ACCOUNTING FOR THE HUMAN WHEN DESIGNING WITH AI - CHALLENGES IDENTIFIED

Nathalie Stembert
Rotterdam University of Applied Sciences
3011WN, Rotterdam, The Netherlands
n.stembert@hr.nl

Maaike Harbers
Rotterdam University of Applied Sciences
3011WN, Rotterdam, The Netherlands
m.harbers@hr.nl

ABSTRACT

Now that the application of Artificial Intelligence (AI) is becoming more mainstream, it is applied in many different fields, and consequently, it is starting to play a more prominent role in design processes. In current mainstream HCI (Human-Computer Interaction) design frameworks, the human (or user) is seen as the main focus, and stakeholders' perspectives are taken into account throughout the whole problem-solving process to design thoughtful solutions. The increased complexity of design processes caused by the rise of AI, however, pose new challenges to these existing approaches, particularly for involving the human in the design process. Five challenges that can be of influence on accounting for the human in design processes involving AI are identified and elaborated upon: 1) insufficient AI literacy of designers and users, 2) the black-box nature of neural networks, 3) where to start: design vs data, 4) customized solutions for narrow user segments, and 5) thinking ahead: an extended collaborative design process. These challenges arise across the exploration, design, implementation, evaluation, and deployment phases. This extended abstract discusses possible approaches per challenge on how to warrant integration of the human perspective.

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KEYWORDS

Artificial Intelligence; Human-Computer Interaction; Human-Centered Design

INTRODUCTION

Although AI is far from a new technology, only recently, due to more data and computing power, it is ready to be applied on a broader scale. Developments in machine learning, deep learning, continuous learning and algorithm-driven design, are not only changing technical possibilities, but also the field of HCI [25]. Designers will increasingly design with AI and embed AI into their products. This yields new challenges throughout several phases of the design process, i.e., during exploration, design, implementation, evaluation, and deployment. Currently, most designers of products or services with interactions ranging from screen, voice, gesture or haptics, are not fully prepared and equipped to design with and embed AI into their products in a conscious and responsible manner [5, 24, 26].

AI developments will continue to influence future work processes and team compositions in design, e.g. designers work in close collaboration with data-scientists and algorithms themselves. Therefore, it is important for designers to be able to design with AI, while warranting a human-centered design process in which thoughtful user experiences are key [20]. Analogue design approaches to empathize with human needs, i.e. user research, brainstorm methods, participatory design techniques, visualization tools and strategic documents, fit the challenges AI introduces only to a certain level [26]. In order to find approaches to help to account for the human in future AI design processes, challenges need to be identified and investigated.

In this extended abstract, we take a first step by identifying and briefly describing five challenges in accounting for the human when designing with AI. In each challenge we especially focus on the role of designers and users of AI-enhanced products, and the changes in design processes that AI brings about. The challenges are based on experiences within our own practices and backed by literature. We emphasize that these five challenges are only a selection from a wider range of identifiable challenges. Per challenge, we discuss possible approaches on how to warrant integration of the human perspective.

CHALLENGES

AI Literacy

AI is rapidly entering our everyday lives, yet for many people it is still a relatively unknown means. AI literacy amongst designers and users of AI-enhanced products is therefore still in its infancy [26]. Limited understanding of a technology, however, does not automatically has to form a barrier when it comes to design or usage. Designers more often work with means they do not fully understand, and if designed intuitively, usage of a product does not have to be an immediate limitation either. Dove et. al. [5], state that designers, when working with AI, use examples from similar solution spaces to gain inspiration and implement corresponding design patterns. When familiar design patterns are implemented, solutions can also be used without notice of the presence of AI.

However, Dove et al. [5], also show that AI currently sometimes is seen as a magic solution, due to a lack of true understanding. This limited understanding of the capabilities of AI can cause designers to have overconfidence in the possibilities algorithms offer. If limitations are known, experiences can be designed to compensate for these drawbacks [18]. It can therefore be argued that limited understanding of AI obstructs a human-centered design approach.

Not all designers have to become AI experts, yet development of guiding frameworks and guidelines could support working with AI across the full length of the design process [16]. Wang et al. [24], introduce an initial version of such a framework. Besides designers, also users would benefit from a certain level of AI literacy, to more consciously operate and collaborate with AI-systems. They are often presented with an illusion of control [10], insight in the role of AI on the user-system interaction should, as a start, be one of the guiding principles.

Black-box nature of algorithms

The non-transparent nature of neural networks makes it difficult to grasp what conditions influence decisions made by the model. Where in knowledge-based AI-systems, knowledge is represented in interpretable if-then rules, in neural networks, including deep-learning models, knowledge is spread over a network and not interpretable for humans. Possible biases hidden in the training data may lead to unfair or wrong decisions [17]. Building a custom model from the ground up requires expert knowledge and choosing for an existing deep-learning model can save time and money. There is already a broad range of AI development frameworks available, each with their own algorithms, specifications, and pro's and con's. The behavior of existing models, however, is not always transparent, making it difficult to grasp what conditions influence certain outcomes [7]. Moreover, using an existing model could mean copying a model with biases, data being unintentionally shared beyond the scope of an organization, or updates in the model happening without intent. Without knowing the exact conditions and limitations of a model, involving the perspective of the human and making informed and responsible design decisions becomes more complex. Nevertheless, a lack of transparency of AI-systems can also cause the user to distrust the decisions made by a system [20], whilst studies show that transparent systems can increase the acceptance rate [8, 23].

A promising direction is the field of explainable AI, which aims to open the black-box and create insight in the most prominent conditions that determine how an AI-system came to a certain outcome [1]. Designers play an important role in designing presentations of an outcome, where more transparent visualizations enable users to make more deliberate choices concerning their interaction with the system.

Where to start: design vs data

Generally, in the exploration phase of a human-centered design process, designers try to gain insight in the context and elicit user needs, whilst data-scientist tend to take a data-first approach. In a design-first approach, finding suitable and high quality data without violating privacy, carries the risk of an extended design process, inhibiting the development process [26], possibly resulting in increased expenditures because of new data creation or an eventually underperforming solution. In a data-first approach, models are often trained by the data that are available, without determining beforehand which output is useful for the user. As purpose is missing [6], this increases the risk of outcomes that do not fit the problem statement nor the user needs [4].

Baumer [2], provides three possible approaches, a theoretical, participatory and speculative strategy, to move towards human-centered algorithm design. Dove et. al. [5] and Yang et. al. [26], speak of a cross-disciplinary approach in which designers, data-scientist and domain experts work in close collaboration to amongst others warrant the human perspective. A model from John Morely & Associates [19], suggests how human-centered and machine-centered processes can iteratively work in parallel. In either case, it requires designers and data-scientists to have a shared understanding of each other's fields of work, and established or new collaboratively shared methods of working are needed to bridge differences in procedures.

Customized solutions for narrow user segments

AI makes it possible to create personalized (sub-)functionalities and behavior for narrow user segments or even individual users [22]. This results in a range of different solutions, making it more difficult for designers to control the design process in detail. Personalized content, based on user behavior is becoming mainstream [12]. However, algorithm-driven design techniques can also produce personalized interfaces [21]. Whereas currently designers choose one (best) solution, in the future, user-generated data might determine what interfaces users get to see. This has implications for evaluation metrics, which should not only consist of optimization criteria, but also include user-centered measures [9]. Moreover, most traditional evaluation methods are not suitable to test a large quantity of different solutions. Simultaneously, with the large amounts of data gathered, predictability of ethical issues is getting more complex. Ensuring a for users explainable and trusted solution could therefore be more challenging.

Vetrov [22], suggests a collaboration between algorithms and designers, where the former are in charge of the routine design work, and the latter design the behavior of intelligent systems. Even if testing and decision-making could be automated, keeping a designer in the loop to control and guarantee responsible data-driven reasoning and decision-making is advisable. This requires adequate tools to keep an overview of a large quantity of (often alike) solutions, without causing an information overload.

Thinking ahead - an extended collaborative design process

Continuous learning models respond to ever changing scenarios [13]. This, in a way, extension of the design process requires designers to think further ahead. Products that involve self-learning algorithms confront the user with ever-changing behavior. As such, the role of designers, who previously designed a fixed product, will in this approach be ambiguous. Whilst, in the stage of usage, traditional design principles, e.g. visibility, feedback, constraints, mapping, affordances, and consistency [15], will remain as, or even more, important to enable the user to consciously interact with AI-enhanced products. The automated goal-adaptive behavior of AI-systems, directly contravenes with the guiding principle of consistency and indirectly feedback. Lugar & Sellen [14], speak of Norman's gulf of expectation between the users expectation and the experience they are provided with. One of their findings shows the importance of revealing system capabilities to users in order to create a positive user experience. Creating human-computer partnerships could be the next step [3]. Mechanisms for collaboration, or interplay, between the human and the system will then play an important role in co-performance with the system [11].

In a continuous data stream, it could for example be desirable to "temporarily switch off the learning mode" or "undo certain actions". Or possibly, going one step further, enabling a truly participatory design process, by providing insight in the different user scenarios and collaboratively creating a new preferable use experience. The question then remains, what is an acceptable scope, how to define the boundaries of the system, and integrate this in a responsible way throughout the design process, as in this stage, the even further growing quantity of possible solutions again decreases the predictability of ethical implications.

CONCLUSIONS

We identified five challenges in accounting for the human in design processes with AI. Per challenge we discussed possible solution directions. In our future work we plan to investigate these challenges in more detail and build on existing solutions to account for the human when designing with AI.

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