

## Characteristics of AI-infused systems

AI-infused systems are 'systems that have features harnessing AI capabilities that are directly exposed to the end user' (Amershi et al., 2019). Drawing on the first lecture of Module 2 and the four mandatory articles (Amershi et al. (2019), Kocielnik et al. (2019), Liao et al. (2020), Yang et al., (2020)). Identify and describe key characteristics of AI-infused systems.

One key characteristic of AI-infused system is that they are probabilistic, meaning that they will inevitably fail at times Kocielnik et al. (2019). Another characteristic of AI is that it can be categorized as a black box where the internal operations of the AI are not understood completely, not even by the developer. For AI to be trusted by the user it needs to be able to explain how it reached its recommendation or conclusion. Explainable AI (XAI) tries to give the user further insight or evidence of why the AI is giving a certain recommendation (Liao et al., 2020).

The uncertainty of capability is one of the challenges to overcome in the design of AI (Yang et al., (2020). The capability is often referred to as what the AI system is capable of doing, examples of this would be, giving personalized ads or optimized biking directions. However, the capability of AI systems does not only include the existing capabilities but also what is technically feasible, but not yet discovered (Yang et al., (2020). In order to design technology, the designer needs to understand both the capabilities and the limitations in order to know the possibilities for design (Yang et al., (2020). Another challenge concerns the output complexity from the AI-system (Yang et al., 2020). This is particularly challenging when trying to prototype since these systems provide many possible outcomes and manual sketching cannot fully capture the ramifications of such systems (Yang et al., (2020).

Identify one AI-infused system which you know well, that exemplifies some of the above key characteristics. Discuss the implications of these characteristics for the example system, in particular how users are affected by these characteristics.

Apples photos application uses machine learning to find out which photos the user cares the most about and visually “removes” photos that the user won’t care about. An example of this would be that it could show pictures from a wedding but removes pictures taken of a whiteboard. The system is able to recognize that the user is much more interested in seeing the picture of the wedding than a picture taken of a whiteboard. The implication of this is that, since the system is probabilistic, sometimes it will be wrong and show the whiteboard instead of the wedding. There is currently no way for the user to know why the system suddenly is showing a whiteboard, and there is no feedback telling the user how correct the system thinks itself is. The implication of this is that it could lead to the user not trusting the system to find important photos, and potentially the user leaving the system.

## Human-AI interaction design

Amershi et al. (2019) and Kocielnik et al. (2019) discuss interaction design for AI-infused systems. Summarize main take-aways from the two papers.

AI-infused systems may display unpredictable behavior that can be disruptive, confusing, or sometimes dangerous, this is because it produces both false positives and false negatives (Amershi et

al., 2019). While achieving personalization and aligning with users' preferences is essentially good for the user experience, it comes with a cost to usability when the system is wrong. One central guideline in UX design is to keep the interface predictable and consistent, which goes against the unpredictable behavior of AI. This is why complementary guidelines for the design and evaluation of AI systems are needed. Amershi et al. (2019) synthesize learnings of AI from multiple sources into 18 applicable design guidelines.

The guidelines were categorized into four different phases of interaction with AI (Amershi et al., 2019). The first one is "initially", communicating reasonable expectations on what the AI is able to do or not do. The second is "during interaction", this is about the context of use, such as setting, task, and attention. The third phase is "when the system is wrong", how the AI communicates when it is (inevitably) wrong, and how to handle that situation. The fourth and last phase is called "over time", and is about the interaction over time when the AI is learning from the user's behavior.

Since AI-technologies are probabilistic and will fail at times, setting the right expectation is central for the user's experience. If the user's expectations are met incorrectly, it could lead to disappointment or abandonment of the service (Kocielnik et al., 2019). The article by Kocielnik et al. (2019) explores different techniques for shaping user expectations of AI-infused systems prior to being used. There are three different types of expectation forming that are being explored, such as external information, understanding, and first-hand experience through a sense of control (Kocielnik et al., 2019). External information is understood as when the user is being told how the AI works by a third party (Kocielnik et al., 2019). Understanding is when the user grasps how the system works through reasoning (Kocielnik et al. 2019). And the third type of expectation forming is when the user interacts directly with the system and is thus called first-hand experience (Kocielnik et al., 2019).

The article explores this topic by using a scheduling assistant powered by AI for email. The researchers wanted the AI to underperform and make the user disappointed in the system, this was done by setting the success rate of the AI at 50%.

The study shows that user satisfaction and acceptance of a system will be higher if the system is optimized for high recall rather than high precision. However, the authors also mention that this insight is not always transferable into other domains or systems and that it's a complex issue. The study also confirmed that directly communicating the accuracy of the AI system will lead to a lower discrepancy between user perception of the system and its accuracy. If the system provides explanations of how the AI system works it will lead to a higher perception of the understanding of the system from the user. By letting the user have an impact on the system, it will increase the perceived control of the system. These guidelines will be useful when designing an imperfect AI-powered system.

Select two of the design guidelines in Amershi et al. (2019). Discuss how the AI-infused system you used as example in the previous task adheres to, or deviates from these two design guidelines. Briefly discuss whether/how these two design guidelines could inspire improvements in the example system.

Online ads tries to personalize the content for the user to be more relevant and engaging. On Facebook there is a feature that gives the user an explanation of why they are seeing a certain ad and why it's targeted toward that user. This is based on information that Facebook has collected on the user over time, the user is also able to retrace how this information was collected. Some guidelines that relate to

this interaction would be, “learn from user behavior” and “make clear why the system did what it did”.

One feature that could improve this interaction would be to tell the user how the personalized content (ads) is changing when new information is put into the system by the user. For example, when the user is moving to a new city and changes location, the system should tell the user what kind of new and more relevant ads will appear. This improvement would relate to the guideline “notify users about changes”.

## Chatbots / conversational user interfaces

Chatbots are one type of AI-infused systems. Based on the lectures, and the mandatory articles, discuss key challenges in the design of chatbots / conversational user interfaces.

There are several challenges that need to be addressed such as that chatbots fail to meet users' needs due to unclear purpose, nonsensical responses or insufficient usability (Brandtzaeg & Følstad, 2017). Luger and Sellen (2016) brings up the fact that users of chatbots (or conversational agents) have poor mental models of how the chatbots work. One challenge will thus become giving meaningful feedback to the user about the intelligence and capability of the system (Luger & Sellen, 2016). The design of the conversation with a chatbot itself has been another much discussed topic within HCI (Følstad & Brandtzaeg, 2017). Følstad and Brandtzaeg (2017) writes that the field of HCI needs to move away from the concept of *explanatory task*, meaning the task of explaining what features and content is available on the website to the user. An example of this is the chatbot used for a portfolio website created by Adrian Zumbrunnen [1]. In this example, the designer removed all visible features and content while the website visitor was only presented with a chatbot to navigate their way around. After shutting down the chatbot, the creator remarks that if the use case isn't simple, chatbots are not the right tool for the job [1]. Følstad and Brandtzaeg (2017) writes that rather than focusing on *explanatory* HCI practitioners should focus on *interpretational*, that is understanding what the user needs and how to she may best be served. For chatbots to be considered successful in the eyes of a user they need to be able to hold a conversation and keep multiple interactions from the user while providing useful output (Følstad & Brandtzaeg, 2017).

Revisit Guidelines G1 and G2 in Amershi et al. (2019). Discuss how adherence to these could possibly resolve some of the challenges in current chatbots / conversational user interfaces. Optionally, you may read Følstad & Brandtzaeg (2017), Luger & Sellen (2016), and Hall (2018) from the optional literature to complement your basis for answering.

G1 - Make clear what the system can do, is very relevant in the design of chatbots. By telling the user before use about common interactions with the chatbot, it will lower the discrepancy between the user perception of the system and its accuracy, leading to a better experience. Many chatbots today use a vote up or down function on the answers, this is meant to be used by the user to tell the system when it's wrong or not helpful. If the system made this accuracy-number visible for the user, it could also indicate to the user how helpful other people thought the answer was. This idea comes from the guideline G2 - make clear how well the system can do what it can do. By making the accuracy visible (in some form) to the user the user experience of the system is improved, as discussed by Kocielnik et al. (2019). These ideas will not solve all the challenges with chatbots, however it might change people's perception and mental model of what the chatbot is capable of doing.

## References

[1] A. Zumbrunnen (2020). My chatbot is dead. Retrieved from <https://uxdesign.cc/my-chatbot-is-dead-8e6784fca05>

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