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Demystifying UX for AI: A Balanced Design Approach for ML

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Abstract: ML is often seen as a 'plug-and-play' learning methodology that can be thrown at raw data for whatever problem comes to hand. Given this fact, this study aims to develop design principles in an AI context by taking into account various design guidelines, processes, and tools. The study explores how designers and AI engineers conceptualize the guidelines from different "points of view" to co-create AIX. By exploring the relevant body of existing work, the paper develops design framework based on a set of hypothetical model metrics. For generalization, it is suggested that the proposed design principles need to be validated in different contexts in further research. Last, but not least, it should be taken into account that it ML models merely provide advice as to which features of the problem seemed to be important and which seemed unimportant rather than offering a full intuitive understanding of the topic at hand.

Introduction

This study aims to develop design principles in an AI context. Taking into account the intersection of AI creation and human-centered application design- referred to as- AI experience design (AIX), HCI researchers have put forth design guidelines [3, 29], processes [94], and tools [85] which emphasize the designer's responsibility to understand the AI design material.

This study explores how designers and AI engineers conceptualize the guidelines from different "points of view" to co-create AIX. This theme can be formulated in theform of the following research question:

- How might designers and AI engineers conceptualize design perspectives based on human-AI guidelines to co-create AIX?

Review of Existing Studies

In HCI (human-computer-interaction), experiences of a system are typically mediated by a person's mental model of that system. However, a mental model explanation is insufficient when it comes to designing for AI. Even more,explaining AI can confuse even experts [16,12], as the term has changed over the years. Nilson describes AI as "that work dedicated to making machines smarter ... [where] intelligence is the quality that makes a business more efficient and foresight" [10]. According to Schank's definition, AI systems are rated after ideas about the human mind [4] - are used in a variety of application domains[29].

Numerous design guidelines for AI applications have emerged from both academic and industry research spanning across different design aspects such as functionality [45], end-user interactions [3, 29, 34], learnability [27], explainability [87], privacy [32, 47], transparency [21], etc. When it comes to designing AI experiences, design unfolds into the different AI components, including the model's behavior, learning characteristics, assumptions, and nature of training data rather than in a linear or top-down manner. From a material point of view, design includes the following aspects to be completed in an iterative way:

(1) fabrication—ways to produce materials with specific properties,
(2) application—ways to transform materials into products, and
(3) appreciation—reception of material by the end-users [19].

To overcome design challenges, a process model as shown in Figure 1 – originally developed by [1] that combines top-down (UX-first) and bottom-up (AI-first) workflows to distribute agency between designers and engineers might be useful. As represented by the bi-directional arrows, the AI and UX components are designed in parallel leaning towards more proactive engagement through accessible user-data proxies and data probes during the co-creation process.

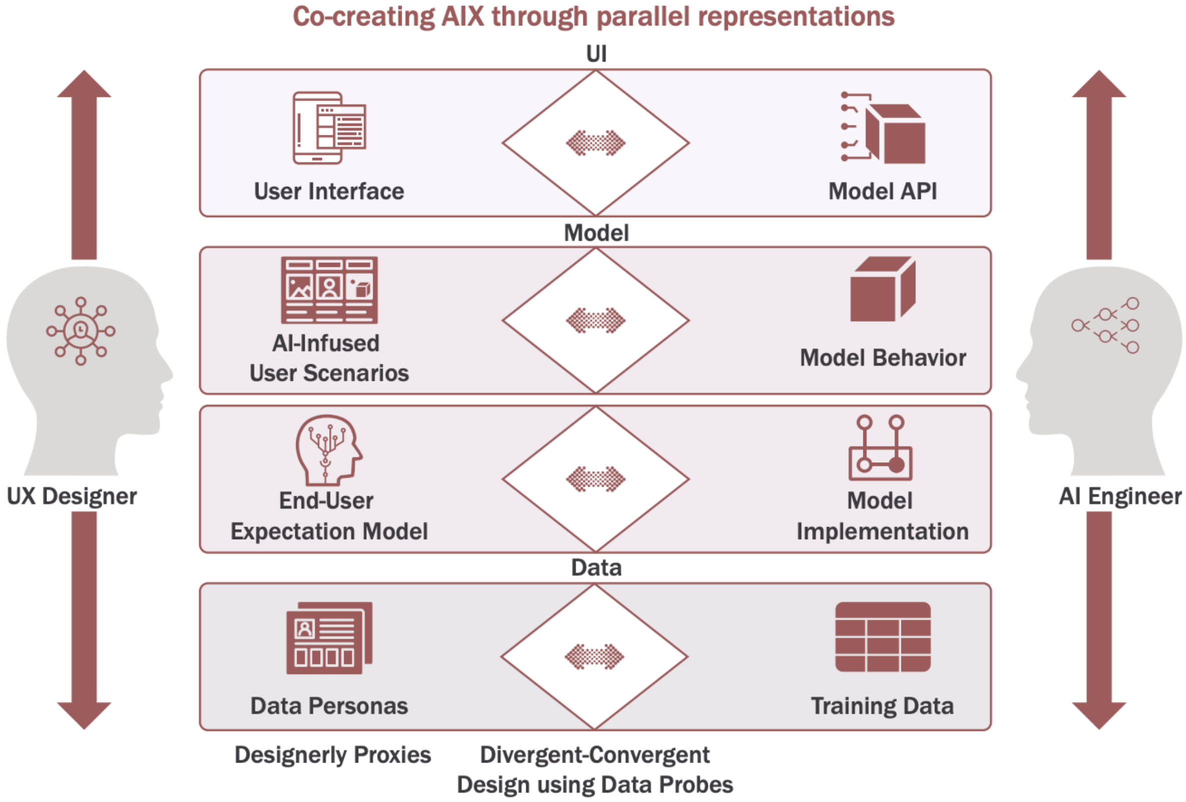

Fig 1. An overview of AIX development process [1]

By adopting the approach shown in Figure 2, UX designers can engage in a "conversation with the materials [90]," and "talk back to the designer [90]." For engineers, they need to offer descriptions of AI properties, assumptions, learning rules, and API details back to designers. Through user interface prototyping with data, the application programming interface (API) can also be co-designed based on data probes serving as a scaffold for divergent design thinking, material testing, and design validation.

When prototyping AI features, designers need to choose whether to automate the task entirely, ways to augment human effort with AI, and whether the AI should be proactive or reactive (acting only upon human invocation), etc. [37]. Following human-centered walkthroughs of scenarios, a co-creation process involves discussions about the attributes, priorities, and values important to users and the technical AI capabilities required.

Standard UI prototyping tools such as Wireframe.cc [66], Figma [20], and Adobe XD [1] allow designers to work at the user interface level alone through horizontal prototyping [5]. Also, the AI-generated content should be visually different to allow end-users to adjust their expectations about AI features (and, in turn, diminish frustration). Based on decisions about AI feature integration into interface design, designers may need to revisit the model inputs and outputs (i.e., the API).

On the other hand, one should also be aware of possible 'dark patterns underpinning any AI-driven platform. Although dark patterns focus on UX/UI and layout design on the surface, it also contains a much larger set of concerns and harms and represents deeper technical, infrastructure, business models and decisions, and policy issues. Such issues may relate to nudging, persuasive design, addictive design, malicious design, confusion design, manipulative and general 'bad design.' One recommendation might be to build impact and harm analysis into the process when analyzing dark patterns. It is important to name the explicit types of design choices that are dark patterns, as it cannot be divorced or separated from the context of where it is appearing.

Moreover, there needs to be a deep understanding in how some dark patterns directly target vulnerable populations, such as populations who are lower income and financially impacted, etc. To that end, algorithms should also be structured to support in-app parameterization, allowing users the freedom to select which data attributes to apply these algorithms to by taking into account the following data aspects:

• **Data suppression:** With a dataset's schema identified by the application, users can select the fields to be suppressed (i.e., completely removed) from the dataset. For example, users may choose to suppress the name field from the action data, given its highly sensitive nature.

• **Data hashing:** With the dataset schema as a reference, users can select the fields to which they would like to apply a 'SHA-256' hash. For example, users may hash the 'actionId' field from the action data.

• **Geolocation k-anonymization:** Optimized for the platform schema, this algorithm gradually suppresses the country, region, and city keys within an action's geolocation key, until there are at least k-users containing each combination, satisfying k-anonymity [21] (assuming that geo-location is the only identifying attribute).

• **User cleansing:** Optimized for the platform schema, this multistep algorithm (i) replaces 'userId's in a dataset's actions key with a 'SHA-256' hash of each 'userId', (ii) removes identifying information, which may include names and emails, from a dataset's users key.

• **Advanced user cleansing:** This algorithm scans the entire dataset to detect remaining instances of identifying user information, such as names and IDs, replacing them with hashed versions thereof. This handles edge cases in which the data contains, for example, identifying information captured via user-generated inputs. The scan is performed using regular expressions, hence matching close representations of user information (e.g., John Doe matches variations like john.doe@institution.domain).

Algorithms may consume data in very different formats, and, if the format of the dataset is unclear, it's easy to introduce bugs caused by misinterpretations of the underlying data.To maintain its usefulness, raw data is ideally stored in a lossless format by recording all the information that is produced, keeping the temporal relation between the data items (e.g., ordering of steps and episodes), and without making any assumption on how the dataset is going to be used in the future. Researchers can use the datasets in order to analyze, visualize or train a variety of ML algorithms, which, may consume data in different formats than how it has been stored.

Design Methods

One of the most popular design methods is design thinking which is anhuman-computer interaction (HCI) approach to problem-solving with a focus on who is being designed for. The aim is to create design artifacts that address real user needs, and then test those artifacts with real users (Norman, 2013; Giacomin, 2014).

Dollinger et al. (2019) compare different approaches of human-centered design (HCD) and provide an overview of participatory frameworks (co-design, co-creation), followed by a case study of how designers co-created analytical platforms with the target users. Martinez-Maldonado et al. (2015) propose a workflow to engage users in iterative prototyping and evaluation cycles before deploying an analytical system. Holstein at al. (2019) argue that the co-design of systems requires new kinds of prototyping methods and introduce Replay Enactments (REs) as a prototyping method to address unique challenges of co-prototyping analytical tools.Ahn et al. (2019) report on their design experience developing dashboards to support user practices and offer ways to adapt common HCD methods, such as contextual design and design tensions, when developing visual analytics systems. Rehrey et al. (2019) suggest implementation strategies that consider the human factor in adopting new technologies by practitioners.

To support ethical considerations and human values in systems, Chen and Zhu (2019) introduce two cases of applying Value Sensitive Design methods (e.g., stakeholder analysis, value analysis) to design. The authors note that engaging stakeholders in the early stages of the design and using stakeholders' insights and feedback to guide the system development is important to increase their acceptance and perceived impacts of the system. Prieto-Alvarez et al. (2018) stress the critical role of giving voice to users in the design process and provide a case study focused on co-designing tools with users using different co-design techniques such as focus groups, storyboarding, and prototyping. In general, this research encourages the active user involvement in the design process and provides demonstrations of successful co-design processes for some tools with users. However, existing user-centered design workflows provide limited methodological guidance for effectively involving users throughout the entire design process, including understanding user needs, idea generation, prototyping, and testing. Moreover, the reported case studies are focused on the participatory design of tools and platforms (macro design level) rather than the systematic design of the underlying indicators (micro design level).

A design methodology should start with an understanding of the users' real needs and goals and then designs indicators that best address these needs and goals. The final objective is to give answers to the following questions: Which indicators are needed to support the design? and How to systematically design these indicators? This is achieved through two cyclical processes aiming at (1) understanding users' needs and expectations and (2) empowering users to take control over the indicator design process, as depicted in Figure 2.

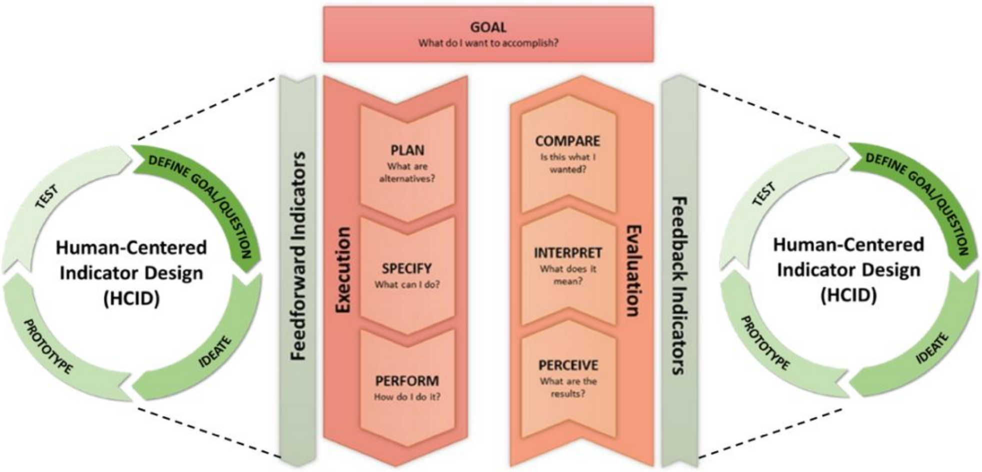

Fig 2. AIX design methodology [1]

As shown in Figure 2, the AIX design process is cyclical and it is composed of three general phases: (a) goal setting, (b) executing, and (c) evaluating. In an HCI context, Norman (2013) discusses seven stages of action that provide a guideline for developing usable and understandable new products or services, following a human-centered design approach. By associating the typical three phase model and Norman's seven stages of the action cycle, the design process can be modeled as a cyclical seven stages activity, as shown in the middle part of Figure 2.

To provide further details, there are three major phases to andesign activity: goal setting, executing, and evaluating:

- The execution phase is further subdivided into three stages that follow from the goal: *plan*, *specify*, and *perform*.
- The evaluation phase is further broken down into three stages: *perceive*, *interpret*, and *compare*.
- The design activity cycle starts from the top with the user goal (goal) and then goes through the three stages of execution: planning the possible user activities to achieve those goals (*plan*), specify a user activity path (*specify*), and perform the user activity (*perform*).
- The cycle then goes through the three stages of evaluation: perceiving the results of the user activity (*perceive*), trying to make sense of it (*interpret*), and comparing the outcome with the goal (*compare*).

It is important to stress that most activities require multiple feedback loops in which goals lead to subgoals, and the results of one activity are used to trigger further ones.

Moreover, design activities do not always have to include all stages, nor do they have to proceed in a linear manner across all stages. Each of the seven stages represents a possible question to ask towards anydesign activity.

Below is a summary of the questions related to the stages of the execution and evaluation phases along with the description of the indicators needed to answer these questions:

• **Goal** (What do I want to accomplish as a user?): Provide information about the defined goals of the learning activity.
• **Plan** (What are alternatives?): Provide information needed to understand the possible actions that can be taken in order to reach the goals.
• **Specify** (What can I do as a user?): Provide information to help learners decide on the appropriate learning activity path.
• **Perform** (How do I do it as user?): Provide information on best strategies in order to perform a task in an effective and efficient way.
• **Perceive** (What are the results?): Provide information to communicate the results of the performed tasks and the current state of the learning activity.
• **Interpret** (What does it mean?): Provide information to help learners understand the results and the impact of the learning activity in context.
• **Compare** (Is this what I wanted as a user?): Provide information about progress towards goals.

Based on Norman's human-centered design (HCD) process (Norman, 2013) this design methodology provides a theory-informed approach for the systematic design of ML agencies, thus enabling to "get the right indicator" and to "get the indicator right". The main aim of AIX is to empower users to take control of the indicator design process in order to effectively meet their needs and goals.

Such a HCD methodology introduces new design opportunities for collaboration among different ML agencies and human-beings. Given the proliferation of ML algorithms into our daily lives, design tools can become more autonomous, making creative decisions on behalf of the users. Two different taxonomies emerge to understand mechanisms of ML agencies from the AIX design perspective:

- First, resource roles indicate which type of resources, or benefits, each ML agency offers. These further divide into two types based on whether the resource was an 'idea' or something more tangible and skill-based, like 'labor' or 'expertise'.
- In contrast, process roles indicate in which part(s) of the process the ML agency is intended to work. At a high-level, process roles include aiding ideation, aiding implementation, and aiding evaluation.

There are situations where process and resource roles are strongly connected. As shown in Figure 3,by splitting role types, we can distinguish between the benefits offered by the ML agency and where/how they are offered within the system workflow.

	Taxonomies	Codes
Roles	Resource roles	Vision
		Skill
	Process roles	Idea Generation
		Curation
		Execution Assistance
		Producing
		Understanding
		Critique
Interactions	Directness	Direct
		Indirect
		No Input
	Predictability	Predictable
		Unpredictable
	Output	Implementing
		Influencing
Technologies	Technologies	Learning Algorithm
		Non-learning Algorithm
		Software UI
		Sensor
		Fabricator
		Robot
Users	Users-Expertise	Novice
		Expert
		Both
		Not Specified
	Users-Specific	General Populations
		Specific Populations

Fig 3. AIX taxonomies and codes

In order to implement a human-centered approach for AI model, the following phases can be followed.

Interaction Approaches Used

A single tool can have multiple interaction behaviors corresponding to multiple functions. While the traditional types of interactions (e.g., mouse, voice, touch, direct manipulation, etc.) are part of this analysis, AIX designers are more concerned with the properties and intents of the interaction relative to the creative process.

Input Directness

One can categorize input directness in relation to whether an ML agency is receiving direct inputs or not.

One example is natural language queries given by the user. These queries would be used to request various functions to the tool (e.g., searching or generating artifacts), but queries themselves are not artifacts.

Another type of indirect input is a manipulation of parameters, like those for cameras, such as exposure levels. It is more of partial information about how the artifact should be, but not the representation of the artifact.

Predictability of Impact

A predictable ML agency is one in which it behaves exactly according to the user's specifications or anticipation. Agencies that are unpredictable are those that produce output that is difficult for the end-user to model. The end-user is aware that critiques are being produced but can't accurately model what they will be. Unpredictable tools rarely require users to give very specific information on how the tool should behave. In fact, it is this ambiguity that makes them unpredictable.

Learning algorithms

ML agencies based on learning algorithms were those that were trained on data. They include many ML algorithms, ranging from Hidden Markov Model, neural networks, and Generative Adversarial Network [49, 101]. One use of these algorithms is to recognize and understand artifacts or user inputs.

Non-learning algorithm

ML agencies that are not data-driven are classified as non-learning algorithms. This type included hand-tuned, rule-based algorithms, or optimization algorithms.

Software UI

Agencies that were principally centered around software UIs often involved designs to improve user control.

Sensors

Sensors have been used in ML agencies to expand the modality of the expressions. Their usage range from photo-sensing to audio-, depth- and gyro-sensing.

Fabricators

Some agencies use new fabricators or materials (or leverage existing ones). For instance, ExpandFab [66] introduces a fabrication process of expanding objects using foam materials.

Robots

Though rare, some agencies have mechanical or robotic infrastructure. This enabled them to interact in physical spaces. For example, Robovie [65] is a physical robot designed to give inspiring prompts on garden designs.

Design Framework

Based on the existing research studies, this paper suggests the following design principles based on a set of hypothetical model metrics as shown in Figure 4.

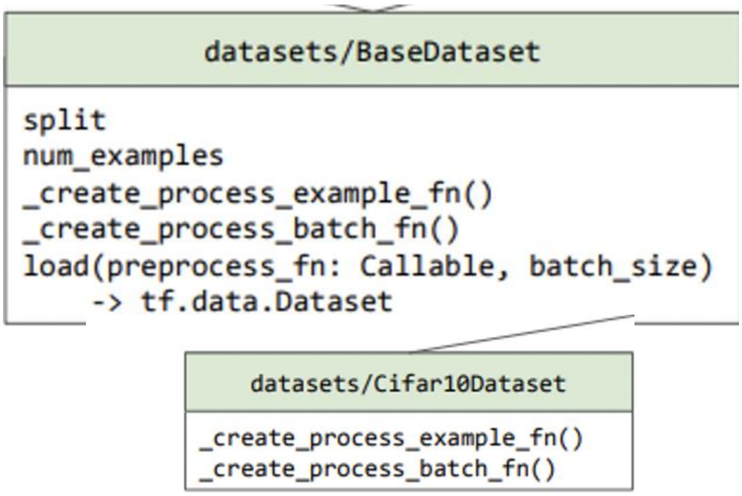

Figure 4. Suggested Data Model of AIX design

According to this model, the following aspects should be taken into account:

Transferability

Typically, developers choose training and test data by randomly partitioning examples from the same distribution. They then judge a model's generalization error by the gap between its performance on training and test data. However, human-beings exhibit a far richer capacity to generalize, transferring learned skills to unfamiliar situations.

Informativeness

While the ML objective might be to reduce error, the real-world purpose is to provide useful information. The most obvious way that a model conveys information is via its outputs. However, it may be possible via some procedure to convey additional information to the human decision-maker. An interpretation may prove informative even without shedding light on a model's inner workings.

Safety

A safety condition is based on the assumption that the initial state of an environment arranged by human-beings will contain information about their preferences for safe and unsafe behavior (Shah et al., 2019]). Gehring and Precup [2013] consider agents to be safer when they avoid higher-variance outcomes.

Explainability

This framework would also provide explainability for decision makers, offering insights on trends via its compartmental structure. Machine-learned rates can be used to map them to take advantage of the vast amount of available data with informative signals.

Recommendations

AI designs have been criticized for focusing too much on merely making users aware of data, but with too little focus on the actions they might take from this feedback [12]. In addition, users may vary in their capability to interpret, make sense of, and use the analytics for a particular application[13]. These issues are true of relatively simple designs which display typical summary data from system logs capturing visible user activity. They are compounded by more complex models both due to issues of 'algorithmic literacy', and the potential black-box nature of algorithmic systems in AI gives rise to issues in fairness, accountability, transparency and explainability (FATE) [14, 15], which may obscure important information needed by users to make informed decisions.

Since "raw data is an oxymoron" [17], that is, data is curated, crafted, and used by users to represent particular things in contexts, a critical lens is needed in probing and holding accountable design interpretations and outputs. Additionally, AIX comes with inherent imperfections in computational models which require careful consideration. Indeed, analytics are proxies and indicators of constructs, and AIX is somewhat limited in terms of what data can be accurately captured from complex user activities [4, 16, 19]. Consequently, the contexts in which AIX occur and how they are made sense of and interpreted by users are important; data is represented and interpreted in particular contexts, to particular actors, with a range of possible - intended or unintended – outcomes [13, 20]. This paper therefore emphasizes that critical engagement with analytics is an essential analytical skill which refers to "the act of questioning engagement with data, analytics and computational tools with an understanding of its limitations and assumptions, alongside the analytical ability and agency to challenge its outcomes when necessary".

Such critical interaction enables AIX designers to understand the engagement between their design, and user analytics as one of a number of technological tools at hand for them. Central to this view are four key claims:

1. Critical engagement with analytics is fundamental for design agency because it is activity-oriented, targeted at doing. Varioustools, such as user dashboards, should reflect this need for critical engagement through activity-oriented design for critical awareness and reflection, aiming to develop users' cognitive, behavioural or emotional competences [12], to build their agency.

2. Critical engagement is a metacognitive capacity and therefore designers must be able to, and should be encouraged to, question analytics (while its absence may indicate poorer understanding of both data and design constructs). New forms of feedback that are different to what humans are used to receiving have emerged, which require additional critical skills for interpretation and application. Just as the emergence of AI in other contexts provokes debate about what makes us 'truly human' and how we should relate to machines, the emergence of AI-powered feedback adds new dimensions to the concept of what 'good feedback' looks like, offering opportunities for timeliness, specificity, and augmentation of human intellect, as well as risks.

3.While there is a general tendency to associate automated tools for accuracy, it should be noted that these are bound by imperfections and biases in algorithms. Imperfectness that is inherent in measurements and machine understanding can sometimes lead to incorrect feedback. Black box systems can reduce agency by obscuring important model features and their implications, from students, expert teachers, and indeed research transparency.

4. Critical engagement plays an important role in improving both the design and the use of analytics for design. Contextual factors affect how data is captured, presented and used by the user, and these go well beyond immediate tools such as dashboards, to wider systems of feedback, platformcontent, user-interaction structures and so on [21].

AIX design tools do not exist by themselves and are emergent in relation with other people and things in their contexts [24]. These tools are both digital and non-digital, however a complexity in prior AI research is that much work focuses on constrained digital interaction within a particular platform, and thus does not have access to wider material resources used, and the reasons for this use. This approach addresses the need to investigate how design tools mediate and are mediated by their context of use.

Directions for Future Research

A fruitful area for future research may be an exploration of which design features seem to foster hate and harassment. Examples of conscious design include how widely messages should be allowed to spread in other channels such as WhatsApp [88], or whether users should have to reach a certain level of community trust—for example, subscribers on YouTube [143]— before being allowed to monetize content.

Design concepts from the privacy community can also protect users from surveillance or lockout and control. For example, delegated access to a user's sensitive information (e.g., location, photos) might expire without that user's explicit re-approval. This mirrors recent strategies such as automatically deleting a user's location history after a set period [117]. Some safe design features include the following methods:

A. Nudges, indicators, and warnings

Nudges or warnings need not be isolated to platform developers. Community feedback has previously been shown to shape user behavior [12], [33], [39], but intervention by bystanders may never manifest due to a belief that someone else will step in [48].

Indicators and warnings can also surface proactive security advice. For example, two-factor authentication and security checkups can stem the risk of unauthorized access—similar to a for-profit abuse context [52]—reducing the risk of surveillance, lockout and control, and content leakage. Ensuring that visible notifications are always displayed whenever a resource (e.g., camera, GPS sensor) is being actively accessed can protect against covert access. Likewise, platforms can send users reminders about their sharing settings for sensitive content like location logs, photo backups, or delegated access to their online account to raise awareness of potential ongoing surveillance.

B. Human moderation, review, and delisting

At present, moderation is most often done at a platform level by human-raters [58], [74]. Such spheres of control implicitly provide more context in order to tackle the “gray areas” of hate and harassment.

- At a user level, this would be as simple as “I do not want to see this content”, similar to existing flagging infrastructure.
- At a community level, the owners of a page, channel, or forum would be equipped with tools to set the tone and rules for user-generated content, and to potentially receive flag information from the community.
- Finally, platform-level moderation would provide a baseline set of expectations for all user-generated content. A multitude of systems have explored how to design collaborative moderation and reporting tools.

C. Automated detection and curation

Solutions in this space need not implicitly result in automated decisions like removing a post or suspending an account; instead, classifier scores can feed into moderation queues, content ranking algorithms, or warnings and nudges.

Existing datasets of toxic content originate via crowdsourced labels of Wikipedia and news comments [84]; user-reported flags of harassment in gaming communities [11], [104]; content containing blacklisted keywords [67]; content that carries a negative sentiment score [62]; or content posted by suspended accounts (which may conflate various types of online abuse rather than solely harassment) [34]. Constructing unbiased and representative datasets—that either generalize or are tailored to users, communities, platforms, or regions—remains a core challenge for tackling online hate and harassment.

The following design principles are also recommended for designing an AIX environment in detail.

- *Choosing familiar topics:* When designers are offered familiar issues, they are better able to focus on acquiring new knowledge, such as designing for AI in a specific context. This aspect also increases their motivation to solve the tasks and promotes their ability to think in a problem-solving manner.
- *Providing tasks that encourage problem-solving thinking:* With problem-based and project-based learning, two methods for planning the overall designprocess should be considered, leading to an even more intensive approach to problem-solving strategies.
- *Appling an interdisciplinary approach*: It is advisable to utilize mixed design methods in an interdisciplinary way. Applying this design method results in a combination of narrative, image, and programming language, programming skills and literacy are promoted simultaneously.
- *Considering using a playful approach:* The playful approach is especially important when introducing UX designers to AI as it enhances the combination of programming and storytelling and promotes collaboration and communication skills.
- *Encouraging UX designers to create their own ideas:*Creativity is perhaps the most important skill that designers need to learn, and it is the beginning of many innovations.

Conclusions

ML is often seen as a ‘plug-and-play’ learning methodology that can be thrown at raw data for whatever problem comes to hand. Finding the best way to generate a relevant design involves a mixture of theory, experience, and experimentation. The design principles developed in this study are developed in a specific context and cannot yet be generalized. For generalization, the proposed design principles need to be validated in different contexts in further research. Nevertheless, the design principles presented are a valuable contribution to the existing knowledge on promoting development of AIX.

Last, but not least, design for AI involves “guiding intuition” whereas intuition is defined as the ability to make decisions that are better than random guesses. Intuition cannot be captured in countless predefined rules or patterns found in vast amounts of data. In other words, you don’t gain intuitions by running millions of examples and observing the percent of times certain patterns recur. This means that it was not the ML models that provided the scientists with an intuitive understanding of the concepts, theorems conjectures put forward. ML models only provide advice as to which features of the problem seemed to be important and which seemed unimportant.

Future work is planned to introduce this method to UX designers and investigate their attitudes and willingness to use the method in their future UX work.

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