

AI Is Not a Wildcard: Challenges for Integrating AI into the Design Curriculum

Rahel Flechtner
HfG Schwäbisch Gmünd
University of Applied Sciences
rahel.flechtner@hfg-gmuend.de

Aeneas Stankowski
HfG Schwäbisch Gmünd
University of Applied Sciences
aeneas.stankowski@hfg-gmuend.de

Abstract

AI technologies are becoming increasingly important for the design of human-computer interactions and user experiences. Through their specialized knowledge and creative problem-solving skills, designers are well-positioned to drive stakeholder-centered adaption of artificial intelligence (AI) technology. However, these possibilities also pose new challenges for designers and design education. Even though AI has increasingly been entering design education, the structural implementation of AI technologies in the design curriculum remains an unsolved challenge. In this paper, we discuss and reflect on our experiences over several years

of AI education at design schools. We outline the knowledge and technical intuition on AI we believe students must engage meaningfully with regarding AI technology and present our observations on developing and applying these intuitions in different teaching formats. Furthermore, we discuss the challenges that might hinder the structural integration of AI into the design curriculum.

CCS Concepts • Human-centered computing – Human computer interaction (HCI).

Keywords: Design Education, Artificial Intelligence

DOI: <https://doi.org/10.1145/3587399.3587410>

1. Introduction

Artificial intelligence (AI) technologies are becoming increasingly important for the design of human-computer interactions and user experiences. Through specialized knowledge and creative problem-solving skills, designers are well-positioned to drive stakeholder-centered adaption of AI technology and its application in various contexts. However, these possibilities also pose new challenges for designers [4,12,15,18]. In the design, design education, and Human-Computer Interaction (HCI) communities, there is discussion about which new skills must be learned and whether processes must be adapted [12,15].

From literature and our own experience, we see a wide range of requirements for future designers in the creative engagement with AI: Designers should be able to assess the capabilities and limits of the most relevant machine-learning technologies. For

an informed use of AI technologies in the design process, their understanding of these must be profound enough to evaluate the cost of development and computation to assess its adequacy concerning a given design objective. Prospective designers should learn how to communicate the design intent of their proposals regarding the possible use of AI technology when collaborating with engineers. Designers who work with AI must also be able to recognize and effectively and convincingly communicate possible harm and unintended future consequences.

Currently, there is a broad range of resource collections (e.g., <https://www.aixdesign.co/>, <https://machinelearning.design/>), online courses (e.g., <https://ki-campus.org/>, <https://www.element-sofai.com>), and labs or research projects (e.g., <https://www.gestaltung.ai>, <http://aixdesign>).

© Rahel Flechtner and Aeneas Stankowski | ACM 2023. This is the author's version of the work. It is posted here for your personal use. Not for redistribution. The definitive Version of Record was published in EduCHI 2023: 5th Annual Symposium on HCI Education (EduCHI '23), April 28, 2023, Hamburg, Germany. ACM, New York, NY, USA, 6 pages.
<https://doi.org/10.1145/3587399.3587410>

space/, <https://creative-ai.org/>, <https://www.burg-halle.de/en/university/facilities/burglabs/xlab/>) that provide access to practical knowledge about AI technologies or aim to integrate this knowledge into design education. However, the structured integration of AI technologies into the design education curriculum remains an unresolved challenge.

2. Related Work

AI technologies are developing fast and are frequently implemented in designs of human-computer interactions and user experiences. They enable new forms of interaction and a new dimension of individualization and adaptability. The challenges for design professionals when designing AI-based systems and the impacts of the technology on the design process are currently under discussion within the AI and design communities.

2.1. Challenges of Designing AI-Based Systems

Several challenges arise when designing with and implementing AI technology [18]. One of the fundamental impediments is that designers often lack an understanding of the technical capabilities of a given AI technology. The extensive interest in machine-learning technologies from an HCI or a design perspective is comparatively recent [16], and a structured integration into design education has not yet been developed [4,15]. Although there are numerous resource collections, online courses and labs, and research projects that address the teaching of AI knowledge (see section 1), practicing designers (compared with design students) are on their own in regard to appropriating the technology. The complexity, pace of development, and heterogeneity of possible use cases of the technology cause even designers with intermediate and advanced knowledge of AI to struggle to anticipate what can be accomplished with AI in the short, medium, and long terms. This uncertainty often leads them to „treat it way too much like magic“ [4].

The speed at which AI technology develops makes it particularly difficult to stay abreast of developments. Even for AI-savvy designers, as much as engineers, it is hard to predict developments in the field. As Yang et al. [18] state, „What might seem like a blue-sky AI design idea may suddenly become possible because of a newly available dataset.“ Another challenge Yang et al. [18] mention is that designers have difficulties envisioning novel, implementable AI solutions for a given User Experience (UX) problem. These challenges might be strongly interconnected with those discussed above. Dove et al. [4] make a similar observation, stating that

„we have rarely seen a UX team conceive of an entirely new way to use ML [machine learning] and then taken this to a development team to implement,“ implying that design-led innovations in machine learning are still rare. The reverse case, where designers use existing AI solutions to solve a problem, seems to have similarly little potential for innovation as existing tools usually only provide a very narrow subset of the whole landscape of AI capabilities [18] or require considerable further development to be adapted for new functionalities. Another problem Yang et al. [18] note is that designers have difficulty prototyping human-AI interactions and testing them in iterative processes. According to Windl et al. [15], this often leads designers to resort to „Wizard of Oz“ methods [13] when prototyping and testing AI-based interactions. However, as these methods are not bound by actual technical constraints and cannot fully represent the output complexity or possible inference errors, there is a risk that design processes driven by these methods will lead to fictitious design possibilities rather than realistic products [17]. Other challenges outlined by Yang et al. [18] include difficulties in collaborating with AI engineers due to the lack of common workflows or language and the difficulty in appropriately shaping user expectations for AI systems.

2.2. Engaging with AI within Design Processes

Another important point about AI and design is how AI affects the design process. This can refer to either how AI-based tools change the work of designers or whether or how design processes must be adapted to the challenges that the technology poses for designers. With no claim to completeness, we see three different categories of designers' engagement with AI in design processes. These categories require different levels of technical knowledge about how AI technologies work.

2.2.1. Conceptual Approaches

In the design, design research, and HCI communities, various approaches are discussed concerning design-related questions on a conceptual, reflective, or speculative level, such as speculative design [6], critical design [5] and design fiction [2]. These approaches have in common that they deviate from the widespread commercially oriented „problem-solving“ attitude of design. Instead, they aim to speculate about possible futures, raise questions, and foster critical debate. In technology development, these approaches serve as a valuable tool to promote a discussion on what kind of future for a technology is desirable and what is not.

Regarding AI technologies, these approaches can be beneficial for discussing their social, cultural, and ethical implications, as seen in the „Intimate Futures“ project by Søndergaard and Hansen [14], who used design fiction to address gender issues in the development of digital personal assistants. Another approach is to speculate about the future capabilities of a technology and develop fictitious products or services on this basis, as in the student project „AICA,“ a speculative design project of a discrete digital assistant for in-person human-to-human conversations [1]. These speculative or critical approaches allow for an engagement with the topic on an abstract and theoretical level. For this kind of engagement, practical knowledge about how AI technologies work is valuable and quality-enhancing but not necessarily a prerequisite.

2.2.2. Alternating Approaches

In this category, the goal of the design and development process is a design proposal in the form of a functional product, but design and technical development are mostly separated. Designers are not often engaged in the data aspects of the project. Yang et al. [18] describe such a process when they discuss designers using existing AI libraries or prebuilt models to solve a problem. Windl et al. [15] have formulated four approaches adopted by interaction designers working with AI, two of which we combine in this first category: In one approach, which they call „a-priori,“ the model is considered completed before the design process begins, so the challenge for the designers is to meet the requirements of the model. In a second approach, which they refer to as „post-hoc,“ the design is completed before the model, meaning the model must then meet the design requirements.

2.3. Collaborative approaches

Design and technical development are closely intertwined in this category, requiring close collaboration among designers, data scientists, and AI specialists. One example is the „model-centric“ approach described by Windl et al. [15], where the model is at the project’s core and developed by an integrated team. AI experts share their expertise with the designers, who are strongly involved in nearly all technical aspects. To support the iterative process, intermediate models with limited functionality can be built and used for the design. By enhancing their own knowledge of the capabilities and limitations of the AI solution to be developed, designers can also build prototypical AI tools in anticipation of trained models. According to Windl et al. [15], such a process allows the model and

the interface to be developed in parallel. In this process, designers inevitably develop, if they do not already have, a profound knowledge of the functionalities of the AI technology to be designed. Establishing an efficient common language at the boundaries of both disciplines, design and AI engineering, is essential for this process [9,11].

2.4. Implications for Design Education

The challenges and various approaches to engaging with AI in the design process raise questions about how future designers can be prepared to design AI-based products and user experiences. Different approaches to address these questions have been discussed: According to Yang et al. [18], the technical literacy of designers must be improved, and they must build basic data literacy [16]. To enable designers to work in cross-disciplinary teams together with data scientists and AI experts, it is essential to develop a mutual understanding and a common language at the boundaries of both disciplines [9,11]. Establishing guidelines and principles for human-AI interaction can also help designers in the design of AI-based products and user experiences [18]. Similarly, the establishment of AI-specific design processes can support designers in their work [18]. Rebecca Fiebrink [7] proposes an experiential learning approach supported by scaffolding tools for machine-learning education for creative practitioners to embrace the creative potential of AI technology. All these aspects provide important indications for the education of future designers. However, a structured integration of AI into design education has been lacking thus far [4,15].

3. Teaching AI to designers—thoughts and observations from practice

As lecturers, we have taught machine-learning formats for designers at the Berlin University of the Arts, Potsdam University of Applied Sciences, University of Arts Burg Giebichenstein Halle, and Offenbach University of Design. Since 2022, we have been visiting professors for Creative AI at the University of Design Schwäbisch Gmünd and part of the state-funded KITEGG research project. In the KITEGG project, a consortium of five German universities is working on how AI can be integrated into design education. We have devised or supported different teaching and learning formats in our teaching. We aim to improve these formats and integrate them into the design curriculum to give students the necessary intuition for AI technologies and prepare them to create meaningful and technically feasible AI-based systems and user experiences to bring design expertise closer to research

and development and facilitate shaping a desirable future with AI that considers the perspective of as many stakeholders as possible.

3.1. Thoughts on Intuition for AI Technologies

In this section, we share our thoughts on what an intuition for AI technologies means to us and how we think students should be able to use it in design processes.

Being able to make a conscious decision for or against AI technologies: Students should be able to assess the capabilities and limits of the most prevalent machine-learning technologies and commonly used models. Their understanding of these should be sufficient enough to evaluate the cost of development and computation and its adequacy in relation to a given design objective. In such a scenario, AI can be one of several technologies in a designer's toolbox that can be employed to solve a particular problem.

Using existing technologies in a targeted and creative way: Optimally, students should be able to use available models and AI technologies in a creative and unconventional way to discover new applications. Given a specific problem, they should know if and how an existing AI technology might be implemented, if it would work out of the box or needs to be adapted, and if that is possible for a given model. Students should also be able to implement entry and intermediate-level scaffolding tools, for example, teachable machine [3], InteractML [10], or Wekinator [8], in prototypes to test AI-based interactions they design.

Being aware of the possible consequences of implementing AI technologies: Students should be able to indicate possible side effects that might emerge from implementing an algorithm. They should be able to evaluate if it is possible to mitigate or avert possible side effects by design, for example, by effectively communicating the model's limits or prohibiting harmful use. In general, designers who work with AI must be able to recognize and effectively and convincingly communicate possible harm as well as unintended future consequences.

Using speculative and conceptual approaches consciously instead of using AI as a wildcard: Students should be clear about whether a concept for the use of AI is in the realm of the current or shortly possible, if it is a proposal for medium-term development; or if it is within the realm of speculation.

Developing a precise language for communicating about AI topics: Prospective designers should learn how to communicate the design intent of their pro-

posals regarding the possible use of AI technology when collaborating with engineers. In this regard, acquiring a basic machine-learning vocabulary can be helpful. Precise language can also help to avoid perpetuating an unrealistic and science-fiction image of the technology

3.2. Teaching AI Intuition—Observations on Different Teaching Formats

In this section, we describe our observations and experiences from various teaching scenarios that we have conducted or accompanied over several years to introduce design students to different technologies and topics. These topics have usually either been integrated through specific workshops and courses that highlight a particular technology to inspire and develop a basic intuition for it (3.2.1), or they have been woven into studio projects that focus more on adapting and developing use cases (3.2.2).

3.2.1. Building AI Intuition: Introductory Workshops and Courses

To build AI intuition, we have mainly used two teaching formats focusing on imparting knowledge about the technology: a) inspirational short workshops and b) semester-long supplementary courses.

(a) These formats were often conducted as few-day or weeklong workshops. Typically, they took an exploratory approach and were often built around specific tools, for example, teachable machine [20], Tiny Motion Trainer [19], or ml5.js [21]. The focus of these formats was typically the experimental, creative exploration of a particular AI technology such as image or sound classification or gesture recognition.

(b) These formats were held as semester-long foundational courses on AI. In these formats, learning about AI was often preceded by acquiring coding and mathematical skills. Through the increased duration, a combination of practical hands-on exercises and theoretical topics could be achieved. Theoretical topics were, for instance, technical foundations, emerging user experiences and interaction qualities, or societal and ethical implications of the use of AI technologies. For practical hands-on exercises, scaffolding tools like edge impulse [22] or ml5.js [21] were introduced as they usually enable students to generate prototypes and visualize ideas quickly.

On one hand, we had some positive experiences with the explorative and practical approaches in our formats: Through their exploration, students were able to develop a practical intuition of the possibi-

lities and limitations of the technology they were engaging with, for example, a sense of the amount and variety of data used, as well as some foundational and generalizable AI-specific concepts like transfer learning, overfitting, and supervised-learning techniques. Sometimes students could even develop a tacit understanding of more advanced concepts within the technical realm of machine learning, like the training and optimization process or building blocks of a model's architecture, such as convolutions or diffusion. On the other hand, we also observed that the acquired knowledge could often not be sustained as the workshops were quite dense. This especially applied to complementary topics sprinkled throughout the workshop, like technical foundations, mathematical basics, ethical implications, or a review of the state of the art in various AI subfields.

In the semester-long courses, we addressed these topics in more depth. Nevertheless, in our experience, these courses were still limited in scope as the attempt to provide mathematical understanding and programming skills stood in the way of deeper engagement in practical applications or in the theoretical examination of technology and its implications across the breadth of the discipline.

3.2.2. Establishing AI Intuition within the Design Studio or Project

Within the design studio or projects, we have mainly seen three different manners of engagement with AI technologies: a) within a given design brief, students decided to use AI technologies for their design proposal; b) using AI technologies was part of the design brief; and c) students were given the task of exploring future scenarios related to human-AI interaction.

(a) In these formats, students were given a regular design brief and opted for AI as a technology to achieve an objective or solve a problem. Since the use of and engagement with AI technologies were optional in these projects, we took a more advisory role in these formats in our position as AI experts. For example, we advised individual groups on their projects. In our observation, using AI as a wildcard technology that delivers crucial functionality to a use case has become somewhat prevalent. Many design educators have limited knowledge of AI themselves and therefore have difficulty advising their students or expressing reasonable doubt. Misconceptions about how an algorithm works and what is technically feasible prevent students from exploring meaningful solutions for its implementation within an artifact or interface. Often, we were consulted quite late in the design process. Ho-

wever, our feedback could guide students toward technical feasibility and improve awareness of unresolved challenges, unwanted implications, and ethical problems.

(b) These formats focused on using AI technologies to achieve a design objective or solve a specific problem. From our observation, these briefings are very popular among students due to their exploratory nature. Usually, they allow students to develop their research and ideation practices and to follow their curiosity to a certain extent. Once students decide on a topic, their proposals are judged on whether they consider real-life constraints. We accompanied a few such formats in our role as AI experts and observed they create difficulties for the teachers leading the studio or project. Teachers needed to pick a subset of problems to which they think the technology is applicable to be solved with machine learning or AI. As a result, the format required a significant amount of preparation and in-depth understanding by students and teachers. It also occurred that very different concepts arose during the studio, which again challenged the teacher's understanding of AI. Again, we observed that, given no expert guidance, students regularly only linearly extrapolated widely known use cases. Even concepts that seemingly stay relatively close to an established use case of the technology regularly strayed far from the technically feasible. Demonstrating a lack of a foundational understanding and technical intuition on how the technology works, the boundary between speculative and propositional projects was often unintentionally crossed.

(c) In these formats, students were tasked with speculatively exploring future scenarios of possible human-AI relationships and interactions. Briefings of this particular variety were designed to support a critical and open-minded approach without being too concerned with technical details. This allows for a more explorational approach that mixes elements from speculative design, critical design, or design fiction with traditional design approaches. Societal aspects of implementing AI technology can play a central role, along with possible unintentional consequences that might arise.

When accompanying some of these formats, we observed similar problems as in a) and b). While such briefings would often allow for speculative or critical approaches, projects again often converged toward linear extrapolation of popular AI use cases but also fictional scenarios along humanlike capabilities of AI. These proposals often lacked consideration of essential design questions, for example, how the technology is ultimately implemented through

interfaces and how it would impact processes or the lives of potential stakeholders.

4. Discussion

Based on our reflections on AI intuitions and our observations on the development and application of these intuitions in teaching, we discuss in this chapter the shortcomings of our formats in terms of the challenges and implications that AI technologies bring to design and, in particular, to design education.

First, our observations and reflections revealed that approaches to developing and applying AI intuition often happened in separate course formats. It is reasonable for teaching basic AI skills to occur in foundation courses at the beginning of the program. However, we also found that these course formats often lacked a meaningful connection to more in-depth formats. Thus, engagement with the topic of AI often remained at a superficial level. We observed that while the formats did spark students' interest in the topic, this could only be effective if there were follow-up formats on the application of AI and if qualified educators could supervise these. This connects to another observation that we consider crucial: We noticed a strong interest among students in engaging with AI in design. However, we also increasingly observed that AI technologies are used as a wildcard in the design process. The technology often served as a universal tool for solving a problem, whereby the technical implementation and sometimes even the technical feasibility were ignored. We see a reason for this in the challenge of understanding AI capabilities [18] as a lack of intuition about the possibilities and limits of AI technologies often leads to unintentionally speculative design proposals [4]. We observed a similar situation in teaching formats that follow conceptual design approaches and intentional speculation: students were often not aware whether their concepts for the future use of AI were in the realm of what is currently possible or what will be possible in the near future, whether they were a proposal for medium-term development, or whether they were in the realm of science fiction. This lack of clarity is particularly critical as, combined with media-driven images of AI, it fuels unrealistic expectations or fears about the technology.

Both observations are based on the assumption that students and teachers lack the necessary intuition for AI technologies. Consequently, establishing a basic understanding of the possibilities and limits of the technology is crucial [18] but complicated by the fact that these limits change quickly and are often difficult to grasp [4,18]. This challenge places

high demands on design educators: they must have a sound basic knowledge of the breadth and depth of AI technology and invest much time in keeping up with technological progress. Only then can they meaningfully advise students in the context of design studios or projects.

For us, this raises the question of whether the expectation to engage with AI technology to this extent can and should be placed on design educators per se. We do not see this as practicable and have therefore considered alternative approaches. One format we are currently testing at University of Design Schwäbisch Gmünd is that of an AI lab as a place of specialization. This lab offers entry-level formats for building an AI intuition in primary teaching and is linked to studio education and project-based teaching. It serves as a contact point for students who can find targeted advice and technical support for their projects. In the long term, the lab is also intended to be a contact point for educators. They, too, are to receive inspiration and support for their engagement with AI technologies to be able to apply and discuss the technology in their teaching. At a later point, given a successful integration into the design programs, we also imagine this approach being compatible with hosting studio projects that focus more on AI-related design topics, using the skills the students have previously acquired through supported projects. Like others, we note that there are several essential design questions to be answered about machine-learning-enabled interactions and artifacts by designers with domain expertise and the ability to work in interdisciplinary AI teams.

This leads to another point. We have not yet included collaborative processes with AI or data engineers in our teaching. In our formats, the design process has thus far been treated separately from the technical implementation. Especially in terms of developing a common language and getting to know the capabilities of the technology, closer collaboration with AI experts could offer significant advantages in teaching. This could also be a way to meet the challenge to envision novel, implementable AI solutions for a given problem [18].

5. Conclusion

In this paper, we discussed and reflected on our experiences from several years of AI education in design schools. We outlined the AI intuitions we believe students must work with in their design practice and shared our observations on developing and applying this intuition in various teaching formats. Furthermore, we discussed the challenges that might hinder a structural integration of AI edu-

cation into the design curriculum. We view the high demands that AI technology places on educators as one of the main problems. Therefore, we shared our thoughts on alternative teaching formats and proposed the concept of an AI lab as a place of specialization and support for both educators and students. With the installation of the AI+D Lab at University of Design Schwäbisch Gmünd, we intend to test this format intensively over the next few years.

We consider the structured implementation of AI technologies in the design curriculum to be an unsolved challenge to which we would like to further contribute in the following years through the methodological implementation and evaluation of various teaching and participatory formats for students and teachers. With our paper and thoughts, we hope to inspire discussion and further research on how AI can be integrated into the design curriculum.

Acknowledgments

The AI+D Lab at University of Design Schwäbisch Gmünd is established as part of the research project KITEGG—Making AI Tangible and Comprehensible: Connecting Technology and Society through Design, funded by the German Federal Ministry of Education and Research under grant agreement No. 16DHBKI067.

References

- [1] Arpit Bhatia, Meghna Gupta, Abhishek Gupta, and Nishtha Singhal. 2020. AICA: Artificial Intelligence Conversation Assistant. In *Companion Publication of the 2020 ACM Designing Interactive Systems Conference*, 569–573. <https://doi.org/10.1145/3393914.3395899>
- [2] Julian Bleeker. 2009. *Design Fiction: A Short Essay on Design, Science, Fact and Fiction*. Retrieved from <http://www.nearfuturelaboratory.com>.
- [3] Michelle Carney, Barron Webster, Irene Alvarado, Kyle Phillips, Noura Howell, Jordan Griffith, Jonas Jongejan, Amit Pitaru, and Alexander Chen. 2020. Teachable Machine: Approachable Web-Based Tool for Exploring Machine Learning Classification. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–8. <https://doi.org/10.1145/3334480.3382839>
- [4] Graham Dove, Kim Halskov, Jodi Forlizzi, and John Zimmerman. 2017. UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 278–288. <https://doi.org/10.1145/3025453.3025739>
- [5] Anthony Dunne. 2005. *Hertzian tales: electronic products, aesthetic experience, and critical design*. MIT Press, Cambridge, Mass.
- [6] Anthony Dunne and Fiona Raby. 2013. *Speculative everything: design, fiction, and social dreaming*. The MIT Press, Cambridge, Massachusetts; London.
- [7] Rebecca Fiebrink. 2019. Machine Learning Education for Artists, Musicians, and Other Creative Practitioners. *ACM Transactions on Computing Education* 19, 4: 1–32. <https://doi.org/10.1145/3294008>
- [8] Rebecca Fiebrink and Perry R Cook. 2010. THE WEKINATOR: A SYSTEM FOR REAL-TIME, INTERACTIVE MACHINE LEARNING IN MUSIC. In *Proceedings of The Eleventh International Society for Music Information Retrieval Conference (ISMIR 2010)*.
- [9] Fabien Girardin and Neal Lathia. When User Experience Designers Partner with Data Scientists. In *2017 AAAI Spring Symposium Series*.
- [10] Clarice Hilton, Nicola Plant, Carlos González Díaz, Phoenix Perry, Ruth Gibson, Bruno Martelli, Michael Zbyszynski, Rebecca Fiebrink, and Marco Gillies. 2021. InteractML: Making machine learning accessible for creative practitioners working with movement interaction in immersive media. In *Proceedings of the 27th ACM Symposium on Virtual Reality Software and Technology*, 1–10. <https://doi.org/10.1145/3489849.3489879>
- [11] Klaus Krippendorff. 2005. *The Semantic Turn: A new foundation for design*. CRC Press. <https://doi.org/10.4324/9780203299951>
- [12] Thomas Olsson and Kaisa Väänänen. 2021. How does AI challenge design practice? *Interactions* 28, 4: 62–64. <https://doi.org/10.1145/3467479>
- [13] Laurel Riek. 2012. Wizard of Oz Studies in HRI: A Systematic Review and New Reporting Guidelines. *Journal of Human-Robot Interaction*: 119–136. <https://doi.org/10.5898/JHRI.1.1.Riek>
- [14] Marie Louise Juul Søndergaard and Lone Koefoed Hansen. 2018. Intimate Futures: Staying with the Trouble of Digital Personal Assistants through Design Fiction. In *Proceedings of the 2018 Designing Interactive Systems Conference*, 869–880. <https://doi.org/10.1145/3196709.3196766>

- [15] Maximiliane Windl, Sebastian S. Feger, Lara Zijlstra, Albrecht Schmidt, and Pawel W. Wozniak. 2022. 'It Is Not Always Discovery Time': Four Pragmatic Approaches in Designing AI Systems. In CHI Conference on Human Factors in Computing Systems, 1–12. <https://doi.org/10.1145/3491102.3501943>
- [16] Qian Yang, Nikola Banovic, and John Zimmerman. 2018. Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Innovation. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, 1–11. <https://doi.org/10.1145/3173574.3173704>
- [17] Qian Yang, Justin Cranshaw, Saleema Amershi, Shamsi T. Iqbal, and Jaime Teevan. 2019. Sketching NLP: A Case Study of Exploring the Right Things To Design with Language Intelligence. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–12. <https://doi.org/10.1145/3290605.3300415>
- [18] Qian Yang, Aaron Steinfeld, Carolyn Rosé, and John Zimmerman. 2020. Reexamining Whether, Why, and How Human-AI Interaction Is Uniquely Difficult to Design. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–13. <https://doi.org/10.1145/3313831.3376301>
- [19] Tiny Motion Trainer by Google Creative Lab. Retrieved from <https://experiments.withgoogle.com/tiny-motion-trainer/view/>
- [20] Teachable Machine. Retrieved from <https://teachablemachine.withgoogle.com/>
- [21] ml5.js: Friendly machine learning for the web. Retrieved from <https://ml5js.org/>
- [22] Edge Impulse. Retrieved from <https://www.edgeimpulse.com/>