Investigating How Users Design Everyday Intelligent Systems in Use

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ABSTRACT

Intelligent systems learn and evolve depending on what kinds of input are given and how people actually use them after deployment. While such a characteristic may be a troubling property for AI user experience designers, it also imbues an intelligent system with an open-ended quality, empowering end-users to 'design' their own system in use to achieve more desired experiences. In light of this, we conducted in-depth interviews with 16 users of various AI-based everyday recommender systems, investigating how people design their AI user experiences in actual use contexts. Exploring people's current experiences of adopting and adapting those systems to achieve their own desired experiences, we discovered three styles of end-user design of their experiences: *teaching*, *resisting*, and *repurposing*. We end with a discussion of the implications of our findings, recognizing end-users' motivation to challenge a prescribed experience of an intelligent system.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

human-AI interaction, intelligent systems, open-ended systems, user control, design-in-use, interactive recommender systems, human-centered AI

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1 INTRODUCTION

Intelligent systems are now commonplace in everyday lives. People are familiar with intelligent services provided by those systems, such as personalized recommendations, search results, social media news feeds, and personal home assistance, to name a few. Applied with various Artificial Intelligence (AI) techniques, those systems change and develop depending on what kinds of input are given and how people actually use them after deployment. As a result, AI user experiences are subject to take shape when a system is situated in contexts of use *in situ*.

This evolving nature of AI user experiences has been a long-standing topic of interest in the field of human-computer interaction (HCI) design research. For example, early discussion on how autonomous and adaptive behaviors of intelligent systems would challenge the traditional usability principles such as control, transparency, and predictability dates back to the 1990s [33]. Until recently, Yang et al. [83] have also identified capability uncertainty as one of the two attributes of AI that complicate the design of human-AI interaction (HAI) and AI user experiences. This has spurred many research commitments to minimize the uncertainty in AI user experiences, for example, by alleviating the technical opacity of 'black-boxes' to achieve predictability [19] or ensuring user experiences are determined designer-side as much as possible [3, 27, 76, 84].

This paper takes an alternative approach to the evolving nature of AI user experiences: embracing it, and viewing it as a design opportunity to spare room for users to explicitly impact its development and construct their own personalized experiences after it leaves the designers' hands, i.e. a chance to let users design intelligent systems in use to attain desired experiences. In this sense, we treat the evolving nature of AI user experiences as something that imbues intelligent systems with an open-ended quality, that is, a design quality that allows for users' manipulation of experiences and change of meanings inscribed by designers. In fact, design research has written a long history of championing the value of open-endedness, illustrating how design of experiences extends into what we understand as 'use.' For example, researchers have proposed how deployed design products and systems that are open to user interpretation [49, 69], allowed for appropriation [11, 16, 17, 81, 82], intentionally unfinished [70], or ambiguous [26] can help users demonstrate their creativity and tailor a product or system to better suit their needs in actual use. Following this line of thought, we see a similar potential in the context of newly emerged intelligent systems and ***explore how end-users design their intelligent systems to achieve their own desired experiences***. Because intelligent systems are different from other traditional open-ended products and systems in that the former behaves autonomously, investigating users' design-in-use practices in such systems would reveal other interesting issues not observed in prior studies. For example, unlike an analog product or non-AI-powered software whose mechanics or codes can easily be dismantled, understood, and controlled, some AI-related factors of intelligent systems such as learning models and their scrutability might affect users' design decisions and their exercise of enough control, preventing them from creating desired experiences with much freedom.

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In light of this issue, we conducted an interview study with 16 users of various AI-powered everyday recommender systems, in which we explored how end-users achieved their own experiences those systems. In the remainder of this paper, we provide a review of related literature that this paper builds on. We follow this by describing our interview study which investigated people's practices in achieving their own desired experiences in various AI-powered recommender systems while using those. We then present our findings on three styles of end-user design-in-use practices, namely *teaching*, *resisting*, and *repurposing*. We close with a discussion of the design implications of our findings for supporting users' designing of AI user experiences in actual use.

2 RELATED WORK

In this section, we review related work that addresses the evolving nature of user experiences in everyday intelligent systems and the notion of design-in-use to position our work in the literature. We also review HCI and design studies on granting users power in controlling their experiences of intelligent systems, grounding our framing of a user role in interactions with those systems.

2.1 The evolving nature of AI user experiences

User experiences of intelligent systems are subject to surface and change after deployment as the systems autonomously learn and evolve. As this property creates challenges in designing predictable and well-defined user experiences in such systems at design time [83], previous studies have focused on minimizing the undeterminedness of AI user experiences. For example, there has been a spur into technical solutions such as interpretable machine learning [19] to alleviate technical opacity so that developers and designers can handle intelligence with increased predictability. Also, design guidelines [3, 27] and processes [76, 84] were developed to keep end-user interactions and experiences with intelligent systems in as much control of developers and designers as possible.

While these strands of research provide valuable insights for the design of HAI, we also notice a growing movement to embrace the evolving nature of AI user experiences. For example, the notion of co-performance [40, 44] has been proposed to understand how the role of artificial agency and AI service qualities are shaped together with users rather than being "*scripted at design time*" [44]. Morrison et al. [56] demonstrated how AI capabilities and experiences can evolve in and through socially situated interactions, identifying the differences between the imagined and actual use of intelligent systems. Benjamin et al. [5] illustrated how the world that people experience can be textured by machine learning uncertainty, proposing to understand it as a design material rather than an obstacle. This corpus of research collectively suggests that AI user experiences are inevitably crafted in situ, in actual use by end-users. Accordingly, we seek to understand how users interact with deployed intelligent systems, in particular exploring their 'design-in-use' practices to deliberately craft personalized experiences in everyday contexts.

2.2 Design-in-use

Building on third wave HCI agendas [7] and user-centered design approaches, the relationship between 'design' and 'use' has been a central concern for designers since long before. Studying people and their use of products and systems has been a recommended design practice that can inform 'professional' design processes, particularly in relation to interactive digital systems and services [4, 35]. Through ethnographic studies and participatory design approaches [66], potential users have been involved in the design phase as informants or aides to professional designers.

However, recognizing that people are already engaged in various design-related behaviors [28, 57, 71, 80] through their everyday activities, design research has extended the focus to how people who were traditionally thought of as 'users' can not only be involved in the envisioning stage but also actively devise, rather than merely adopt and use, their ways of working with designed products and systems in use time, i.e. design-in-use. In the early 60s already, Christopher Alexander [1] introduced the concept of *unselfconscious design*, in an attempt to account for the activities usually taken for granted but nonetheless exercised by all kinds of people in order to maintain the equilibrium of designed systems, well beyond the professionals' intervention. More recently, researchers have captured diverse workplace practices of "*interpretation, appropriation, assembly, tailoring and further development of computer support in what is normally regarded as deployment or use*" [6, 15, 32]. Expanding this inquiry into more everyday settings, Moran [55] has proposed users' adopting and adapting designed systems to their needs as everyday adaptive design, and Brandes [11] and Wakkary & Maestri [81, 82] have provided interesting illustrations of some of the resourceful and creative accounts of everyday design in home, adding to the understanding of appropriation [16, 17]. Further, researchers have suggested that many other end-user activities such as customization [52], hacking [64], repair [34, 51], reuse [60], do-it-yourself [45], end-user development [48], and more [8, 43, 70] are also another form of design.

Collectively, this corpus of literature illustrates that design is considered as a complex concept not limited to a particular professional role but encompassing diverse practices of devising "***courses of action aimed at changing existing situations into preferred ones***" by different people not labeled as Designers at different points in the life cycle of any products and systems [55]. Our work is an attempt to use this lens to broaden the perception of user control in intelligent systems so as to imagine higher-level, human-values-led kinds of end-user engagement, framing users as active protagonists who determine the qualities of AI user experiences by enacting as much sense of agency as the activity of *designing* connotes. Understood in this way, design-in-use becomes a powerful concept that highlights the role of end-users in 'completing' the design of intelligent systems by incorporating their own values and needs instead of serving for intelligent systems to optimize performance and efficiency, inviting designers to further explore how such design-in-use can be supported.

2.3 User participation in crafting experiences of everyday intelligent systems

Responding to user needs to exert control over their intelligent systems [24, 37, 53], prior studies have suggested various ways to afford end-users agency in shaping their own AI user experiences. For example, researchers have explored ways to help users control their own user models [61], choose algorithms used for personalization [23, 29, 30], express preferences [38, 68], and gauge the impact of their feedback [67]. More recent works have demanded shifts in the conventional roles or 'scripts' followed by users and systems. For example, although not explicitly framing users as designers, researchers have also investigated how users can govern a system's learning behaviors at a higher level, for example by cooperating with [40], teaching [63], and providing guidance to [41] the system to better personalize its experiences.

This body of literature collectively suggests that end-users have the potential of going beyond being passive recipients of intelligent services and becoming more tightly involved in a deployed intelligent system's evolving process to determine its experiential qualities. Building on this trend in HCI and design research, our study investigates how people actively reflect on what kind of experience they truly want from intelligent systems and take actions in light of it, providing empirical evidence that end-users can act as self-directed designers of their own experiences in everyday intelligent systems.

3 STUDY METHOD

We set out to explore how people design their experiences in intelligent systems in use, through in-depth interviews with users of everyday recommender systems of various domains. We particularly chose recommender systems for entertainment content as the context of the inquiry, as they are the most familiar and representative types of real-world intelligent systems that provide room for user-driven personalization. Also, as every person has his or her own unique tastes and habits for consuming entertainment content, we expected that users would have a strong desire to reflect their needs and preferences and therefore actively engage in the design of their experiences. We underline that our focus did not lie on informing the development of the 'recommendation' part, such as investigating the characteristics of 'good' recommendations or desirable types of feedback for a recommended item. Instead, we were interested in exploring how users adopt and adapt a system that exhibits an intelligent capability of personalization in recommendation services. In what follows, we describe the participant information and the study process.

3.1 Participants

We recruited users who were in any way consciously personalizing their recommender systems. To ensure this, we recruited participants via a questionnaire that asked, along with basic demographic information, 1) what recommender system(s) that they were actively using; 2) how long they were using the system(s); 3) what kinds of behaviors they attempted to deliberately make the system(s) better fit their needs; and 4) how actively they were doing so (on a scale of 1-5, with 1 being 'least actively' and 5 being 'most actively'). Although the last questionnaire item was a self-reported one, when viewed together with the third item, it helped us to discern people who already had strong desires for designing their own experiences for their systems. Participants were recruited through advertisements posted on campus, social media, and word of mouth.

The questionnaire allowed us to recruit 16 participants (Female=10) (Table 1) diverse in terms of the domains of recommender systems used, the duration of usage, and the ways they interacted with the systems. Participants were in their 20s or 30s, the average age being 27.4 (SD=2.2, MIN=24, MAX=33). We note that all of our participants had no expertise in AI, and therefore were not knowledgeable about technical concepts in relation to machine learning and recommendation algorithms such as collaborative or content-based filtering.

3.2 Interview procedure

Participants were invited for one-on-one semi-structured interviews. All interviews were conducted online via Zoom, lasting from 45 to 70 minutes.

Before the interviews, we asked participants to open up and refer to the systems that they were using to easily reflect upon current experiences during the interviews. However, we chose not to force participants to share their screens with researchers in real time, as we were concerned with participants' reluctance to reveal sensitive, private information like activity logs and search history. We thus told participants in advance they could share screens only if they want, and instead, we asked whether they could capture related screenshots when we spotted particularly interesting points in participants' responses and send those to researchers after the interview was over. While all participants except one refused to share screens in real-time, they gladly captured and sent screenshots.

Beginning the interview, participants were introduced to the study and signed online an informed consent form approved by the Institutional Review Board (IRB No.KH2021-044). We then asked participants to describe their general usage and understanding of the system(s) that they were using, as well as their perception of personalized recommendation. After this, we asked more direct questions that delved into their motivation for designing their experiences (e.g., *How did you come to think you can design your own experiences?*), current practices for doing so (e.g., *What personalization service experience(s) in each platform were especially your target of such practices? What were your intentional and thoughtful actions to make the experiences better fit your needs? Why did you do so?*), and problems encountered (e.g., *What problems did you experience while doing so? How did the current system designs support or hinder your practices?*).

In particular, we personally got familiar with all the systems that participants were using before the interview and asked specific questions tailored for different types of systems such as the influences of a particular system's control mechanisms (e.g,. *Does the existence of an onboarding stage or the 'Not Interested' option help? Then how and why? How do you perceive a system's proactive request for feedback on a recommended item?*), content type (e.g., *How do you compare your strategies on Netflix and Spotify? Were there any differences?*), or any other design factors (e.g., regarding the adaptivity of user input: *Do you feel that the system responds to your actions well? How does it affect your actions?*) to facilitate discussion.

Additional questions were flexibly added, depending on participants' responses in the questionnaire for recruitment and interesting comments made during the interviews. Also, participants mentioned other recommender systems that they were using but

Table 1: List of participants. Participant ID, gender, age, the recommender system(s) that participants used, and the duration of use in years.

ID (Gender, Age)	Recommender system(s)
P1 (F, 29)	Vivino* (6 months), YouTube (5 years), Netflix (5 years), Watcha* (1 year)
P2 (F, 27)	Netflix (3 years), Instagram (5 years), YouTube (1 year)
P3 (M, 24)	Spotify (4 months), YouTube (2 years)
P4 (F, 28)	Instagram (3 years), YouTube (+3 years)
P5 (M, 26)	Watcha (4 years), YouTube Music (10 months)
P6 (M, 33)	Spotify (4 months), MiniMap* (1 year)
P7 (M, 25)	YouTube (3 years)
P8 (F, 30)	Spotify (1 month), Youtube (3 years), Instagram (9 years)
P9 (F, 26)	Spotify (2 years), YouTube (3 years)
P10 (M, 29)	Apple Music (1 year), Spotify (3 years)
P11 (F, 28)	YouTube (5 years)
P12 (F, 27)	Netflix (7 years), YouTube (1.5 years)
P13 (M, 25)	YouTube (4 years)
P14 (F, 28)	YouTube (8 years)
P15 (F, 29)	Netflix (1 year), YouTube Music (6 months), Instagram (+6 years)
P16 (F, 25)	Spotify (1 year), YouTube (3 years)

*These are lesser-known systems, so we clarify that their domains are wine (Vivino), movie and TV show (Watcha), and game (Minimap).

did not deliberately control and personalize the experiences. Discussing why they were doing so for some and not others guided us to richer insights.

All participants were compensated KRW 10,000 in cash for their time and participation. All the interviews were video-recorded with the participants' consent.

3.3 Data analysis

All the interview recordings were transcribed verbatim. The qualitative data from the interviews were analyzed using the thematic analysis method [10]. Two researchers each scrutinized the responses and developed an initial set of codes. We then participated in iterative discussions where we organized and developed codes in search of emergent themes and patterns until we reached a consensus. This surfaced key patterns of participants' design-in-use practices and issues in doing so, revealing an overarching theme of design-in-use in terms of how participants were challenging a scripted experience of a system.

4 FINDINGS

In this section, we present a descriptive account of how users design their AI-powered recommender systems in actual use, i.e. design-in-use. We describe three styles of design-in-use: participants engaged in ***teaching*** useful information that could enrich personalized experiences; ***resisting*** learning models in a system to make experiences less personalized; and ***repurposing*** a system to redefine its potential usage and experiences in their personal everyday contexts. We describe each in turn.

4.1 Teaching

We observed the cases of participants (n=12; YouTube, YouTube Music, Netflix, Watcha, Spotify, Instagram, Minimap, Apple Music) who had clear 'design goals' for their recommendation experiences. These participants were clearly aware of their preferences, which motivated them to design personalized experiences by making recommendations better reflect those firmly set preferences. The design goals were often formulated in the form of the characteristics or attributes of recommendations, e.g., a system that recommends music of certain genres or videos of certain topics. For example, P15 strictly constrained Netflix to recommend crime dramas only. Sometimes, participants defined their goals in a more subjective manner, as P16 who wanted Spotify to recommend songs that help improve her musical knowledge.

Accordingly, participants made their systems align with such specific, their own defined personalization goals by ***proactively teaching useful information about their (non-)preferences***, mostly by interacting with the content. In most cases, teaching started to occur as soon as participants began to use a system, aiming to accelerate an early learning process. An onboarding stage designed in several platforms seemed to help initial teaching to a certain extent, for example, by asking users to choose their favorite genres or artists, but in general participants themselves decided upon what a system should learn and handpicked relevant examples. For example, P12 reported that she spent the first two to three days on Spotify and Netflix manually searching for songs and movies that they already knew and rating all of them, going much beyond the minimum amount that their systems required to launch personalization:

> *"The system will learn my preferences anyway. I just make it happen faster."*

Participants constantly taught their systems along with ongoing use as well, coming up with various teaching strategies based on folk theories [25] about the algorithm's preference learning mechanisms. P16 paid attention not to play or hit 'heart' on K-pop songs on Spotify in order to teach her dislike in that genre. P1, P5 and P9 created playlists in which diverse contents were grouped to express their favorite topics, mood, or genres as a whole, expecting that YouTube and Spotify learn from the playlists. P8 consciously skipped clips before they were auto-played in order to ensure that Instagram could avoid learning what was not of her interest. Similarly, P15 also consciously managed her activities on Netflix by avoiding watching or even searching for content other than crime dramas:

> *"If there is something that I just wanna try or something that I want to search for, I sign in to my sister's account, watch it, and delete the history, because I don't want to leave a mark on mine."*

Despite their efforts, participants pointed out a need for more sophisticated means of teaching. In particular, participants complained that current interaction mechanisms and feedback channels did not support instilling nuanced preferences and articulating abstract concepts. For example, P1 described how she failed in teaching Netflix that she hated violent, culturally insensitive, and misogynistic movies because there were no proper communication channels for explaining such high-level values. Also, P16 reported the failure in her attempts to teach by demonstration her viewing habits on YouTube:

> *"How can I teach that? I watch news clips every morning, but it never gives me those in the morning. I mean, I watch the news almost always on YouTube only, and I watch them as soon as I get up. But I don't get to see my morning feed full of news clips. I show a clear pattern, but it doesn't seem to get that. I wish I could have more explicit control, like scheduling maybe?"*

Further, participants also pointed out the inefficiency of current interaction channels in terms of teaching preferences. For example, P12 reported that Netflix and YouTube lacked a way to provide information about herself more straightforwardly. P6 even criticized that the rating systems in all the systems that he used were inappropriate for teaching because rating interactions could convey a dual meaning of evaluating an item itself and teaching preferences for getting future recommendations:

> *"Even if I don't like something, the system doesn't get that I don't like it until I search for and hit 'Thumbs down' on a bunch of other things of similar kinds. The same goes for teaching what I like and why I like it… "* (P12)

> *"I'm supposed to give a high rating to this one game that I used to have fun playing in the past, but I don't want to get recommendations for similar games now, at this point. I mean, it was fun at that time."* (P6)

However, although such limitations of current interaction designs hindered achieving the most desired form of personalized recommendations, participants still enjoyed teaching when the very act could derive other personally meaningful experiences. For example, teaching Netflix and Instagram delivered P12 and P15 with a pleasant experience of self-expression, described as a "*manifestation of my inner side*" (P15). Also, observing how Spotify had been understanding her was another experience that P16 enjoyed from her teaching; the playlists generated and their titles, regardless of whether she liked the songs inside or not, provided her an opportunity to "*be self-reflective on things like [my] music tastes*" (P16). As shown in these examples, additional by-products of teaching seemed to work as important rewards besides the improved performance of a system.

Collectively, our findings illustrate how participants attempted to create their desired personalized experiences by proactively driving, beyond simply assisting or giving feedback on, a system's data collection and preference learning process. Even though current interaction designs had limitations, other experiential values compensated for those.

4.2 Resisting

Unlike the above case of participants who made the most of a system's ability of learning and personalizing, we also observed the cases (n=10; YouTube, YouTube Music, Netflix, Spotify, Instagram) where participants focused more on what potential harms the ability could accompany and how those harms could undermine the defining features of their desired recommendation experiences. Chiming with previous findings on why users would embrace serendipity in personalized recommendations [75] or unpredictability in autonomous systems [78], these participants criticized that the learning and personalization logic embedded in their systems would block opportunities for widening their interest areas and therefore sabotage the value of discovery and diversity. They perceived that their systems were designed to learn about their users "*too much*" (P3) and tailor recommendations to a only specific set of preferences, thereby reproducing recommendations similar to what they had already liked or received. Further, they criticized that this would create possibilities for being manipulated by their systems and losing autonomy. They described overly personalized recommendations by using expressions such as "*contamination on the feed*" or "*clickbait*" (P11), even if the recommendations were of their interests, indicating that too much personalization caused negative user experiences such as addiction to services and loss of "*free will*" (P13), as P2 and P13 described:

> *"It's because I want to stop the positive feedback loop that YouTube brings to me. It's like 'Stop. I don't want it [the topic].' You know what I mean? I don't like to be too into it."* (P2)

> *"The more game videos I watch, the more those videos are recommended to me. I don't want to fall into that swamp."* (P13)

Accordingly, participants attempted to attain their desired experiences by ***resisting learning models in their systems***. In particular, all participants in this case *purposefully decelerated a system's learning* by purposefully not engaging in interactions that might get their preferences inferred. They consciously refrained from using the system affordances designed to let them explicitly express their preferences, such as hitting 'Likes.' They also entered the Incognito mode to prevent the occurrence of learning or even occasionally deleted watch history to make a system 'forget' what it had already learned. Participants believed that clarifying their preferences too explicitly might boost a personalization loop that catered to only a few sets of interests and "*close off the possibility*" (P2) of the emergence of unexpected experiences. For example, P4 hesitated to explicitly specify her current preferences on YouTube from early on, expecting recommendations not to be personalized quickly from the outset:

> *"It should start with more popular, trending things in general so that I can go on and discover what fits my tastes... Tapping ['Likes' on] certain artists is like saying 'Give me this artist' only."*

Another tactic that participants used was to constantly *reorient their systems* to 'break' a loop of personalization. For example, all participants in this case actively tapped 'Not Interested' or 'Dislike' on items that repeatedly appeared in an attempt to signal that they wanted their systems to stop personalizing toward the current direction, as P11 described:

> *"It's because it responds to me too fast. I mean, I only watched three or four movie review clips and suddenly my feed is full of that? I hate it and so I quickly watch new things or hit 'Not Interested' on those videos... "*

Frequently refreshing a personalized feed and deleting activity logs were also commonly observed strategies, especially in platforms that did not provide negative feedback interactions (e.g., 'Dislikes'). Some participants triggered newly directed personalization in a more direct manner by deliberately typing in new keywords in a search box (P16) or engaging with unfamiliar items to "*override*" current recommendations (P7, P14). Participants described such practices using expressions like "*cleaning up*" (P2) or "*making my feed get some fresh air*" (P11), implying their clear intent for preventing their systems from being overpersonalized.

Overall, our findings illustrate how participants had to resist their systems' behaviors of learning and personalizing in order to attain their desired experiences. As we recall its definition that design refers to any "*courses of action aimed at changing existing situations into preferred ones*" [55], resisting is clearly a type of design act, as participants did so in an attempt to achieve what they desire to experience. We note that although participants did not overtly complain about the existing interaction designs like those who taught their systems, we observed that these participants also relied on indirect workarounds. Distinguishing between the practices of resisting and teaching may be difficult because they often involve the same interactions, but we noticed that there were clear differences in participants' intention behind (e.g, tapping 'Not Interested' to *hamper* hyper-personalization vs. to *accelerate* hyper-personalization by teaching disinterest).

4.3 Repurposing

Lastly, we observed that a few participants (n=4; Vivino, Watcha, Spotify) failed to find the value of a system's usage as-is due to the misalignments between their usual routines or practices in content consumption and the services provided by the system. The discrepancies were so critical that they refused to use and take pleasure in the originally intended services. For example, P10 complained about the entire mechanics of personalized experiences on Spotify. The system automatically generates various types of tailored playlists (e.g., '*Daily Mixes*,' '*Discover Weekly*,' '*Pop Mixes*,' etc.), but P10 said he did not use those features as-is because the ways that those playlists were created were out of step with his own routine of setting up a playlist. He preferred playlists with more specific themes and a much smaller number of songs, but what Spotify provided him was "*perceived to be a sort of hodgepodge*" (P10).

Nevertheless, instead of abandoning their systems, participants found other creative ways of utilizing those. They came to defy experiences that were originally designed in a system by ***repurposing it for new unintended uses***. For example, P5 found over time that the list of recommended movies and explanations generated along with the recommendations in Watcha said something meaningful about his movie tastes. This inspired him to appropriate the system to be a *self-analysis tool*, using it as a useful anchor to discover new movies on his own. This even led him to develop an individualized way of interaction; at the end of each year, he scrutinized and modified if necessary the entire scores that he had given so that the system could learn from an accumulated set of data to exactly mirror and embody his overall taste:

> *"When Watcha makes recommendations, it kind of clearly explains why it recommends those movies, for example, because I liked this director or I liked a movie with this actor. That's why I try to manage my ratings with care (...) So for example, let's say it recommends the actor Ma Dong-seok. Then I mull over stuff like, 'Is there any movie that makes me think Ma Dong-seok is such an impressive actor?'."*

Similarly, P1 found the *Match for You* feature in Vivino, i.e. showing a percentage of how confident the system is that a user will like that wine, more useful than its main service, i.e. wine recommendation, thereby repurposing the system as an *assistant tool* for judging whether a wine would fit her taste:

> *"When I go to the [wine] corner, and for example, I have like five candidates. I search them on the app, and I pick the one with the highest percentage."*

P8 and P10 also put Spotify into a new purpose as a *search engine*. While they refused Spotify's original intent of its service design—to help users experience the recommended playlists as-is, they found Spotify's recommendation algorithms worked well and was worth exploitation. They then trained Spotify recommender systems with only a limited set of songs to search for, or as P8 described, to "*dig*" out new songs which they manually added to a new empty playlist on Spotify (P10) or even on another music app (P8) to create their own playlists.

Collectively, these findings illustrate how participants understood intelligent services through a new lens and discovered new potential uses. Seeing alternative utility in an algorithmic model and redefining its uses, these participants were, in a way, devising their own services that could best provide their desired experiences.

5 DISCUSSION

In this paper, we used a design-in-use lens to understand HAI, illustrating diverse end-user behaviors to exercise control over their experiences in everyday intelligent systems. This approach enabled a shift in framing of the user role from trainers of machine learning models to active creators of their desired experiences. Much of the prior research has been founded on tech-centric premises that adopt an output-feedback model to understand HAI. In this view, designers might fundamentally assume a passive role for users and privilege the pre-determined nature of service goals and experiences. Supporting user control over their experiences then becomes a matter of supporting interactions for training machine learning models more efficiently [14, 20, 65]. While the focus on the efficiency of end-user participation in a model-training loop will be appropriate in some professional, high-stakes decision-making AI tools where optimization and performance accuracy will be a matter of the utmost importance, as for more mundane types of intelligent systems in people's daily lives, we believe the focus of interaction design will lie on how people can create and enrich their own meanings and uses of the systems. As Dourish [18] suggests, design should focus not just on how to make people get their work done, but on how to make people create and communicate their own meanings in use. Our work is an effort to reiterate and pursue such a way of experience-centered approach in HAI design, shedding light on new design research agendas and research questions for human-centered AI.

In the following sections, we now discuss the implications of our findings. From our descriptions of design-like behaviors of end-users, we showed that users proactively drove a personalization process by overcoming the limitation of feedback-oriented interactions, constantly counteracted personalization, and altered an originally intended usage goal of a system. These collectively indicate participants' motivation in *challenging a prescribed experience* of an intelligent system in order to attain their own desired one, and recognizing this motivation reveals new avenues for how to support users in having more control over their AI user experiences, extending prior studies that have repeatedly identified a need for empowering user agency in intelligent systems [22, 39, 46, 72, 74]. Reflecting on each style of design-in-use, we discuss how our findings can be applied to the design of future intelligent systems.

5.1 Support for teachability

From the case of design-in-use through teaching, we observed that people with a strong, clear idea of what they want from personalization would *challenge their conventional role as passive sources of data.* They refused 'magically personalized' experiences provided by a system that inconspicuously and automatically infers user preferences based on its own assumption, and instead, they would effortfully formulate a personally meaningful goal, deciding for themselves how experiences should be personalized based upon what data. While prior studies have suggested interaction design ideas for explicit user participation in personalization, such as how to let users explicitly state their preferences [31, 36, 68] or how to formulate questions that better ask for a user input [14], such user-system interactions are often described as 'preference elicitation,' 'feedback,' or 'collection' of user input, implying that users are at most capitalized on by their systems. We argue that future intelligent systems should go beyond this perspective and reconsider the form of agency that a user desires to have in personalization experiences.

In light of this, supporting this style of design-in-use will require everyday intelligent systems to be ***more proactively teachable***. Such systems should first be designed with interactions that allow users to set up a specific teaching goal. For example, users who would engage in this type of design action may prefer a system that directly asks for their design goals in the first encounter interaction (e.g., '*What should I recommend for you?*'). Applying a reflective strategy to help people recognize their underlying needs and goals may further assist this kind of interaction for goal setting. For example, a system may ask follow-up questions [47] (e.g., '*Why do you want such recommendations?*') or suggest an opposite viewpoint (e.g., '*How about recommendations on this topic? Do you also want that?*'), helping users overcome near-term decision bias [54] and develop more sophisticated goals.

Also, depending on what users tell, the system should let the users engage in the proactive and rich provision of information directed by the defined goal. Reflecting on our findings, such interactions should support users in reflecting upon what to teach in order to curate quality preference information that is rendered most useful for achieving their teaching goals, articulating subjective and abstract concepts, and deriving personally meaningful rewards from their endeavors as teachers (e.g., the pleasure of self-discovery). Despite their primary focus on a training phase before deployment, previous studies on the design of machine teaching interactions [50, 58, 62, 73] in the field of interactive machine learning might serve as inspirational sources for future design ideas.

5.2 Support for depersonalization

Our findings on the practice of resisting indicate people's motivation for *challenging the benefits of machinery optimization* that an intelligent system normally promises with its capability of learning and personalizing. In our study, participants found little value in immediate adaptation and targeted curation of relevant content, and even perceived those seemingly smart behaviors as erroneous and creepy. Rather, they believed that *less* learning and personalizing would better deliver experiences that they truly desired, such as discovering unknown interests and tastes as well as retaining a sense of agency.

Accordingly, we suggest that designers should consider how to support users in purposefully ***depersonalizing*** their intelligent systems. This does not mean making users interact in a way that hinders a system's machine learning and algorithmic user profiling (e.g., obfuscating [12] or tricking [79]). Instead, it means to provide means for preventing a system from becoming too personalized or supporting the restoration of an already over-personalized system. After all, what our participants criticized was not personalization itself, but the purportedly 'virtuous cycle' of personalization that ironically brought about negative service experiences. That our participants attempted to intentionally 'negate' technology as such resonates with previously suggested concepts such as un-designing [59] which acknowledge such deconstructive mode of thinking and design also as an important design act.

Then how can we enable users' depersonalizing of their systems through design? Reflecting on our findings, one approach may be allowing users to add constraints or 'speed bumps' to a learning process. For example, a user may set limits on the type and amount of personal data that is used by the learning model (e.g., allowing a recommender system to learn only from their 'Dislikes' and ignore other types of activities or employing machine unlearning techniques [9] to let users delete learned data) or on the scope of service experiences (e.g., setting only ten percent of songs in a system-generated playlist to be personalized based on user preferences) so that personalization can be delayed or partially applied. Another approach may be providing more direct measures for triggering service reorientation. Indeed, we found that people have mostly been relying on improvised controls [77] to interfere with personalization; they had no choice but to laboriously refresh a feed several times or remove each individual item, hoping that their systems would understand their signals at some point. Considering this, users will appreciate more direct channels for communicating with their systems or access to clear saved preferences from the systems. Also, allowing users to create various 'save points' of the progress of personalization may be another idea, which would allow the users to go back to an earlier point at any time and trigger personalization toward a different direction.

5.3 Support for creative reinterpretation

Lastly, with participants who repurposed their systems, we noticed that people would define their own usage goal for an intelligent system *without being bound to the system's algorithmic models and its intended role.* Supporting this type of design-in-use would be important because it can address the needs of users who desire to be creative [49, 81] enough to hack and exploit an intelligent system to devise their own uses beyond the original intent of designers, especially when a prescribed service brings little value to them and consequently may lead to the abandonment of a system.

This then implies the need for designs that foster users to ***critically reason about and reinterpret the role of their systems*** so that they can discover personal significance and add new meanings in their own contexts. We encourage designers to refer to previous literature that has proposed valuable design guidelines and strategies for supporting reinterpretation and appropriation of a system by users [16, 69] while also considering what it means to apply those strategies in the unique context of intelligent systems. For instance, given that seamful design could trigger users' own interpretation of an algorithmic system [25], designers may choose to apply a design strategy of "*specifying usability without constraining use*" that Sengers and Gaver suggested [69]. A system, for example, may introduce itself in terms of the types of data it learns and how it generates what kinds of potential output rather than directly prescribing its use as a 'recommender system,' allowing users to grasp its ability to 'recognize patterns in user data' but leaving the ultimate purpose left open for the users to decide. At the same time, however, an AI model may not be able to make its functioning clearly explained, or it may not always respond to user input and make updates immediately, requiring users to interact with it over a longer period of time in order to understand the likely effects of their actions. This then leads us to reflect on how to design interactions for an exploratory mode in the unique context of intelligent systems (e.g., [21]) to encourage users to freely experiment with their systems to develop understandings that best align with the actual working logic.

6 LIMITATIONS AND AVENUES FOR FUTURE RESEARCH

The limitations of this study include that although we did not impose any prerequisites regarding participants' age during recruitment, we came down to interview those who were in their 20s or 30s only. Participants in this age group were considered to be heavy users of technological systems and digital content who have likely developed rich algorithmic folk theories to understand their own experiences with a system, and we expected this characteristic would allow them to exhibit diverse design-like behaviors. Nevertheless, it may be the case that users in other generations employ different approaches for designing their AI user experiences (e.g., middle-aged and senior users who might have developed their own forms of folk theories of intelligent systems [2]). Investigating design-in-use by end-users of more diverse age groups will be an important area for future work.

Also, given the main goal of this research, we had to ensure the recruitment of users who were mindfully personalizing the experiences of their systems. A corollary is that, although none had a precise understanding of the inner workings of recommendation algorithms, our participants already had a certain level of AI literacy or algorithmic awareness [13, 42]. This limits the generalizability of our findings for other user groups with much lower or no such awareness, yet we suggest this as an interesting topic for future work.

Regarding the research context, even though our study explored user experiences in nine different recommender systems across various domains, the scope of our findings is limited to recommender systems for entertainment content. Other types of everyday intelligent systems can also provide room for users to craft their experiences but may provide different sets of platform affordances and constraints that may influence design-in-use activities. For example, consider personal assistants that provide different services besides entertainment content recommendations and have different interaction modalities (e.g. conversational interfaces), social media platforms where a user's social interactions with others affect the personalization process (e.g., obliged to 'like' a post to please a friend), or self-driving systems in autonomous vehicles that cannot fully reflect user preferences and values due to safety issues. Exploring how users design other types of everyday intelligent systems like these would be an interesting topic for future research.

Finally, in this study, we chose to focus on exploring design-in-use practices of a single user, but we believe that investigating how multiple users design an intelligent system to achieve collectively desired experiences together will shed additional light on interaction designs that support design-in-use. For example, we can imagine a family who shares the same YouTube account together for a family TV. In such a case, the family members may have to 'negotiate' with each other to design experiences based on common needs. How can interactions be designed to support such a process? We believe this area of research merits discussion and encourages further studies.

7 CONCLUSION

This work aimed to address what it means for end-users to design their experiences of everyday intelligent systems in use in order to find their own meaningful experiences. We have described users' three styles of designing experiences in the actual use of everyday recommender systems: people challenged a prescribed experience through teaching, resisting, and repurposing a system. Based on these findings, we have discussed what user control connotes in the design of human-AI interactions and presented design implications of our findings regarding how to support users in better crafting their own desired experiences. As an attempt to understand human-AI interaction through the notion of design-in-use, we hope our work inspires interesting future research with the novel framing of the 'use' and 'users' in the context of everyday intelligent systems.

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REFERENCES

[1] Christopher Alexander. 1964. *Notes on the Synthesis of Form*. Vol. 5. Harvard University Press.

[2] Oscar Alvarado, Hendrik Heuer, Vero Vanden Abeele, Andreas Breiter, and Katrien Verbert. 2020. Middle-Aged Video Consumers' Beliefs About Algorithmic Recommendations on YouTube. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 121 (oct 2020), 24 pages. https://doi.org/10.1145/3415192

[3] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N Bennett, Kori Inkpen, et al. 2019. Guidelines for human-AI interaction. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–13.

[4] Mathilde Bekker and John Long. 2000. User involvement in the design of human—computer interactions: some similarities and differences between design approaches. In *People and Computers XIV—Usability or Else! Proceedings of HCI 2000*. Springer, 135–147.

[5] Jesse Josua Benjamin, Arne Berger, Nick Merrill, and James Pierce. 2021. Machine Learning Uncertainty as a Design Material: A Post-Phenomenological Inquiry. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.

[6] Susanne Bødker. 1999. Computer applications as mediators of design and use. *DAIMI Report Series* 542 (1999).

[7] Susanne Bødker. 2006. When second wave HCI meets third wave challenges. In *Proceedings of the 4th Nordic conference on Human-computer interaction: changing roles*. 1–8.

[8] Andrea Botero, Kari-Hans Kommonen, and Sanna Marttila. 2010. Expanding design space: Design-in-use activities and strategies. (2010).

[9] Lucas Bourtoule, Varun Chandrasekaran, Christopher A Choquette-Choo, Hengrui Jia, Adelin Travers, Baiwu Zhang, David Lie, and Nicolas Papernot. 2021. Machine unlearning. In *2021 IEEE Symposium on Security and Privacy (SP)*. IEEE, 141–159.

[10] Richard E Boyatzis. 1998. *Transforming qualitative information: Thematic analysis and code development*. sage.

[11] U Brandes, S Stich, and M Wender. 2008. Design by use: The everyday metamorphosis of things (Board of International Research in Design). *Basel, Switzerland: Birkhuser Architecture* (2008).

[12] Finn Brunton and Helen Nissenbaum. 2015. *Obfuscation: A user's guide for privacy and protest*. Mit Press.

[13] Michael Ann DeVito. 2021. Adaptive Folk Theorization as a Path to Algorithmic Literacy on Changing Platforms. *Proc. ACM Hum. Comput. Interact.* 5, CSCW2 (2021), 1–38.

[14] Anind K Dey, Stephanie Rosenthal, and Manuela Veloso. 2009. Using interaction to improve intelligence: how intelligent systems should ask users for input. In *Workshop on Intelligence and Interaction: IJCAI*.

[15] Yvonne Dittricll, Sara Erikseji, and Christina Hanssonl. 2002. PD in the Wild; Evolving practices of Design in Use. In *Proceedings of the participatory design conference*. Citeseer, 23–25.

[16] Alan Dix. 2007. Designing for appropriation. In *Proceedings of HCI 2007 The 21st British HCI Group Annual Conference University of Lancaster, UK 21*. 1–4.

[17] Paul Dourish. 2003. The appropriation of interactive technologies: Some lessons from placeless documents. *Computer Supported Cooperative Work (CSCW)* 12, 4 (2003), 465–490.

[18] Paul Dourish. 2004. What we talk about when we talk about context. *Personal and ubiquitous computing* 8, 1 (2004), 19–30.

[19] Mengnan Du, Ninghao Liu, and Xia Hu. 2019. Techniques for interpretable machine learning. *Commun. ACM* 63, 1 (2019), 68–77.

[20] John J Dudley and Per Ola Kristensson. 2018. A review of user interface design for interactive machine learning. *ACM Transactions on Interactive Intelligent Systems (TiiS)* 8, 2 (2018), 1–37.

[21] Malin Eiband, Charlotte Anlauff, Tim Ordenewitz, Martin Zürn, and Heinrich Hussmann. 2019. Understanding Algorithms through Exploration. (2019).

[22] Malin Eiband, Sarah Theres Völkel, Daniel Buschek, Sophia Cook, and Heinrich Hussmann. 2019. When people and algorithms meet: User-reported problems in intelligent everyday applications. In *Proceedings of the 24th international conference on intelligent user interfaces*. 96–106.

[23] Michael D. Ekstrand, Daniel Kluver, F. Maxwell Harper, and Joseph A. Konstan. 2015. Letting Users Choose Recommender Algorithms: An Experimental Study. In *Proceedings of the 9th ACM Conference on Recommender Systems* (Vienna, Austria) *(RecSys '15)*. Association for Computing Machinery, New York, NY, USA, 11–18. https://doi.org/10.1145/2792838.2800195

[24] Michael D. Ekstrand and Martijn C. Willemsen. 2016. Behaviorism is Not Enough: Better Recommendations through Listening to Users. In *Proceedings of the 10th ACM Conference on Recommender Systems* (Boston, Massachusetts, USA) *(RecSys '16)*. Association for Computing Machinery, New York, NY, USA, 221–224. https://doi.org/10.1145/2959100.2959179

[25] Motahhare Eslami, Karrie Karahalios, Christian Sandvig, Kristen Vaccaro, Aimee Rickman, Kevin Hamilton, and Alex Kirlik. 2016. First I" like" it, then I hide it: Folk Theories of Social Feeds. In *Proceedings of the 2016 cHI conference on human factors in computing systems*. 2371–2382.

[26] William W Gaver, Jacob Beaver, and Steve Benford. 2003. Ambiguity as a resource for design. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 233–240.

[27] Google. 2019. People + AI Guidebook. https://pair.withgoogle.com/

[28] Leslie Haddon, Enid Mante, Bartolomeo Sapio, Kari-Hans Kommonen, Leopoldina Fortunati, and Annevi Kant. 2005. *Everyday Innovators: Researching the role of users in shaping ICT's*. Springer.

[29] Jaron Harambam, Dimitrios Bountouridis, Mykola Makhortykh, and Joris van Hoboken. 2019. Designing for the Better by Taking Users into Account: A Qualitative Evaluation of User Control Mechanisms in (News) Recommender Systems. In *Proceedings of the 13th ACM Conference on Recommender Systems* (Copenhagen, Denmark) *(RecSys '19)*. Association for Computing Machinery, New York, NY, USA, 69–77. https://doi.org/10.1145/3298689.3347014

[30] F. Maxwell Harper, Funing Xu, Harmanpreet Kaur, Kyle Condiff, Shuo Chang, and Loren Terveen. 2015. Putting Users in Control of Their Recommendations. In *Proceedings of the 9th ACM Conference on Recommender Systems* (Vienna, Austria) *(RecSys '15)*. Association for Computing Machinery, New York, NY, USA, 3–10. https://doi.org/10.1145/2792838.2800179

[31] Chen He, Denis Parra, and Katrien Verbert. 2016. Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities. *Expert Systems with Applications* 56 (2016), 9–27.

[32] Austin Henderson and Morten Kyng. 1995. There's no place like home: Continuing design in use. In *Readings in Human–Computer Interaction*. Elsevier, 793–803.

[33] Kristina Höök. 2000. Steps to take before intelligent user interfaces become real. *Interacting with computers* 12, 4 (2000), 409–426.

[34] Lara Houston, Steven J Jackson, Daniela K Rosner, Syed Ishtiaque Ahmed, Meg Young, and Laewoo Kang. 2016. Values in repair. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 1403–1414.

[35] Juhani Iivari and Netta Iivari. 2006. Varieties of user-centeredness. In *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06)*, Vol. 8. IEEE, 176a–176a.

[36] Michael Jugovac and Dietmar Jannach. 2017. Interacting with recommenders—overview and research directions. *ACM Transactions on Interactive Intelligent Systems (TiiS)* 7, 3 (2017), 1–46.

[37] Hyunjin Kang and Chen Lou. 2022. AI agency vs. human agency: understanding human–AI interactions on TikTok and their implications for user engagement. *Journal of Computer-Mediated Communication* 27, 5 (2022), zmac014.

[38] Jie Kang, Kyle Condiff, Shuo Chang, Joseph A Konstan, Loren Terveen, and F Maxwell Harper. 2017. Understanding how people use natural language to

ask for recommendations. In *Proceedings of the Eleventh ACM Conference on Recommender Systems*. 229–237.
[39] Nadia Karizat, Dan Delmonaco, Motahhare Eslami, and Nazanin Andalibi. 2021. Algorithmic folk theories and identity: How TikTok users co-produce Knowledge of identity and engage in algorithmic resistance. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–44.
[40] Da-jung Kim and Youn-kyung Lim. 2019. Co-performing agent: Design for building user-agent partnership in learning and adaptive services. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.
[41] Keunwoo Kim, Minjung Park, and Youn-kyung Lim. 2021. Guiding Preferred Driving Style Using Voice in Autonomous Vehicles: An On-Road Wizard-of-Oz Study. In *Designing Interactive Systems Conference 2021*. 352–364.
[42] Abby Koenig. 2020. The algorithms know me and i know them: using student journals to uncover algorithmic literacy awareness. *Computers and Composition* 58 (2020), 102611.
[43] Cindy Kohtala, Sampsa Hyysalo, and Jack Whalen. 2020. A taxonomy of users' active design engagement in the 21st century. *Design Studies* 67 (2020), 27–54.
[44] Lenneke Kuijer and Elisa Giaccardi. 2018. Co-performance: Conceptualizing the role of artificial agency in the design of everyday life. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
[45] Stacey Kuznetsov and Eric Paulos. 2010. Rise of the expert amateur: DIY projects, communities, and cultures. In *Proceedings of the 6th Nordic conference on human-computer interaction: extending boundaries*. 295–304.
[46] Angela Y Lee, Hannah Mieczkowski, Nicole B Ellison, and Jeffrey T Hancock. 2022. The Algorithmic Crystal: Conceptualizing the Self through Algorithmic Personalization on TikTok. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–22.
[47] Min Kyung Lee, Junsung Kim, Jodi Forlizzi, and Sara Kiesler. 2015. Personalization revisited: a reflective approach helps people better personalize health services and motivates them to increase physical activity. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 743–754.
[48] Henry Lieberman, Fabio Paternò, and Volker Wulf. 2006. *End user development*. Vol. 9. Springer.
[49] Youn-kyung Lim, Daesung Kim, Jaesung Jo, and Jong-bum Woo. 2012. Discovery-driven prototyping for user-driven creativity. *IEEE Pervasive Computing* 12, 3 (2012), 74–80.
[50] Martin Lindvall, Jesper Molin, and Jonas Löwgren. 2018. From machine learning to machine teaching: the importance of UX. *Interactions* 25, 6 (2018), 52–57.
[51] Leah Maestri and Ron Wakkary. 2011. Understanding repair as a creative process of everyday design. In *Proceedings of the 8th ACM Conference on Creativity and Cognition*. 81–90.
[52] Sampada Marathe and S Shyam Sundar. 2011. What drives customization? Control or identity?. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 781–790.
[53] Nolwenn Maudet. 2019. Dead Angles of Personalization: Integrating Curation Algorithms in the Fabric of Design. In *Proceedings of the 2019 on Designing Interactive Systems Conference* (San Diego, CA, USA) *(DIS '19)*. Association for Computing Machinery, New York, NY, USA, 1439–1448. https://doi.org/10.1145/3322276.3322322
[54] Katherine L Milkman, Dolly Chugh, and Max H Bazerman. 2009. How can decision making be improved? *Perspectives on psychological science* 4, 4 (2009), 379–383.
[55] Thomas P Moran. 2002. Everyday adaptive design. In *Proceedings of the 4th conference on Designing interactive systems: processes, practices, methods, and techniques*. 13–14.
[56] Cecily Morrison, Edward Cutrell, Martin Grayson, Anja Thieme, Alex Taylor, Geert Roumen, Camilla Longden, Sebastian Tschiatschek, Rita Faia Marques, and Abigail Sellen. 2021. Social Sensemaking with AI: Designing an Open-ended AI experience with a Blind Child. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.
[57] J Nelson, S Buisine, and A Aoussat. 2009. Design in use: some methodological considerations. In *CIRP MS'09, 42nd CIRP Conference on Manufacturing Systems*. 3–5.
[58] Felicia Ng, Jina Suh, and Gonzalo Ramos. 2020. Understanding and supporting knowledge decomposition for machine teaching. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference*. 1183–1194.
[59] James Pierce. 2012. Undesigning technology: considering the negation of design by design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 957–966.
[60] James Pierce and Eric Paulos. 2011. Second-hand interactions: investigating reacquisition and dispossession practices around domestic objects. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 2385–2394.
[61] Verus Pronk, Wim Verhaegh, Adolf Proidl, and Marco Tiemann. 2007. Incorporating User Control into Recommender Systems Based on Naive Bayesian Classification. In *Proceedings of the 2007 ACM Conference on Recommender Systems* (Minneapolis, MN, USA) *(RecSys '07)*. Association for Computing Machinery, New York, NY, USA, 73–80. https://doi.org/10.1145/1297231.1297244
[62] Gonzalo Ramos, Christopher Meek, Patrice Simard, Jina Suh, and Soroush Ghorashi. 2020. Interactive machine teaching: a human-centered approach to building machine-learned models. *Human–Computer Interaction* 35, 5-6 (2020), 413–451.
[63] Microsoft Research. 2021. Research talk: Bucket of me: Using few-shot learning to realize teachable AI systems. https://youtu.be/WpvOkIJjg-A
[64] Daniela Rosner and Jonathan Bean. 2009. Learning from IKEA hacking: i'm not one to decoupage a tabletop and call it a day.. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 419–422.
[65] Téo Sanchez, Baptiste Caramiaux, Jules Françoise, Frédéric Bevilacqua, and Wendy E Mackay. 2021. How do people train a machine? Strategies and (Mis) Understandings. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–26.
[66] Elizabeth B-N Sanders and Pieter Jan Stappers. 2008. Co-creation and the new landscapes of design. *Co-design* 4, 1 (2008), 5–18.
[67] Tobias Schnabel, Saleema Amershi, Paul N Bennett, Peter Bailey, and Thorsten Joachims. 2020. The Impact of More Transparent Interfaces on Behavior in Personalized Recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 991–1000.
[68] Tobias Schnabel, Gonzalo Ramos, and Saleema Amershi. 2020. "Who doesn't like dinosaurs?" Finding and Eliciting Richer Preferences for Recommendation. In *Fourteenth ACM Conference on Recommender Systems*. 398–407.
[69] Phoebe Sengers and Bill Gaver. 2006. Staying open to interpretation: engaging multiple meanings in design and evaluation. In *Proceedings of the 6th conference on Designing Interactive systems*. 99–108.
[70] Jin-min Seok, Jong-bum Woo, and Youn-kyung Lim. 2014. Non-finito products: a new design space of user creativity for personal user experience. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 693–702.
[71] Elizabeth Shove. 2007. *The design of everyday life*. Berg.
[72] Ignacio Siles, Johan Espinoza-Rojas, Adrián Naranjo, and María Fernanda Tristán. 2019. The mutual domestication of users and algorithmic recommendations on Netflix. *Communication, Culture & Critique* 12, 4 (2019), 499–518.
[73] Patrice Y Simard, Saleema Amershi, David M Chickering, Alicia Edelman Pelton, Soroush Ghorashi, Christopher Meek, Gonzalo Ramos, Jina Suh, Johan Verwey, Mo Wang, et al. 2017. Machine teaching: A new paradigm for building machine learning systems. *arXiv preprint arXiv:1707.06742* (2017).
[74] Ellen Simpson, Andrew Hamann, and Bryan Semaan. 2022. How to Tame" Your" Algorithm: LGBTQ+ Users' Domestication of TikTok. *Proceedings of the ACM on Human-Computer Interaction* 6, GROUP (2022), 1–27.
[75] Sehee Son, Hyeji Kim, Hoyeon Nam, and Youn-kyung Lim. 2021. User Expectations of Serendipitous Recommender Systems. In *IASDR Conference 2021*. International Association of Societies of Design Research (IASDR).
[76] Hariharan Subramonyam, Colleen Seifert, and Eytan Adar. 2021. Towards a process model for co-creating AI experiences. In *Designing Interactive Systems Conference 2021*. 1529–1543.
[77] Kristen Vaccaro, Dylan Huang, Motahhare Eslami, Christian Sandvig, Kevin Hamilton, and Karrie Karahalios. 2018. The illusion of control: Placebo effects of control settings. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
[78] Jhim Kiel M Verame, Enrico Costanza, Joel Fischer, Andy Crabtree, Sarvapali D Ramchurn, Tom Rodden, and Nicholas R Jennings. 2018. Learning from the veg box: designing unpredictability in agency delegation. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
[79] Sarah Theres Völkel, Renate Haeuslschmid, Anna Werner, Heinrich Hussmann, and Andreas Butz. 2020. How to Trick AI: Users' Strategies for Protecting Themselves from Automatic Personality Assessment. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–15.
[80] Eric Von Hippel. 2006. *Democratizing innovation*. the MIT Press.
[81] Ron Wakkary and Leah Maestri. 2007. The resourcefulness of everyday design. In *Proceedings of the 6th ACM SIGCHI Conference on Creativity & Cognition*. 163–172.
[82] Ron Wakkary and Leah Maestri. 2008. Aspects of everyday design: Resourcefulness, adaptation, and emergence. *Intl. Journal of Human–Computer Interaction* 24, 5 (2008), 478–491.
[83] Qian Yang, Aaron Steinfeld, Carolyn Rosé, and John Zimmerman. 2020. Re-examining 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.
[84] Zhibin Zhou, Lingyun Sun, Yuyang Zhang, Xuanhui Liu, and Qing Gong. 2020. ML lifecycle canvas: designing machine learning-empowered UX with material lifecycle thinking. *Human–Computer Interaction* 35, 5-6 (2020), 362–386.