Interfaces of AI

Two examples from popular media culture and their analytical value for studying AI in the sciences

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1. Introduction: Perspectives from critical interface studies

Deep learning algorithms are currently introducing new forms of agency into many different fields at the same time: from various scientific disciplines like archaeology, art history or medical diagnostics to public sectors such as transportation or security and surveillance to popular media culture – forms of machine learning-based pattern recognition and generation are expected to affect many areas of private and professional life.[1] As can also be observed from the history of other media such as photography or personal computers, this "democratization"[2] of AI technologies leads to the strange circumstance that the same basic technologies (e.g., ML-based pattern recognition and generation) are applied to achieve completely different tasks in different areas.[3] Despite their universal appeal, these technologies inscribe themselves in very disparate ways in different fields of application.

1 As Pasquinelli and Joler (2021) describe it: "In this sense, pattern recognition has truly become a new cultural technique that is used in various fields." (1268)

2 For the ambivalent use of the term "democratization" regarding AI technologies see Sudmann 2019b: 11.

3 Adrian Mackenzie (2017) describes for instance how an image recognition system (kittydar) trained on cat images from Social Media and the Web could be applied to very different areas of use: "Based on how kittydar locates cats, we can begin to imagine similar pattern recognition techniques in use in self-driving cars (Thrun et al. 2006), border control facial recognition systems, military robots, or wherever something seen implies something to do." (19)

Within the field of media studies, the ubiquity of AI technologies has led to a variety of publications in recent years that can roughly be sorted into three main categories.[4] First, there are publications that address the development of AI technologies from a media-theoretical or philosophical point of view by discussing for instance theories of the artificial (e.g. Negrotti 2000), the history and foundations of pattern recognition (e.g. Apprich 2018), human-machine relations (e.g. Kasprowicz 2022), the role of *aisthesis* in machine learning (e.g. Krämer 2022) or the general question of creativity (e.g. Mersch 2019; 2022) and forms of intelligence that might differ from an anthropocentric understanding of it.[5] Secondly, there are publications that investigate specific media environments where AI is currently introducing new forms of agency, temporalities, decision making processes, politics and/or new aesthetics (e.g. Sprenger/Engemann 2015; Beverungen 2019; Manovich 2019; Sudmann 2019a; Ashri 2020; Karnouskos 2020; Sprenger 2020). Third, there are publications that deal with the question how different media are creating and shaping cultural imaginations and narratives of AI, which in turn can influence the actual development of AI tools (e.g. Bucher 2017; Kazansky/Milan 2021; Schulz 2022).

In all these publications there is a growing awareness that ML-based technologies are transforming media cultures in such a comprehensive way that we are already dealing with "media cultures of artificial intelligence" (Ernst et al. 2019: 19). This transformational development allows us to reexamine existing methods and approaches of media and culture studies like discourse analysis and media history or theory as well as integrate them into interdisciplinary research fields like software studies, platform studies or critical data studies. Especially in the field of critical data studies there is a growing amount of research that focuses on ML-induced bias and discrimination (e.g. Chun 2021; Apprich 2018; Kember 2013), dispositives of classification (e.g. Bechmann/Bowker 2019), questions of infrastructure, platformization and AI industries (e.g. Luchs/Apprich/Broersma 2023), and/or the material costs

4 This categorization is by no means able to encompass the many facets of research on AI-based technologies in the field of media and culture studies, but simply serves as an orientation for the purpose of this paper.

5 The question of a non-anthropocentric understanding of the agency of AI technologies can be traced back to similar discussions about the computer as a medium in the 1990s asking for a non-anthropocentric understanding of human-computer interaction, see Krämer 1997.

and planetary consequences of AI (e.g. Crawford 2021; Crawford/Joler 2018; Pasquinelli/Joler 2018).

The field of AI research is growing with rapid pace and there is a need to discuss more precisely what the various subfields of media and culture studies can contribute to this field (cf. Sudmann 2019c). One often neglected aspect in AI research is that the operability of AI technologies in everyday scenarios depends on interfaces that allow non-expert users to perform certain actions. Ultimately, developers must provide easy-to-use interfaces that are working towards embedding the operativity of AI-services into everyday culture. However, interfaces are not neutral. They mediate AI technologies in various ways. The emerging subfield of critical interface studies[6] can provide productive approaches that allow to address these mediations. While the allocated space of this article does not allow me to outline a conceptual toolbox of interface studies in all its variety, I will focus on its apparent key concept: the interface.

2. Interfaces as thresholds

So, what is an interface? To answer this seemingly simple question (that has produced different definitions in different research fields) we could start with another question: What makes a computer, a machine or a technology 'ready-to-hand'? Ready to use? Ready to be integrated into larger chains of action? Complex technologies, that have left behind the analogy of Heidegger's popular example of the hammer which enables intuitive handling through its 'handy' design, need some sort of second order mediation. This can be some sort of knowledge (expertise) about how the complex machine is to be handled[7] or a mode of mediation that translates this kind of knowledge into user interface

6 I use the term "critical interface studies" in this context to point to an emerging and interdisciplinary field of research that critically examines the role of interfaces in contemporary media cultures. The research field is in the process of forming and has not yet become institutionalized. Examples of relevant publications in this field are cited throughout the article.

7 This explicit knowledge can become implicit or tacit after multiple use. A manifestation of this knowledge can be found in textual form in so-called instruction manuals and it is interesting to note that the manual has step by step disappeared in the history of popular computing. What can now be observed instead of a manifestation of functional knowledge in the manual is a decentralized shift of repair knowledge to countless online forums (cf. Schröter 2018).

functions that are more easily comprehensible by human users (like pressing the right button).[8] Drawing on Gilbert Simondon's philosophy of technology we can differentiate between closed machines, that are understood as fully automatic machines with a predetermined way of functioning, and open machines. Open machines are defined by a higher degree of technicality, which presupposes human intervention in form of constant organization or coordination and therefore is always connected to human ways of relating to environments (Simondon 2012 [1958]: 11). As Erich Hörl (2011: 36) elaborates, Simondon puts the emphasis on the collective rather than on single actors by reconfiguring the evolution of the technical object from elements to ensembles and thus opens up a perspective to think technical activity in terms of a media ecology of distributed agency. Based on these considerations, an understanding of 'artificial intelligence' could follow, which does not attribute intelligence to the computer system alone, but assumes a distributed, collective performance, which is produced by a complex network of "distributed, hybrid human-machine-computer networks", as Rainer Mühlhoff (2019: 56f.) suggests. Although AI-based applications are not necessarily supervised or organized by human actors – especially in the case of subsymbolic forms of AI – human agency is still in the loop in many steps of the development process (supervised learning, human labor in trainings data sets, etc.) as well as in the environments in which these technologies are put into use. And here, 'being in the loop' mostly means being involved with interfaces; handling something in this context means dealing with displays and terminals: From human clickwork/crowdwork that generates training datasets for machine learning, to the implementation of machine learning operativity into the user interfaces of popular media apps.[9] Simondon's consideration of open machines can be extended by Alexander Galloway's (2012) conception of interfaces, which he describes as thresholds, as "zones of interaction that mediate between different realities" (vii). By not conceptualizing interfaces as things but rather as processes, Galloway makes us aware of the double nature of 'effectiveness' in computer-based interactions:

8 For an elaborated discussion of the complex relation between user interfaces and implicit knowledge see Ernst 2017.

9 Kate Crawford (2021: 68) e.g. critically describes the general obfuscation that 'interface effects' foster in complex AI-systems where we cannot be sure when exactly we, as human users, are interacting with an AI system: "We engage only with the facades that obscure their inner workings, designed to hide the various combinations of machine and human labor in each interaction."

> Interfaces themselves are effects, in that they bring about transformations in material states. But at the same time interfaces are themselves the effects of other things, and thus tell the story of the larger forces that engender them. (ibid.)

In a more practical reading, the focus on the interface points us to larger formations that shape our relationship with technology, such as data extractivism, surveillance capitalism or the overarching problem of complexity and blackboxing. Interfaces function as thresholds through which the agential/performative/operational potential of machine learning methods is mediated and made accessible and compatible with human practices. The user interface provides agency and enables us to be productive, but at the same time it is a threshold in the sense of a barrier: not everything is possible/visible/doable. Branden Hookway has clearly highlighted this ambiguity of the interface:

> The interface describes a fundamental ambiguity between human and machine; it is both a mirror of multiple facings and a zone of contact. This ambiguity bears on the human relationship with technology. For what is first encountered is not the machinic in any pure form but rather the interface itself. (Hookway 2014: 45)

But what does this mean for the study of AI? From the perspective of interface studies, an everyday human user can encounter AI-systems only through "the interface itself" (ibid.). In other words: Human-AI relations always depend on interfaces as central mediators of AI. However, the interface is not simply a medium for a linear relationship in the sense of mediating input towards output. On the contrary, following Hookway in his observation that the interface is "both a mirror of multiple facings and a zone of contact" (ibid.), we see that the interface is a relational entity that mediates in-between users and algorithms on different scales. Analyzing the "interface itself" (ibid.) does not mean to analyze a thing-like entity. Rather, it means to investigate how interfaces constitute a variety of connections and tensions that emerge between human users and the operativity of ML algorithms. To make this more concrete, I will briefly outline two examples of popular media apps that partly rely on AI. My goal here is not to investigate these examples in all their detail. I simply aim to illustrate *some* of the questions and potential points of inquiry that a critical interface studies perspective would follow here.

3. Example A: Curating social media feeds

The first example belongs to the broader field of content selection and recommender-systems. Social media feeds appear as the dominant organizing principle of current platform cultures, which network a high number of potential 'prosumers' and manage large amounts of audiovisual media content and user interaction (cf. Kohout 2018; Schulz/Matzner 2020). Feeds of platforms like Instagram, Facebook, Twitter or TikTok promise to filter content in an individualized and 'intelligently' curated way for each user of the platform. As it is advertised on the Instagram website, the formulated goal of the feed lies in defining what is relevant for each user and what is not. The goal is "[to predict] the most relevant media for each person every time they scroll the Explore page" (Medvedev et al. 2019). The Instagram Explore feed shows users an algorithmically curated selection of posts ranked with the help of artificial neural networks.[10] In a post on the Facebook AI blog, Ivan Medvedev, Haotian Wu and Taylor Gordon (2019) describe it as an "AI system based on a highly efficient 3-part ranking funnel that extracts 65 billion features and makes 90 million model predictions every second." Similar to other commercial content ranking algorithms, the criteria for the algorithmic composition of the Instagram feed are not fully transparent and therefore subject to speculation (Leaver et al. 2020: 8–38). By reviewing developer statements that often seem to follow a policy of strategic vagueness, it is only possible to reconstruct certain core categories of AI-enhanced algorithmic curation like "interest", "recency" or "relationship" in the case of the Instagram Explore feed (ibid.). In addition to an interest factor, according to which a certain user might be interested in a certain content, the timeliness of the content also plays a role. Further, the previous interaction behavior of each user is taken into account and, for example, posts from accounts that are followed or with which interaction (e.g., through likes, saves or comments) has already taken place, are prioritized. Secondary factors such as the frequency with which users access their accounts and feeds, their network (which accounts they follow), or their average time spent on the platform or individual posts are also included as selection criteria. This means that users are continuously contributing to the real-time composition of their Instagram Home and Explore feeds with their interaction behavior, even if they are not aware of it. Even if we are "absentmindedly scrolling through nothing" (Lupinacci 2021), just skipping through our feeds, we generate analyzable user

10 For a more detailed discussion of the various Instagram feeds see Wirth 2021.

data. The goal of the platform is to keep users engaged for as long as possible and the user interface is designed to achieve this goal in the most targeted way, generating what Alexandra Anikina (2021) has called the "affective scroll" (128f.) with regard to TikTok. In addition to this often involuntary and implicit work on the feed, the Instagram platform encourages its users to actively shape their feeds and provides specific control tools through the user interface: Certain accounts can be marked as favorites so that posts from these accounts are ranked higher in the home feed and displayed more often. Through so-called "Not interested" flags, users can actively hide certain content or participate in Instagram's "Sensitive Content Control" by masking posts that do not exactly violate the community guidelines but can still be perceived as offensive.

By considering the many factors that are part of the curatorial 'force' that constitutes social media feeds, it becomes evident that we are dealing with a complex curatorial assemblage of distributed agency where the algorithmic capture, evaluation and individually tailored selection and ranking of content is linked to the affordances and design strategies of user interfaces as well as the practices of users, who "become more aware of how algorithms micro-target them as audiences by surveilling their consumptive practices" (Jones 2023: 2). Machine learning technologies are one part of this 'messy assemblage'. Therefore, in media environments like social media platforms, 'intelligent' curation can also be understood as an "emergent and distributive capacity of hybrid human-machine networks" (Mühlhoff 2019: 64). Curatorial agency here is distributed and relational in the sense that all curatorial decisions affect the whole assemblage. However, we are not dealing with a flat hierarchy in which the individual points of the network have similar weightings, but rather with massive asymmetries of power that often remain opaque for users as well as researchers.[11] The role of the user interface within the curatorial assemblage that constitutes the Instagram feed can be described as follows: The user interface acts as a 'boundary condition',[12] a threshold between user practices, processes of data extraction, their algorithmic (partly ML-based) evaluation

11 For a conception of the computer interface as an apparatus of power see e.g. Distelmeyer 2017: 29f.; Distelmeyer 2021: 65ff.

12 Referring to the notion of interface in 19th century physics (specifically fluid dynamics) Hookway (2014: 66) describes the interface as "a boundary condition that both separates and holds contiguous as one body those parts whose mutual activity, exerted from each part onto the other, is directed into and channeled across that boundary condition in such a way as to produce a fluidity of behavior."

and the aesthetic mode of presentation that dynamically and constantly decides what becomes visible and what remains hidden. The feed interface is an ephemeral interface where the mode of 'passing-through' is enacted on multiple layers between dataflow and visualization: it is the result of a complex assemblage of human and non-human actors and simultaneously creates new affordances of interaction for human users that are ultimately feeding the dynamics and the future extractive potential of the assemblage. The design elements of user interfaces (like interface gestures, layout, icons, digital-material metaphors[13], etc.) need to be considered in their role of affording user interactions and thereby creating habits and embodied relations to/with the algorithmic agents of the assemblage (Anikina 2021: 129f.).

Consequently, the user interface integrates algorithmic (AI-based) classification decisions into everyday practice by presenting algorithmic processes as 'intelligible' and operable for human users. But at the same time, the visible feed as an interface obfuscates algorithmic decisions and data practices of the 'black box'. Thus, interfaces can be understood both as enablers and obfuscators of AI at the same time.

4. Example B: Editing images with AI-based photo apps[14]

The second example is located in the field of AI-based image generation and image editing. In this case, not the extractive, but rather the generative potential of AI-technologies and its impact on popular media culture is what I would like to focus on. Popular image editing software has made the rapid modification of digital images an everyday standard and a new impetus is currently coming from popular applications that offer AI-based editing functions. Their user interfaces provide editing options to everyday users that were previously only accessible to experts, e.g., photographers, literate in image editing programs like Adobe Photoshop. A popular example for this trend is the app FaceApp. Released in 2017 by Russian startup Wireless Lab (later renamed FaceApp Technology Limited), the image and video editing app allows users to perform a range of elaborate photo and video edits, such as aging or rejuvenating faces, morphing two faces together, adding complex facial expressions

13 For an elaborated theory of "digital-material metaphors" see Boomen 2014.

14 The following paragraph is a condensed version of Wirth 2023.

such as smiles, or applying the controversial "gender swap" feature. In journalistic reviews, FaceApp's features were mainly celebrated for their supposedly realistic results (e.g. Pickell 2019). FaceApp explicitly presents itself as an AI application that offers AI-based image editing functions to everyday users and is designed to deliver fast, but high-quality results: as the developer website advertises: "No more hours spent on photoshop" (FaceApp n.d.).

The user interface of FaceApp suggests similar functionality to popular photo filters or filter presets by making editing available quickly and easily at the tap of a finger. But in contrast to this user experience, FaceApp features apply deep AI-based modifications to the photographic source image. Therefore, the term filter no longer seems appropriate here (Bergermann 2019: 56). As Yaroslav Goncharov, founder and CEO of FaceApp Technology Limited, told *TechCrunch* in 2017, FaceApp uses "deep generative convolutional neural networks" (Lomas 2017) to process users' selfies. When applying the FaceApp image processing functions, the CNN transfers specific features to the respective portrait image or selfie, that has previously been extracted from the training data set. The applied image recognition methods enable an exact application of the automated feature modifications, which in the result achieve the already mentioned photo-realistic effects. This way, FaceApp manages to retain certain individuality markers of the respective face, even though the image is otherwise fundamentally changed (Chakraborty 2020). For users, this creates the illusion of an aged or rejuvenated version of their personal faces.

Like recommender systems, FaceApp participates in the general promise of AI technologies to make things predictable (Sudmann 2018: 193). FaceApp's so-called 'aging-feature' can be read as a popularized condensation of this prognostic promise. Prognostics forms a central element of ANNs, since it is always a matter of predicting an outcome for a newly inserted value – one that is not already part of the training dataset. In the form of predictive analysis, AI technologies currently present themselves in many areas of professional and private life as a future medium or medium of the future, in that they present the future as a computational and techno-economic regime (Ernst/Schröter 2020: 89). At the same time, the prediction of the future is characterized by an immanent reference to the past, as Matteo Pasquinelli and Vladan Joler (2021) have pointed out: "Machine learning prediction is used to project future trends and behaviours according to past ones, that is to complete a piece of information knowing only a portion of it." (1273).

The prognostic promise of AI, however, can only be delivered through interfaces that make AI-based prognosis accessible for the human sensorium. Once more, the interface's function as a translator of AI comes into play. In the case of my example, the app's user interface makes ML-based methods of prediction accessible for everyday practices. By providing ready-at-hand functions and reducing complexity, FaceApp's user interface (like many other AI-based photo editing tools) allows to implement AI-based object recognition and photo editing into established cultural techniques and photo practices and therefore works towards a domestication of AI. In the field of visual culture, the now ubiquitous availability of AI-based functionality, mediated by popular user interfaces, intervenes as a fundamental rupture in cultural production processes.[15]

The popular app interface thereby offers a subject position from which it is possible to perform expert-operations without expert-knowledge. As Christoph Ernst (2017) points out with reference to Donald Norman, interaction design and user interface design generate conceptual models that contain "ideas about possible operations *of* the system and about possible actions *with* the system" (100). The user interface of FaceApp and the marketing discourse surrounding it significantly shapes the imaginary of what 'AI can do'. In the case of commercial AI-supported apps like FaceApp, the subject position offered by the user interface is intrinsically linked to processes of objectification, namely to the datafication of users, their images and interaction behavior.[16]

5. From popular apps to AI in the sciences: Why interfaces matter

Using two examples from popular media culture, I have tried to demonstrate how even a brief look at the role of interfaces connected to AI technologies reveals critical functions that these interfaces fulfill when integrated into everyday practices. They can serve to *translate* the operativity of machine learning techniques and make their potentials – such as their potential for prognosis

15 For a comprehensive description of the relationship between AI and cultural production see Manovich 2019.

16 By offering a broader perspective on popular interface cultures Søren Pold und Christian Andersen (2014: 31) have described the intertwining of "intimate interface[s]" and extremely regulatory mechanisms that turn personal data into currencies as a typical feature of the current "controlled consumption culture".

and prediction or image generation – 'ready-to-hand' for non-expert users, while at the same time *obfuscating* the mechanisms of AI-based algorithms and related practices of data extractivism. Furthermore, user interfaces integrate the operativity of AI systems into cultural practices and play an important part in forming "human-machine assemblage[s]" (Mackenzie 2017: 216) of distributed agency. The evolving perspective of critical interface studies can help us highlight such functions and investigate them – both through a historical and contemporary lens – as parts of complex media entanglements. Overall, a critical interface perspective poses the question of the 'usability' of AI and investigates the user interface as a designed entity with its own agency and affordances.

The question of the interface draws attention to the often-hidden transitions between popular media culture and scientific practice. Adrian Mackenzie (2017: 190) describes the 'entangled evolving' of machine learning techniques and popular media (like social media platforms and search engines) which are mutually dependent in their development. Popular applications and easy-to-use interfaces first generate the structured data sets that AI systems need to improve their functionality, and, on the other hand, popular applications would not achieve their (mostly) flawless functionality without machine learning techniques.[17] The study of interfaces of commercial, (partly) AI-based apps shows that these primarily act as thresholds for monetizable data practices. This setting may be fundamentally different in the science context, but here, too, dependencies on large corporations, that e.g. generate training data sets for AI systems or provide functional AI units as service packages, can be found. So ultimately, research that wants to critically reflect on the application of AI tools in science must also critically address these dependencies.[18]

The more pressing question for research on AI in science, however, might be how interfaces are involved in the production of knowledge. In the near future, interface design will most likely play a significant role as a scientific research tool. As Johanna Drucker (2014: 139–146) points out from a historical perspective, data-heavy projects (e.g. research projects in the field of digital

17 Rainer Mühlhoff (2019) uses the example of the company reCAPTCHA to show how popular interfaces are specifically constructed and used to obtain high-quality, i.e. human-validated, data sets/classifiers for training AI systems.

18 As Alexander Galloway (2012: 110) stresses: "doing capitalist work and doing intellectual work – of any variety, bourgeois or progressive – are more aligned today than they have ever been."

humanities) need dynamic interfaces that leave behind the limitations of classical information graphics. Information visualizers are increasingly concerned with the question of how large databases and digital collections can be visualized in dynamic and customized ways (for researchers or public audiences), and what kind of access and exploratory potential interfaces should provide in this process (e.g. Dörk et al. 2020). Interestingly, the field of human-computer interaction is currently debating not only what interfaces for AI applications should look like, but also to what extent machine learning approaches can contribute to the development of 'intelligent' interfaces (e.g. Martelaro/Ju 2018; Ferraro/Giacalone 2022; Keselj 2022). Therefore, an examination of interface design conventions and the history of human-computer interaction seems indispensable for an understanding of 'AI in use'.

While Drucker (2014) raises the question "What kind of interface exists after the screen goes away?" (195) for the future development of interface design, Sybille Krämer points out that even machine learning remains tied to the screen in some way. According to Krämer, epistemological processes in which AI systems are fundamentally involved, are, like diagrammatological writing practices, ultimately still bound to *aisthesis* and thus to a surface such as the screen on which something is made perceivable (Krämer 2022: 149). This raises the question of the extent to which interfaces, as part of epistemic processes that introduce a certain agency into knowledge production within AI-supported research activities, should be studied as carefully and rigorously as other forms of scientific images and imaging techniques.

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