services based on this technology affects business strategy, user experience, and ethical implications such as biased data and discrimination that may arise. Therefore, there is a strong need for designers and innovation leaders to be "AI literate" to make better use of AI technologies in human-centered services and products. This line of thought has led to the concept of "AI as a design material" [1, 5]. AI spans a large variety of aspects, ranging from different *approaches* (e.g., symbolic, sub-symbolic, or statistical AI), different *application types* (e.g., computer vision, expert systems, natural language processing), and different *service types* (e.g., assistive, agentive, or automated services). Designers and product managers need to navigate this space to make informed decisions on how AI can benefit their offering and value-creation and value-capture.

To this end, we have examined a practical learning and innovation program called AI.m[1] that aims to accelerate companies' ability to design human-centered AI-powered services. The model has been iterated in stages, and currently, 15 small and medium-sized companies from different sectors have completed the learning cycle. We present this learning environment and synthesize insights from interviews with participating designers, developers, innovation leaders, researchers, AI experts, and company leaders in the work reported on herein.

1.1 Aim and Research Question

The aim of this study is to provide a framework for how accelerated learning about human-centered AI as design practice can be facilitated in small and medium-sized companies. A second aim of the study is to evaluate the AI.m program experience from three perspectives: the company perspective, researchers' perspective, and the design agency perspective.

The rest of the paper is structured as follows. First, we describe the design and learning context for human-centered design when utilizing data-driven Machine Learning as a design material in Sect. 2. Then, in Sect. 3, the AI.m program process and surrounding ecosystem of actors are outlined. In Sect. 4, we report on the qualitative interview study

[1] www.aimhalland.se.

with representatives from the AI.m program and present the results of the analysis as a framework of design prompts. The paper is concluded in Sect. 5.

2 The Design and Learning Context for Human-Centered AI: State of the Art

As the complexity of digital services increases and becomes integrated into everyday life, organizations and firms face the daunting challenge of understanding how user experiences are affected through an ever-increasing number of touchpoints, channels, and media [6]. Within the field of Human-Computer Interaction (HCI), this has sparked a line of thought that the field is going through a paradigm shift, where interaction design and user experience (UX) design focus on situated and embedded complexities in a messy world [7, 8]. The multi-stakeholder view coupled with holistic experience design over digital and non-digital touchpoints is firmly grounded in Service Design practice [9]. The overlaps between interaction design, UX design, and Service Design have recently been re-framed and re-conceptualized [10].

The recent increase of AI technologies in digital services adds to this development. AI has been dominated by engineering and technology-centered disciplines for decades. Only recently have scholars started to re-conceptualize the *agency* of things in terms of AI and human-centered design (cf. [2, 8, 11–13]). At the same time, Harrisson et al. note that epistemologically, HCI has been moving away from the traditional engineering culture of the previous paradigm [7], rendering “the boundaries between technology and humans increasingly fuzzy” [8].

UX and Service Designers have a long history of crafting design tools that help them visualize, ideate, communicate, and validate their designs. Ever since the transition to the experience economy [14], the connection between the service platform complexity and user experience has required organizations to actively focus on a holistic view of their customers’ complete service experience beyond interface design [15]. However, data-driven and AI-powered services are new territories for designers. The tools that make up the typical toolset of UX and Service Designers – such as Service Blueprints [16], Customer Journey Maps [17], Business Model Canvas [18], Personas and Scenarios [19–21], and Ecosystem Maps [9, 22] – are not explicitly tailored to describe user experience, impact, and value for services that rely on AI and algorithms. In particular, there is a lack of tools assisting in modeling how AI can augment human workers or operators and the resulting end-user (or customer) experience. The opportunities to apply AI technology – such as Machine Learning – in an HCI design context are multi-faceted. Generic challenges include designing for data collection and data maintenance, integrating ML functionality in user interface design, and augmenting human operators and change workflows with the help of AI technologies. Even though decades of work in the space of AI-powered design has produced several sets of HCI guidelines, it is clear that more knowledge and practical know-how are still needed [1, 13].

Just as AI and computation can be considered a specific design material that changes the context for designers [23, 24], the application of big data, algorithms, mobile technologies, and cloud computing also changes the design space for services. This development is sometimes referred to as “the platform economy” or “the third globalization.”

Indeed, Kenney and Zysman [25] claim that: "We are in the midst of a reorganization of our economy in which the platform owners are seemingly developing power that may be even more formidable than was that of the factory owners in the early industrial revolution." (p. 62).

Digital platforms powered by emerging technologies allow firms to monetize human effort, assets, and data through various services that serve different user groups. The complexity of Business, Service, and User Experience design for AI-powered digital platforms is high, and service-providing organizations, therefore, need to understand (a) how key interactions and functionality are integrated to deliver value to the end-user (or customer), (b) how these components are interconnected to the organization and culture, and (c) how the organization generates and captures value through service interactions [26]. This includes orchestrating cooperation and co-learning between humans and AI agents, such as cognitive process automation, boosting human users' cognitive insight capabilities, and cognitive engagement opportunities [25]. It also includes competency development as well as facilitating multi-disciplinary communication within and between teams [1]. This adds complexity to the design context and requires designers and developers to consider such factors when designing AI-powered services. In effect, this shifts the focus from traditional human-centered design to interaction with *agentive* systems [2, 27] and explores what new workflows and skills are necessary for human operators [28, 29]. Indeed, designers often have a cliched understanding of AI and ML, such as viewing AI as a means for automating tasks [30].

Recent literature emphasizes that designers using AI-powered functionality in digital services could expand the design metaphor for enabling interactions to do more than rmerely react or respond as a "tool" [2, 31]. Rather, the metaphor for interacting collaboratively with humans could be seen as a "butler" or "valet" in "teaming" efforts between humans and AI-powered services [4] and focus on both *augmentation* and *automation* as they are interdependent [32]. Therefore, the design context is multi-disciplinary, and organizations need to take business impact, technology, and human behavior into account.

A significant challenge for enabling designers to embrace new technologies as design materials lies in orchestrating efficient learning and discovery of how such fast-changing emerging technologies such as AI can and should be used. Companies that design and develop digital services operate in fast-paced, time-critical contexts where formal, traditional learning opportunities might be scarce. Research indicates that such learning opportunities may exist only on paper, either because the execution of learning activities takes too long or because, once they get back to work, employees do not get opportunities to consolidate what they have learned in the regular work practice [33]. This provides an exciting opportunity for designing efficient and multi-disciplinary learning contexts for professionals that can be connected to everyday work practice.

In order to facilitate learning within and between groups of professionals in such a multi-disciplinary and complex design space, designers, developers, innovation leaders, and managers need to learn together and contextualize domain expertise in both AI and design in their work practice.

3 The AI.m Learning and Innovation Program

The context for the study presented here is an innovation program called AI.m – created by innovation arena and business incubator HighFive[2] and Halmstad University in a Swedish geographical region with a population of 330,000. The program aims to support small and medium-sized regional companies to fast-track their ability to utilize AI technologies in an impactful and sustainable way. A fundamental stepping stone for the program is the notion that the program is not only about AI technology per se but also incorporates business and user experience impact as a starting point. To this end, the program has identified that expert competency in both AI and human-centered design needs to be a part of a productive learning environment.

Following theories on design-based learning that is characterized by open-ended, hands-on, and multi-disciplinary craftsmanship on the one hand [34] and communication and interaction as "making meaning" in creative learning processes [35] on the other, the learning model is set up as a network of actors (see Fig. 1) and a formal process (see Table 1). The model aims to help identify business opportunities that create and capture value by implementing human-centered design and business modeling with AI technology. Tangible outcomes from the learning sequence in the program are one or more proof of concepts, or prototypes, that encapsulate concrete representations of how AI-powered services can enhance a specific company's service offering.

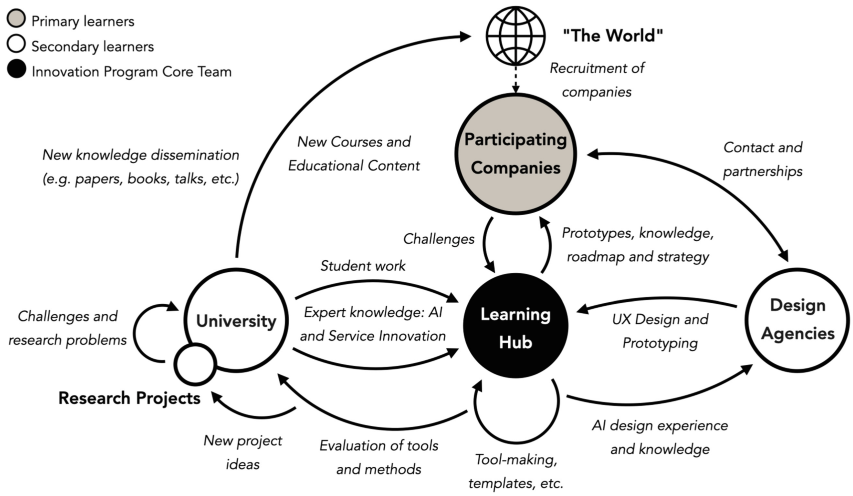

Fig. 1. Overview of the system of learners surrounding the learning program AI.m centered on the Learning Hub of HighFive. Participating companies get support from researchers and experts on AI and service innovation and practical UX design support from professional design agencies. New knowledge is captured in tools, templates, research papers, and other learning materials.

2 https://h5halmstad.se/.

3.1 Learning Actors

The AI.m program consists of a learning hub hosted by innovation arena HighFive. The program is designed to coordinate learning and innovation processes between the actors of the system. The primary target group ("primary learners") are small and medium-sized regional companies from different sectors. Another actor in the network is the region's university (Halmstad University), which has strong research expertise in AI and Service Innovation. The third actor is a contracted group of design agencies consisting of professional UX and Service Designers that are tasked with prototyping work throughout the process. As the university and the design agencies serve by providing their expertise to the primary learners, they are considered secondary learners. However, as is evident from the evaluation of the learning program, both university researchers and design agencies boost their knowledge on how to design and develop AI-driven services as a result of the process (see Sect. 4).

Each company forms a team consisting of 3–5 key roles (including management, technical personnel, and domain experts). Depending on their data and digitalization maturity level, some companies provide several technical roles (CTO, data scientists, and developers), whereas others who might not have such roles defined within the companies typically bring senior management and product owners instead.

The core AI.m program team enlists one AI expert and one service innovation researcher from Halmstad University, one Business Designer from HighFive, a Service Designer, and one or two UX designers from the contracted design agencies. Later in the process, the team can be extended with design or engineering students from the university programs that can help build or evaluate the prototype being built. This allows the students to learn from being exposed to practical prototyping of AI-powered services in an authentic company setting.

The company brings a preliminary challenge hypothesis of how AI and service innovation could benefit their business or organization. The AI expert, Business Designer, Service Innovation Researcher, and Service Designer bring their perspectives and expert knowledge to the table and are later helped by the design agency team and possibly students for hashing out the final prototype or proof of concept. In return, researchers get insights and data about how innovation work using AI is carried out in practice. This also yields new tools and methods that can spawn new research project ideas for the university beyond the AI.m program. The design agencies provide high-quality design craftmanship to the project, and they benefit from rapid and efficient practical experience in building AI-powered services and prototypes.

The participating company gets tangible outcomes in the form of (a) one or more prototypes highlighting service concepts and AI proof of concepts, (b) a roadmap of possible next steps beyond the AI.m program, including financing and grant suggestions for future work, and (c) new contextualized knowledge about how to design and develop human-centered AI-powered services.

Another outcome of the ecosystem is the university's possibility of using case studies, developed tools and methods, research ideas for creating new educational content, and knowledge dissemination in the form of papers and ideas for research grant applications.

3.2 Process

The AI.m program process consists of five main stages. All the main actors from the ecosystem in Fig. 1 are involved in all stages to varying degrees. Table 1 summarizes the stages and sessions of the process. Typically, five companies run their sessions in parallel during a 6–8-week period, where about half of the calendar time is dedicated to prototyping an AI-powered proof of concept. Each batch of five companies is initiated with a kick-off where all the participating companies are gathered to get two inspiration talks; one about human-centered design opportunities and one introduction to AI from a technology perspective. In the same session, the companies spend two hours in a workshop where they outline challenges and opportunities together with AI and design experts from the core learning hub team.

Table 1. The program's learning process stages. Stage 1 is performed with a batch of 5 companies, stages 2–5 are performed with each company in parallel tracks.

Stage	Focus	Sessions and durations
1. Inspiration kick-off	Introducing AI Introducing design	1 two-hour session with inspiration talks and workshops (multiple companies)
2. Business design and innovation management	Aligning business goals with challenges and opportunities	2 two-hour workshops (1–2 weeks apart)
3. Service design	Definition of the desired impact Data inventory and maturity assessment Definition of key user journeys Ethics and risks Scope for prototype (including data requirements)	2 two-hour workshops (1–2 weeks apart)
4. UX design and prototyping	Iterative development of interactive prototypes and AI proof of concepts	3–4 weeks of design agency work and AI development, with continuous check-ins from the rest of the team
5. Dissemination and roadmap	Internal communication Defining next steps and new learning goals	1 two-hour session with a presentation of the concepts (multiple companies) Concluding individual discussion of learnings and roadmap for each company

After the common kick-off session, each company gets its individual schedule for stages 2–5 (see Table 1). In this first session of Stage 2, the company briefly presents its current business and possible steps it might already have taken in terms of AI or data-driven services. Based on this "ground truth," the Innovation Leader and Service Designer facilitate two workshops on possible routes for using AI to address the business challenges. An AI expert from the university is present to give insights on technical aspects of the business. In these workshop sessions, typical business development tools are used, such as business model canvas variants [18, 36] and ecosystem maps [22].

The outcome of the Business Design and Innovation Management stage is a shortlist of 5–10 possible service or project ideas where AI can make a positive impact for the company, as well as suggestions for business model developments based on available data and the company's challenges. At this stage, the company typically understands what kind of data they need to access – or even construct – to provide a business case and use case for the different ideas on the shortlist.

The shortlist of ideas is then reviewed independently by the core AI.m team and the company. During the first Service Design session (Stage 3), one direction is agreed upon, and a user journey mapping process commences. This decision is based on a discussion where the idea's communicative impact, the possibility of sustainable future developments, technical viability and availability of data, business feasibility, and positive user experience are reviewed. Due to the limited project time, the time factor for developing a prototype is also taken into consideration. The Service Designer facilitates two workshops where the user journey and interaction flows are mapped out. The AI expert, Service Designer, and company representatives shape a plausible and possible future state journey where AI technologies have in some way enhanced the service's impact on business and user experience outcome.

At the end of the second Service Design workshop, the UX designers increase their engagement and help set the prototype scope and detail form factor and target platform (e.g., tablet, smartphone, or digiphysical mock-up).

Stage 4 – UX Design and Prototyping – consists of 3–4 weeks of design sprint work, where the UX designers develop the prototype in an iterative fashion. Weekly check-ins on the progress being made so that the company and AI.m team can provide feedback and design critique. This stage is concluded with a presentation of the final prototype, where the AI-specific interactions and impact are in focus. In order to enhance cross-company learning, all five companies in a batch gather for the final presentation to see the other companies' solutions and progress. Stage 5 – Dissemination and Roadmap – also includes recommendations for future work for each individual company. Depending on the maturity level of both the prototype and the company itself, these recommendations typically center on how to bring the prototype into production, including plans for rigorous field tests and user studies. Staff at HighFive also provides recommendations for relevant grants, courses, third-party data sets, and other resources that the company can utilize in order to continue to develop its AI capabilities.

4 Evaluation

The AI.m program has been running in its current form between 2019 and 2021, with a total of 15 participating small- and medium-sized regional companies. The companies have a large spread, ranging from business-to-consumer smartphone app services and web-based online services to business-to-business IT platform solutions, IT security, medical technology, agricultural technology, and manufacturing plants. To evaluate the learning opportunities and effects of the AI.m program, a series of qualitative interviews were conducted.

4.1 Method

At the end of the three project batches of five companies each, respondents were recruited from (a) the participating companies, (b) HighFive, (c) the researchers at Halmstad University, and (d) the design agencies.

Semi-structured deep interviews were carried out individually. The interview themes focused on the learning and knowledge-building impact that the AI.m program experience had on the different actors. Respondents were asked to elaborate on their professional competency development during the project and reflect upon the various ways their understanding and knowledge of how human-centered design and business model innovation are affecting their business using AI technologies as enablers. The topics also included what worked well in the process, as well as problems and negative experiences of the project work. Towards the end of each interview, respondents were asked to talk about what they see as possible steps to continue to learn about AI and service innovation beyond the AI.m program.

In total, the data consist of 24 interviews (15 company interviews, 3 Business Design and Innovation Leader interviews from HighFive, 3 AI Researcher interviews from Halmstad university, and 3 UX designer interviews from three different design agencies). The interviews were analyzed qualitatively by service innovation researchers. Data also include written notes, whiteboard photographs, and digital collaboration areas that were created during the workshops. These auxilliary data were used to complement the interpretation of verbal anecdotes raised in the interviews in the analysis stage. In some cases, respondents used notes and images material in the interviews to explain their thoughts. These notes and sketches were also considered as a complement to the interview data.

4.2 Results

All 15 company representatives deemed the AI.m program to be a success and well worth the time invested. Even though the maturity level of the resulting prototypes varied, each company – except one – concluded the program with a demonstrator or proof-of-concept that captured an AI-powered service solution. The single company where a prototype was not completed had neither enough data nor the digital maturity level or culture to reach the prototype stage. However, they reported that their curiosity was sparked during the program and that the learning outcomes have strengthened their digital maturity and data analytics awareness in general. Several companies reported that the AI.m program enhanced their general data and digitalization awareness and that they are now more confident in further exploring emergent AI technologies as a result of their participation in the program.

The Business Designers and Innovation Leaders from HighFive reported an increased experience with, and understanding of, how data analytics and machine learning provide possibilities as well as challenges for business models and the organization.

Furthermore, a quality that the companies generally did not expect was that they ended up examining their business models in light of what AI and data analytics can provide. An example of this is a manufacturing company that previously considered internet-enabled machinery to be a premium offering with a higher price-point attached to it. This premium offer reduced the number of data-collecting sensors on the market compared to the cheaper machinery without an internet connection. However, during the business design and service design stages in the process, it became evident that the data such internet-enabled sensors could provide back to the company would be very valuable and enable new services such as predictive maintenance. In turn, this could reduce machine downtime for customers. Based on this, the company's approach to charge a higher price for internet-enabled machinery was questioned. This serves as an example of the importance of including business and management in the company's learning initiatives on AI and data analytics, and the impact this has on the way an organization thinks about value-creation in relation to AI- and data-specific features of service and business.

The agency designers reported that they previously had underestimated the characteristics with the design of AI-powered services when the first project started. They highlighted the importance of interdisciplinary communication and that they had acquired several new concepts, design patterns, and terminology from the AI and ML fields during the projects. This has made them better equipped to communicate with data scientists and AI programmers in future projects. The Service Designers, as well as the UX Designers, all expressed that the requirements on prototyping and innovation change when data-driven ML functionality becomes available. Examples of this include adaptivity, personalization, and ethical issues in terms of data collection and usage.

University researchers stressed the importance of seeing theory and data in practice. Practical application in authentic contexts-of-use presents problems that are typically not present in neat lab contexts. Examples include technical limitations in data formats, resolution, and processing speeds in already existing products that are out on the market in the hands of consumers and some companies' lack of resources and skills to handle business model changes internally. The project experience helped highlight such challenges for both researchers and companies alike. Both AI and service innovation researchers appreciated the opportunity to create and modify tools and methods during the process and reported that these had inspired new ideas in ongoing research projects outside the AI.m program (see Fig. 1).

Additional network effects occur in the learning system, as participating companies form bonds with design agencies. Several companies report that they had not considered UX Design as a possible service vendor before seeing what sort of value professional UX design could bring to their products and services. Even though companies are not required to disclose such information, several volunteered that they are renewing their business with the UX Design agencies beyond the AI.m program. From a regional perspective, this is a highly desirable outcome since it strengthens the business networking in the region.

Similarly, since there are five companies in each batch that meet each other at presentations, there are company-to-company partnerships forming as well. Even though some of the companies operate in different sectors and branches, there are examples of collaborations and other joint ventures that arise as a result of the AI.m program. Such experiences highlight boundary-spanning and continuous learning as a result of an orchestrated ecosystem of actors collaborating on common problems.

4.3 Analysis

The interview data were combed for meaning-bearing phrases related to learning experiences and design challenges. Phrases from the interviews were put on digital sticky notes and clustered into categories in a bottom-up fashion. The guiding principle for this categorization was in terms of experience design, learning effects, and business innovation implications for AI-powered services. As clusters emerged, they were named. For example: one company representative said, "we need to get a better sense of how AI makes the end-user experience different from non-AI services." This statement, and others related to functionality and interactions, were grouped in a category named "User Experience". In contrast, another respondent voiced concerns regarding potential negative effects and the ethical risks posed by biased data. Such statements were grouped in the category "Ethics and risks".

In total, 14 categories were generated and then discussed in a group format with the core stakeholders from HighFive, Halmstad University, and one of the design agencies. In the second analysis step, these categories were grouped into five over-arching themes, each corresponding to a different knowledge and skill learning implications for service innovation and design practice. The themes align with other mappings of AI and design-related challenges for service innovation, e.g. [1]. Table 2 summarizes these themes, categories, and learning implications.

Table 2. Summary of derived themes from interviews.

Theme	Categories	Learning implications
1. Knowledge	- Data and analytics - Culture and competencies	Theoretical and practical knowledge about different AI technologies and their impact on user experience design
2. Innovation	- Vision - Problem and consequences	The ability to create innovative solutions based on AI technologies
3. Impact	- Impact and values - Ethics and risks	Understanding long-term effects of AI-powered services on organization, skills, user experience, and value creation
4. Prototyping	- Algorithm effects - Augmentation - Service offering - User experience	The ability to rapidly prototype and evaluate specific use qualities due to AI-powered prediction, adaptivity, and agency
5. Communication	- External communication - Internal communication	The ability to communicate effectively in and between cross-functional teams, as well as with end-users and customers of AI-powered digital services

For each category, a set of *prompts* – formulated as questions – were derived from the interview categories and statements made in the interviews. These prompts provide an action-oriented framework for stakeholders in an extended design team to understand, discuss, and creatively support business model and service innovation using AI as a design material. As such, the themes, categories, and prompts can be seen as boundary objects that can facilitate discussions across professions and democratize the communication, coordination, and knowledge transfer between different roles in an organization [37].

1. Knowledge. ML affects both design and user experience and this relationship is seen as a knowledge gap to overcome by both designers and developers. This theme covers the technical knowledge of data science and analytics, as well as the human-centered design competencies related to data and digital technologies. This theme also includes cultural aspects and how the organization can become more AI- and design-ready.

Data and analytics questions include:

- What data sources do we have access to today? What quality do they have?
- Do we have access to useful information that we might not consider "proper data" today?
- What is our strategy for collecting and update our data?
- What kinds of patterns and relations do we see in our existing data set?
- What data attributes seem to be related?
- What new data attributes can we extract by aggregating existing attributes?
- How can new types of data grow our service offering?

Prompts in the *Culture and competencies* category include:

- What are our drivers, purpose, and attitudes?
- What defines us as an organization?
- What issues can be resolved with cultural drivers instead of more process and regulation?
- How do we track performance?
- How do we make design decisions?
- Do we have ownership issues regarding data within our organization?
- Do we have a "data-ready" culture?
- Are data science perspectives championed at the executive level at the company?
- Are design perspectives championed at the executive level at the company?
- What competencies are required? Which do we already have? Which are we lacking?
- What is our strategy to create a learning culture?

2. Innovation. The ability to use knowledge about AI and human-centered design to create innovative solutions for value-creation and value-capture is found in the positive vision on the one hand and the problems and consequences category on the other.

Vision prompts include:

- What is our vision and impact statement? (Why are we doing this at all?)
- What is unique?
- How is value created?
- How is value captured?

Problems and consequences focus on the negative aspects of the problem space, which can lead to innovative outcomes:

- What primary problem exists in our application space?
- What negative consequences of that problem are we eliminating or resolving?
- What will the consequences be if we do not do anything?

3. Impact. A particular aspect of user- and context-adaptive services is the continuous change and long-term impact enabled by data-driven ML and other AI technologies. To capture these aspects in the learning environment, the following prompts are used:

Impact and values:

- What values do we build for our different end-users?
- What metrics measure successful outcomes?
- What are our overall impact goals for our customers, our organization, and society?

Ethics and risks:

- What ideology is built into the design?
- How can the platform be misused?
- What may our services break or affect negatively (human conditions, other products, and resources)? Is it worth it?
- Whose perspectives have been heard and considered?
- To what extent are human safety, resources, and the organization's reputation at risk?

4. Prototyping is an essential part of human-centered design and consists of four different, but related, perspectives.

Algorithm effects include the ability to understand how ML algorithms affect the problem space:

- What are the possible outputs, outcomes, and impact of new attributes and other algorithmic effects?
- Does ML solve the problem better than other approaches?

Augmentation focuses on techniques for prototyping how AI-powered services affect work and skills:

- What becomes possible for workers?
- How will skills be augmented?
- What tasks will be replaced or augmented?
- Vulnerability: what is the likelihood that human operators working with the AI will distrust its decisions and override them and thereby making the functionality redundant?

The *Services* perspective is focused on prototyping how a complete service is orchestrated. It typically resonates with a Service Designer's lens of prototyping end-to-end holistic service experiences:

- What key service encounters occur, and in what order?
- How are different services on the platform related to each other?
- What does the customer/user experiential journey look like?

The *User Experience* perspective is highly related to the Services perspective but focuses more on the UX Designer's concrete design efforts for specific channels and platforms:

- In what ways does AI render the user experience "magical"?
- What are the UX effects of false positives and false negatives?
- What are the possible UX effects of biased data?
- Is the system's behavior understandable and explainable?

5. Communication. As highlighted by all respondents, developing skills to communicate both within a multi-disciplinary team and with external stakeholders is critical for success.

External communication is vital from a marketing and branding perspective and is essential for companies, but also for designers who aim to "prove" the service brand with their solutions:

- What is the relation between our brand mission and AI-powered services?
- How do we communicate AI-powered service functionality to customers and other stakeholders?

Internal communication prompts are in some ways highly related to Culture and competencies (see Knowledge, above) as they focus on continuous internal development:

- What tools and resources are we using to facilitate cross-functional communication about AI and service between teams?
- What educational initiatives do we need, and for whom, in the organization to build better communication between departments?

5 Conclusion

The AI.m learning ecosystem and process has successfully fast-tracked 15 small and medium-sized companies from a variety of sectors in their capability development of using emerging AI technologies in their business and service offerings.

The derived themes correspond to previous research on challenges with designing AI-powered services (e.g., as reported by Yang et al. [1]) and further develop these challenges into a framework of design and learning opportunities. The categories and associated learning prompts are derived from the input from AI experts, multi-disciplinary perspectives from company representatives, as well as Business, Service, and UX Designers. The themes, categories, and prompt questions presented herein can be used as a framework for addressing organizational and individual learning when designing human-centered services and products powered by AI technologies in a multi-stakeholder design context. As voiced by the participating companies, the AI.m program experience sparked their interest in using human-centered design and AI and increased their confidence in taking on new forms of digital service innovation initiatives. These are viewed as important factors for positive learning outcomes and helped companies view learning about design and AI through prototyping and support from academia as a value-creation activity. The learning ecosystem approach where multiple actors meet, and exchange knowledge and ideas has been fruitful in this case. As new connections between participating actors have formed and lasted several years in some cases, the AI.m program has demonstrated a sustainable way to stimulate regional development and at the same time strenghtened bonds between academia and companies.

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