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How designers find their ways in shaping algorithmic systems

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Abstract. Digital products and services now commonly include algorithmic personalization or recommendation features. This has raised concerns of reduced user agency and their unequal treatment. Previous research hence called for increasing the participation of, among others, designers in the development of these features. To achieve this, researchers have suggested the development of better educational material and tools to enable prototyping with data and machine learning models. However, previous studies also suggest designers may find other ways to impact the development and implementation of such features, for instance through collaboration with data scientists. We build on that line of inquiry, through 19 in-depth interviews with designers working in small to large international companies to investigate how they actually intervene in shaping products including algorithmic features. We outline how designers intervene at different levels of the algorithmic systems: at a technical level, for instance by providing better input data ; at an interface or information architecture level, sometimes circumventing algorithmic discussions ; or at a organizational level, re-centering the outcome of algorithmic systems around product-centric questions. Building upon these results, we discuss how supporting designers engagement and influence on algorithmic systems may not only be a problem of technical literacy and adequate tooling. But that it may also involve a better awareness of the power of interface work, and a stronger negotiation skills and power literacy to engage in strategic discussions.

Keywords: Agency, Artificial intelligence, Interventions, Machine learning, Design, User Experience, Algorithmic Systems.

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1. Introduction

Personalization and recommendation are now key components of many digital products and services, most commonly associated with streaming platforms, online shops, gig work platforms or social networks. The algorithms underlying these personalization and recommendation are generally viewed as belonging to the technical realm of developers and data scientists (Dourish, 2016). Yet these algorithms also shape the user experience, generally viewed as the responsibility of designers. Dove et al. showed that designers consider choices of algorithmic procedures as 'technically complex and challenging' (Dove et al., 2017) which appears to limit their direct engagement in the design of complex algorithmic systems (Seaver, 2017). One response to this observation consists in making machine learning more accessible and familiar to designers (Yang et al., 2018b), through design tools and educational materials (Yang et al., 2016), interactive or not[1].

These initiatives aim at encouraging designers to develop an algorithmic and data-centric culture (Yang et al., 2018b) i.e., become more fluent in grounding the arguments underlying their design choices in large quantitative data and being able to use algorithms as design material, skills seen as necessary to be taken seriously by engineering teams. To better understand how to support designers, previous studies, whether survey (Dove et al., 2017) or interview-based (Yang et al., 2018a), thus focused on designers' attitudes and technical abilities with respect to Machine Learning (ML) and its integration in digital products. This position assumes that to impact algorithmic procedures, designers should intervene as close as possible to their technical definition and implementation.

In this article, we investigate how designers intervene to shape products and services with algorithmic features, going beyond direct technical interventions. In this we follow Seaver's call for algorithmic studies: we consider the various facets of algorithms materialized in a product and the many hands involved in building it, i.e., an 'heterogeneous and diffuse socio-technical system' (Seaver, 2017), in contrast with approaches trying to isolate an algorithm and presuppose its effect on end-users. By broadening our lens, we can pay attention to organizational dynamics that shape algorithms, and better comprehend by whom and how they are effectively *designed* into products.

Specifically, we investigate how designers intervene in designing products with algorithmic features, including but not limited to ML-based systems. This involves understanding their perceptions and opinions of

[1] See e.g., https://dschool.stanford.edu/resources/i-love-algorithms

algorithmic systems; and how this interacts with obligations to include, or ability to negotiate, algorithmic features. In particular, we analyze the means they use to influence algorithmic features, including for instance user research, feedback from user tests, information architecture or user journeys.

To achieve this, we conducted semi-structured interviews with 19 designers working on products and services involving personalization and recommendation algorithms. Our informants worked in organizations ranging from start-ups to large companies ($>$ 5000 employees), to public administrations and an NGO, with positions ranging from UI designer to VP of Design.

We found that whether designers hold an enthusiastic, skeptical or neutral stance on algorithmic systems, they all justified it with an homogeneous discourse on a practice focusing on the needs of end-users (see Figure 1). Designers also differed from previous studies on developers that described homogeneous practices across work environments (Roth and Poiroux, 2022): our informants described highly heterogeneous work and design practices. This reflects their different positions and organizations, as informants had positions ranging from working directly with ML engineers, as external consultants or in dedicated design teams, etc. These positions came with various levels of agency: some were in position to define the outcomes of the algorithms while other were pushed to integrate externally defined algorithms into their design. Depending on their agency and external constraints, we found that designers chose to locate their design efforts at different levels of algorithmic systems.

2. Related work

Research on personalization and recommendation algorithms has a rich history, some of it tied to CSCW. For instance, Riedl and Resnick mention a keynote at CSCW 1992 as an inspiration to what would become the GroupLens project and research group (Resnick and Varian, 1997). A little earlier, Goldberg et al. developed Tapestry at Xerox PARC, which (among other things) let users rank the relevance and usefulness of documents based on user interactions such as notes and comments (Goldberg et al., 1992). The breakthrough of these systems lied in identifying mechanisms to involve humans in the filtering process, i.e., in collecting preferences and other insights that could then be leveraged to filter and recommend relevant information.

Such strategies of voting, rating, and lightweight annotation would later be reused in a variety of systems for recommending or tailoring content. These systems depend on users' implicit or explicit feedback on their suggestions, which informs on their adequacy. Commercial systems used by millions of people rely on such approaches. For instance, the description of Netflix algorithmic choices (Gomez-Uribe and Hunt, 2016) shows how testing with users is central to their approach, i.e., closing a feedback loop between recommendation results and input 'signals' coming from users.

Whereas the representations of users' needs and wants are present all along the development of such algorithms, the organization frames this development as a series of 'hypotheses' and 'experiments', a 'science' (Gomez-Uribe and Hunt, 2016), where users are acted upon rather than actors themselves. Moreover, professions generally described as 'user advocates' (Williamson and Kowalewski, 2018; Chivukula et al., 2021), such as designers and User Experience (UX) researchers, are generally not seen as key players. This contrasts with the rich scholarship on algorithms, fairness and ethics in machine learning, that pays particular attention to engineers, data-scientists, or legal teams.

2.1. Algorithmic studies

The 2010s saw the emergence of research centering on algorithms as an object of study. Rather than relying purely on the presentation of industry or academic researchers specialized in recommender systems, machine learning or computer scientists more broadly, scholars in science and technology studies literature (STS) have started to study the making of algorithms 'in-vivo'. This builds upon a legacy of studies on the collaborative production of code in companies (Lethbridge et al., 2005; Button and Sharrock, 1996), in open-source organizations (Mockus et al., 2002), or in e-science (Paine and Lee, 2014), and could even be tied back to the beginning of HCI, notably through Suchman's foundational work at PARC on expert systemss (Suchman, 1987). In this literature, a challenge and point of controversy (Dourish, 2016; Seaver, 2017) is the definition of what an algorithm is, some scholars using rather expansive definitions of the term, whereas computer scientists would offer much narrower definitions, and for instance separate the algorithm from the code implementing it.

The shift to 'algorithmic studies' (Seaver, 2017) and its increasing popularity compared to past work on the collaborative creation of software can be tied to the increased use of algorithms in sensitive sectors, from private credit scoring and insurance policies, to policing, justice or economic policies (Dourish, 2016). It also relates to concerns that efficient but difficult to audit procedures, such as deep learning, lead to unequal outcomes and harm by propagating and inflating biases in the data they are based on.

Algorithmic studies typically look at how engineers create, maintain, and revise algorithms (Burrell, 2009), or how other professions have seen their practices being challenged by algorithms (e.g., journalists (Christin, 2018; Diakopoulos, 2019)). However, many more professions are involved in the process of developing a system. For instance, Seaver conducted a longitudinal ethnographic study in an North-American music streaming service (Seaver, 2018; Seaver, 2021). He explicitly looked not only at the practices and representations of engineers, but also how algorithms are a shared object of concern for other parts of the organization. Piorkowski et al. (2021) similarly observed that an AI team had to interact with many other professions (domain and business experts, other software developers) to bring a product to life. We situate our work within this approach looking at designers' expertise, position and influence in the creation of algorithmic systems.

2.2. The design of algorithmic products and services

Designers are largely left out of the accounts presented above, even from the ones going beyond engineering work. The survey conducted by Dove et al. provides some hints as to why it may be: the designers 'uniformly described difficulties in understanding what ML was and how it worked' and that 'prototyping with ML is difficult' making it a challenging design material from which most stay afar (Dove et al., 2017).

This concern about the accessibility of machine learning, and the need of education or acculturation seems largely shared among HCI researchers working on the implication of AI for designers. This translates in proposals for educational workshops aimed at designers (Dove and Fayard, 2020), educational resources such as card decks[2,3,4,5], or design patterns (Yang et al., 2016). More technical contributions center around bringing prototyping or sketching abilities to designers (Scurto et al., 2021; Françoise et al., 2021).

Yang et al. inquired more deeply on the challenges of ML design by interviewing 13 designers (Yang et al., 2018a) working mostly in large companies ($> 10,000$ employees) and actively involved in ML products. They observed a need for designers to embrace 'a data-centric culture' in order to build collaborations with data-scientists (rather than becoming more knowledgeable in ML). Based on their findings they suggest that design practitioners could benefit from 'abstractions, exemplars,

[2] https://www.aixdesign.co/shop
[3] https://www.imagination.ooo/project/ai-cards
[4] https://www.trytriggers.com/
[5] https://dschool.stanford.edu/resources/i-love-algorithms

and new tools and methods that support designers collaborating with data scientists'.

Our goal differs in that we try to understand how designers currently intervene in shaping algorithmic systems—if at all. We are as interested in understanding why designers decide to engage directly with algorithmic procedures and why, as we are in understanding the rationale for not doing so. For us and in the context of this study, the specific algorithmic procedure, whether it is machine learning, classical optimization or agent-based AI, matters less than the ways in which designers engage with it.

3. Methods

We used in-depth, semi-structured interviews to gather qualitative accounts of designers' experiences that could help us understand their current roles and practices when working on algorithmic systems. All but one interview were conducted through video-conference. This enabled long and in-depth interviews, but lacked situatedness, as we could not observe the work environment or meet their colleagues and teams. While recruiting we adopted an expansive definition of algorithmic systems, emphasizing automated processes used to select, process and present information rather than a specific type of algorithm.

3.1. Informants and recruiting

We initially interviewed 21 designers, which we complemented with two background interviews, one from an industry researcher in HCI, the other from the founder and CTO of a recommendation platform. We recruited the informants within organizations that rely heavily on algorithmic procedures, and for large organizations we ensured the informants worked in parts of the organization that were involved in shaping the algorithmic systems we were interested in.

We recruited informants through a three stages process:

1. We started by contacting people within our extended personal network, reaching out to designers working on services built around algorithmic procedures (e.g., known for content recommendation). This enabled us to recruit 13 informants[6].

[6] One of these informants, now working as an HCI researcher, had worked in the past on a recommender system and showed interest in the project so they were invited to join the project as a co-author of this paper.

2. In a second phase, we relied on secondary networks, reaching out to engineers, project managers, or designers from the first stage, and asking if they could put us in contact with designers within their team or organization. This allowed us to recruit six other informants.

3. Finally, we recruited the four last informants by reaching out directly through LinkedIn for organizations we knew would be relevant but for which we did not have any contact.

We excluded two interviews from our corpus as one designer worked in too many organizations and could not provide enough details due to non-disclosure agreements, making the interview difficult to compare, and the other because their company did not use significant algorithmic procedures. The following analysis and presentation centers on the remaining 19 designers' interviews.

At the time of the interviews, six informants had the title of (lead) UX designer, five of (senior) product designer, two were director or VP designer, two 'multidisciplinary designer', two designers (without any adjective), one UX researcher and one design Ops. Two worked in start-ups ($<$ 250 employees), seven in medium businesses (250 $<$ employees $<$ 5000), seven in large businesses ($>$ 5000 employees), two in public administrations and one in a small NGO).

This broad range of profession titles reflects the diversity of organizational structures and how Design as a discipline and its corresponding positions are rapidly evolving within organizations. This diversity of profiles, organizations, and work locations reflects our broad sampling strategy. This sampling is useful to capture the variety of discourses and of interventions shaping the design of algorithmic systems, to characterize and analyze them. We do not seek to provide a statistically accurate view of designers' interventions, but rather to ensure that we cover a large spectrum of existing ones.

Six informants worked for music/audiobook streaming platforms, two for video streaming platforms, two for media groups, two for a food delivery platform, two for public administrations, two for an IT company, one for mass market retail, one for a legal-tech start-up, and one for a start-up building a recommender engine as the core of a consumer tool.

The informants were 35 years old on average (median: 37) with 10 years of design experience (median: 9). They had mainly studied visual communication, art and graphic design or project management (four for each of these categories). Three designers had studied (for some, on top of the previous study) UX design, three computer science or engineering, two industrial design, one sociology, one ergonomics, one marketing, one game design and one technical writing.

3.2. Algorithms

For the sake of simplicity, we mostly use the term algorithm in the paper, even if our implicit understanding follows the notion of algorithmic systems as presented in the related work. To us, this term covers widely diverse technical arrangements, ranging from complex data-driven if-then structures used to show different content to different user profiles, to machine learning models. When necessary we provide details about the technical implications of algorithmic choices on designers' work.

Most algorithms were related to personalization, two to prediction and routing strategies, one to filtering or curation (removing offensive content), and one related to natural language processing. The vast majority were developed internally but Adrien from a media group described working with externally developed algorithms, and one informant (Daniel) did not provide details on the development.

3.3. Interview structure

We conducted semi-structured interviews. The interviews lasted one hour in average (between 45 and 192 minutes) and were conducted in two different languages, French and English. Our interview guide is available in the appendix. We asked informants to present their organization, their current position and personal situations within the organization. We also inquired about the type of algorithms embedded in the products and services they work on. We then dug into a specific project involving algorithms on which they worked and how they were positioned in this project. We looked for critical incidents, from which we could unpack design interventions and how these were handled at an organizational level as well.

Our interview guide broadly sought to understand designers' practices in defining algorithmic systems (rather than focusing on one specific aspect of their practice). Our interview protocol was validated by the Cross Schools Research Ethics Committee of the university of the fourth author. Given the positions of the informants, we guaranteed full-anonymity and non-disclosure of the transcripts. Most informants did not communicate about the interview with their hierarchy or colleagues. The interviews were mostly conducted from their home. This might have helped informants express themselves 'without restraint'. Four informants were careful not to communicate information they considered sensitive, which were most often related to products in development or close to launch.

3.4. Interview analysis

We audio-recorded the interviews and created a first automatic transcript with Trint.com, which was reviewed and edited where necessary by a co-author other than the interviewer. We used a thematic coding process (Flick, 2014): thematic coding has similarities with both thematic analysis and grounded theory, in that it calls for the constant comparison between cases (here, interviews) and the use of both inductive and deductive coding to develop a thematic structure outlining a coherent story about the data; here, to understand how our informants make sense of algorithmic systems they work on and how they impact them. We coded the transcripts using a self-hosted Taguette[7] instance.

We analyzed interviews iteratively and using constant comparisons between informants' accounts. Core to our process was the writing-up of summaries that could be compared. We represented and explored the data in various ways, for instance in tables comparing informants' background and their description of technical proficiency to identify potential patterns.

We iterated on codes and discussed patterns in the data and we identified a common narrative: even for designers describing a close relationship with technical teams, they did not describe actively working on algorithmic code or parameters – but many also did describe having an impact, which they were more or less satisfied of. We developed this into the central theme of this article: the range of strategies through which designers, often individually, try to shape algorithmic procedures in products they work on, regardless of the boundaries of their tasks and position description.

4. Informants positions within their organizations

Before turning to the central analysis of designers' strategies, we first describe informants position within their organization to provide context for our results interpretation. The informants held a wide variety of titles and positions. In large organizations, designers' positions and roles were more formalized, but the structures they could join differed, with some working in squads or product teams, others in dedicated design teams, or joined teams with external consulting positions.

[7] www.taguette.org

Pseudo	Age	Exp.*	Education	Title	Org. activity	Org. size**	Team size	Algorithmic goal
Joël	40	9	Visual com., project mgt.	Lead UX designer***	Retail	large	NC	NLP
Aude	28	5	UX design, mgt.	UX designer***	Tech. corp.	large	10	Personalization
Sara	42	7	Technical writing	UX designer	Tech. corp.	large	4	IA engine
Adrien	28	5	Web project mgt.	UX designer	Media group (A)	medium	5	Personalization
Jean-Baptiste	40	13	Industrial design	Product designer	Legal tech	small	10	Search, personalization
Helen	32	9	Visual com.	UX researcher	Food delivery	large	4	Prediction, allocation, routing
Mila	32	12	Fine arts	Product designer	Food delivery	large	3	Prediction, allocation, routing
Justine	38	7	UX design	Multidisciplinary designer	Public admin. (A)	medium	6	Prediction
Clément	38	15	Engineering	VP of Design	Music streaming (A)	medium	6	Personalization
Flavien	34	12	Informatics, UX design	Head of design Ops	Music streaming (A)	medium	6	Personalization
Dora	26	6	Design, project mgt.	Senior product designer	Music streaming (B)	medium	NC	Personalization
Rémi	35	12	Industrial design	Director of design	Music streaming (B)	medium	NC	Personalization
Anne-Julie	40	17	Visual com.	Designer***	Video streaming	small	2	Personalization
Nathan	40	17	Studio Art	Senior product designer	Music streaming (C)	large	12	Personalization
Estelle	34	11	Visual com, interface design	Product designer	Audiobook streaming	medium	9	Personalization
Cristina	38	4	Sociology	UX designer	Video streaming	large	5	Filtering
Victoria	31	3	Graphic design	Designer	Recommender engine	small	3	Personalization
Gabriel	43	21	Ergonomics, marketing	Transverse designer	Public admin. (B)	medium	NC	Personalization
Daniel	37	8	Informatics, game design	UX/UI designer	Media group (B)	medium	3	Personalization

* in (digital) design
** small: < 250 employees, medium: 250 < employees < 5000, large: > 5000 employees
*** in consulting

Figure 1. Informants experience and positions within their organizations.

In smaller organizations (mostly start-ups) positions were much more fluid. Table I offers an overview of the informants experience and positions within their organizations.

Informants discussed the 'degree of design maturity' of their organizations, five designers felt either working 'in silo' or being in minority 'facing a product manager and a team of developers'. Five informants were working in 'purely' design teams where they spent most of their time working with other designers (Adrien, Clément, Flavien, Daniel, Sara). We also observed seven (Mila, Gabriel, Anne-Julie, Justine, Helen, Aude, Joël) situations of external or internal design consultancy in which designers joined a product team of multiple developers with the status of external support, i.e., whereas the development team was rather stable, the length of their stay in the team was more precarious. Aude, for example, described how in her large organization, as projects grew bigger, some core technical part of the product would be outsourced to a dedicated department with the relevant technical expertise (related to data management and processing). In that case, she would continue working on the interface of the product but would lose design power over the design of the algorithm.

In addition, and even more critical than designers' position within the organization, we identified three ways in which designers were on the production or reception end of algorithmic systems creation. 1) Sometimes they had to use an already defined algorithm that was pushed onto them. 2) In some other cases, designers were able to define specifications, which included what an algorithm should do and submitted it to a dedicated team. 3) Finally, in a few cases, designers worked side by side with the engineers to define the algorithm.

4.1. Designers being pushed to incorporate existing algorithms

Most informants (12/19: Aude, Adrien, Clément, Cristina, Daniel, Flabien, Gabriel, Helen, Joël, Justine, Mila, Sara) belonged to organizations that pushed algorithmic systems to be incorporated into products or services, which led designers to incorporate them as a design requirement. In some cases, the algorithms outcomes were at the center of the product that designers had to work on, e.g., for streaming services in which the recommendation algorithms were considered part of the heart of the product. This level of centrality in designers work can be connected, at least partly, to the perceived importance of algorithms for the organization's current and future goals.

However, in other cases, algorithms were perceived as if they did not belong to the heart of the product but rather its margin. In one situation (Adrien), the recommendation algorithm, in the form of a chatbot, was developed by an external company, and acted as an add-on that was not central to the product. Designers in that situation sometimes perceived what Sara calls an 'algorithmic push' (Joël, Aude, Sara, Adrien, Justine). Paradoxically, engineers were never perceived as the ones pushing for algorithmic incorporation in designs. Aude who worked for a large tech company providing consulting services saw the marketing department as the one who was pushing for 'fancy machine learning'. Sara also felt this push, but its origin was unclear:

> 'Even at the design team level, we are very much pushed to integrate [an ML algorithm]. So you go see in your product where you could put even tiny bits [of the ML algorithm]. Maybe through a chatbot? We are explicitly asked to integrate small AI features in our products.' (Sara, 42 y.o., UX designer, tech. corp.)

4.2. Designers specifying algorithmic outcomes

Three (Estelle, Jean-Baptiste, Rémi) of our informants described part of their design activity as revolving around the definition of expected algorithms outcomes. In such cases developers acted as service providers for designers. By focusing on outcomes, a lot of discussions about the inner working of algorithms were circumvented as Jean-Baptiste or Estelle explained :

> 'We express the needs as clearly as possible so that, after, the machine learning engineer can choose the best possible approach in terms of algorithms. And so, no, we don't have our hands on it on the product side, like for example: "wait, what is the algorithm you are using? What are its potential bias?" We are much less in these types of discussion.' (Jean-Baptiste, 40 y.o., product designer, legal tech)

> 'I think that, honestly, I do have lot of control over it, I can't complain about that. Because, it isn't the recommendation team that came to us saying: "here is what we will give you", it's us who went to see them with the product manager to tell them: "here is what we need, how much time will it take you?". I really didn't suffer, I was a player in the definition.' (Estelle, 34 y.o., product designer, audiobook streaming)

4.3. Embedded designers

And finally in four instances (Anne-Julie, Dora, Nathan and Victoria), designers were part of teams that were developing the core algorithms of the products. Nathan and Victoria were part of the team from its inception, they participated in defining the scope and iterating on the features with an attention to the experience it would create on the user side. Dora for example thought that it was very important for designers to have a clear understanding and precise control over how the recommendation algorithm worked:

'I don't see enough attention from designers to it. [...] I'm like what's experience and that includes how do we fetch content and then how is our recommendation working and how are we filtering the content and sorting the content? Then what are we putting emphasis on [...]? Like you can put five different covers for a playlist and that can be one thing, but if the content is not right because of some bias in an algorithm, people won't listen to it.' (Dora, 26 y.o., senior product designer, music streaming (B))

5. Designers' strategies to intervene in the design of algorithms

Informants held different positions in their respective organizations and had heterogeneous levels of agency: some were in position to define the outcomes of the algorithms while others were pushed to integrate externally defined algorithms into their design. Despite this heterogeneity, almost all designers managed to have an impact on the algorithmic system, even if through very indirect means. We now focus on locating designers' interventions in relation with algorithmic systems. Given the diversity of interventions and our limited sample, our plan is to outline the diversity of interventions rather than to draw a representative panorama.

Concretely, how does working with algorithms looks like for designers? On the most integrated side of the spectrum, Nathan could participate in defining broadly the goals for a new algorithmic development. This actually meant that he was able to get many stakeholders to work together to define the algorithm in its technological, interface and organizational aspects.

'We came out with a hypothesis and opportunity space around focusing on [music mix], and we brainstormed together different technical approaches to achieve [mixes] based on people's listening history [...]. It was mostly engineers, designers, product managers and I think we had one data scientist and a user researcher that helped us test something after the end of the sprint.' (Nathan, 40 y.o., senior product designer, music streaming (C))

However, this scene of many stakeholders, including designers, sitting at the table and discussing the creation of algorithms was actually very rare in informants' accounts.

On the other side of the spectrum, for designers such as Adrien, working with algorithms meant that they were simply adding a currently empty 'dynamic box' for personalized content in their UI mockups.

'My main work on the newsletter is its design, and then we use a tool that is based on a recommendation engine, I think. Once we have defined that such or such block is connected to the reader's navigation... Well, I prepare an article block in the newsletter, and then that's with the developers that we said that this part of the newsletter has to be dynamic.' (Adrien, 28 y.o., UX designer, media group (A))

Within this broad range of practices, we found that designers located their design efforts at different levels. The first level is the technical one, engaging with engineers and 'talking their language', the second level is the design one, leveraging interface and user-centric tools designers are familiar with, and the third is the organizational and meta-level one, leveraging strategic interventions within their organization, notwithstanding some deliberate non-interventions.

5.1. Techno and data-centric interventions

Some of the designers interviewed were part of the development team of the algorithms and thought it was a core facet of their job. For instance, Jean-Baptiste and Estelle were able to specify what the algorithm expected outcome should be to the engineering team.

5.1.1. *Precisely controlling algorithmic parameters*

We observed very different strategies to influence the design of algorithms. For designers such as Dora, who were working closest to the engineers in charge of developing the algorithm, they saw their role as exploring the choice and importance of all the different parameters (input, output and calibration) of algorithmic recommendation. While she explained that she does not actually write any code, she is participating in the discussions that will lead to decisions regarding which, and how, data points are going to be used. In her opinion, it is very important for designers to have a clear understanding and precise control over how the recommendation algorithms works:

'I'm not part of writing [it]. What I understand is like what are the different inputs we're using, and that's what I need to control. Let's say that we're going to give recommendations and then the engineer says: "OK, we're going to use age and location to do that. Are we going to focus more on age or on location?"' (Dora, 26 y.o., senior product designer, music streaming (B))

However, this type of direct impact was only accessible to designers who were in close contact with engineers because they rely on the development or data-science teams to implement their requests. Among the informants, we found that efforts to design or modify the algorithms were always mediated by engineers. More than using specific tools, talking with engineers was the main way for designers to shape algorithms.

'So that's saying to the engineer: "well then let's put an emphasis on that." and so he says: "ok, I'll train my algorithm to favor that." For me it's not even possible that on algorithm related topics, engineers would handle them on their own and that it would necessarily work. It clearly does not. So conversation is necessary.' (Jean-Baptiste, 40 y.o., product designer, legal tech)

5.1.2. *Providing better input data to algorithms*

Helen identified that much of the issues users are facing were not caused by problems with the algorithm itself but rather the input data it uses or how the algorithm is perceived and understood by users –that is, couriers, in her case. Therefore, her interest was rather about making sure that couriers understand the logic of the algorithm to provide relevant data in order to have the best outcomes for them and for the company.

> 'So I did some research recently around [...] what couriers understood [providing availability] means, so that we could try to improve from the app side how much availability couriers provide in order to improve the information that the algorithm receives. So I guess it's not so much trying to improve the algorithm, but giving... the more information it has, the better it works.' (Helen, 32 y.o., UX researcher, food delivery)

She tried to address this issue by looking at ways to get couriers to provide 'better data'. This involved seeking ways to capture the information that could then be fed to a specific algorithm: which information could realistically be collected and at which point in users' workflow it would make more sense.

> 'With the shift planning tool, we have the problem of not receiving enough availabilities from the couriers. Instead of trying to improve the algorithm [...] we could also show the couriers the forecasting slots: because then if they see that "oh this day is really busy, I'm more likely to get a shift at that time", then they'll give us the information and then the algorithm can work better.' (Helen, 32 y.o., UX researcher, food delivery)

This is one of many examples Helen gave, which all had to do with capturing input data in a way that worked and was related to stakeholders' existing practices.

5.1.3. *Updating algorithms via user testing*

Among the designers' interventions that had the most direct impact on the algorithm, user testing was a key tool to provide leverage. This was especially true for designers who were working in direct contact with the engineering team. User testing was a way for them to justify and override decisions. Jean-Baptiste explains how constant testing has guided the design and evolution of the personalization algorithm for one of the feature he was working on.

> 'We realized that sending our newsletter once a week is more than enough, but that it has to be personalized. [...] That's something that we tested. At the beginning we did not even have mockups, we went to discuss the idea with people and slowly, we started

> prototyping, simulating fake emails, asking lawyers if that was the level of information they were interested it, etc.' (Jean-Baptiste, 40 y.o., product designer, legal tech)

He also explained how getting user feedback after deploying a feature led them to discover its detrimental impact on women. This user feedback was used to support the withdrawal of the feature altogether.

> 'We had not noticed that [displaying] a lack of activity could mean that the lawyer was pregnant. For us, less activity only meant less clients. And if you are a company looking for a lawyer and visiting this page you would say to yourself: "what happened? why does she suddenly have no clients anymore? I do not want to contact her". That type of thing was clearly an issue. We had not understood that. But when we did, we decided to stop displaying that information.' (Jean-Baptiste, 40 y.o., product designer, legal tech)

5.2. Interface and user-centric interventions

Given their position within the organization, designers did not always have the possibility nor the will to directly influence the design of algorithms, but they nevertheless were able to have an impact using other means, such as information architecture, interface work, or by advocating for the importance of user-experience and user needs.

5.2.1. *Interface and information architecture work*

Recommendation is neither purely technical or curatorial, it is also about what gets to be displayed, when and where it is being displayed. One main avenue leveraged by designers to influence the design of algorithmic system lied in interface or information architecture work, because it is generally the part of the product that they most explicitely have control over.

Clément, because of his position of 'Design VP' has a significant influence over the whole product, including the recommender system algorithm. For him, musical recommendation should integrate both algorithms and human curators, the first one for personalization and the later for current and mainstream trends. Given the company's objective, Clément can choose to emphasize one over the other by ordering them on the front page of the application, without having to consult with anybody or to run any prior testing.

> 'Recommendation, it is also product placement strategy. What we call the "first screen view" in design, that's the most important, what we see without scrolling, this will engage almost all users. Recently we made a simple change. Before, when people stopped the app on the favorite tab for example, and when they came back, they would be brought back to their favorites. I said: "bring me back everybody to the [home page]"' (Clément, 38 y.o., VP of design, music streaming (A))

Locating their action at the UI, navigation, or information architecture level allows designers to make decisions without having to rely on engineers in charge of implementing desired algorithmic behaviors. This is the most widespread form of intervention across our informants. While developers are still involved, it is typically different teams involved in front-end development. These interventions consist in transforming technical discussions into product discussions, thereby negotiating with 'product leads' rather than technical leads.

Providing and displaying better information to users about how algorithms work is another way designers try to address issues, For example, in the case of parental filter on a streaming platform, Cristina tried to explain the limits of the algorithms to the parents who chose to enable the child-focused feature, rather than shaping the algorithm itself.

> 'It's written very clearly that it is an algorithm that will choose and that there can be errors. And our job is to test with people to make sure they understand that errors will occur, a video may be violent and so on. ' (Cristina, 38 y.o., UX designer, video streaming)

In between these situations, an alternative consists in engaging in UI work to provide users with parameters so that they can control the algorithm themselves. Anne-Julie worked on the design of a video streaming service that removed its recommendation feed, arguing that 'a real blog roll', i.e., a feed that can be configured would be better aligned with the vision and values of the NGO she worked for. Dora explained that making recommandation decisions 'by herself' was not very ethical and that she would prefer giving that control to users directly, even though that feature was just an idea at the time of our interview.

> 'Giving control to the users is the best way to account for it [...]. What I could do is saying to them: "here's a few filters so you can decide". [...] We could have a default 50/50 [women/men recommendation], like, here's what we recommend [...]. The moment you get people the control to toggle it, it's not something they can ignore.' (Dora, 26 y.o., senior product designer, music streaming (B))

5.2.2. *Getting the voice of the user heard*

Designers saw themselves as being the representative of the users. Getting the voice of the user heard was a way to try to have an impact on the engineering team, even if it was in an indirect way.

For Helen, the goal was not to directly define how the algorithm works, but to influence the people who will make decisions.

> 'So with the upcoming piece of research that I'm doing with the Tech Lead from the router team, him and his team will be joining in on the research sessions so that they

> can also hear about these problems themselves firsthand and therefore be able to make more informed decisions with this knowledge [...] As a research team, we are trying to work harder to bring this voice closer to the teams that are making the decisions.' (Helen, 32 y.o., UX researcher, food delivery)

Here, designers are in a situation where they have little control on the outcomes of their interventions –in some way, they are restrained to stand in a position of hope, playing the role of a 'middle-man' between the users and decision-makers. In that sense, designers see themselves in a neutral position, however, 'getting the voice of the user heard' also means to amplify or attenuate those voices, depending on priorities stemming from a roadmap, the product team, etc.

In some situations, user-centricity was more of a rhetorical argument Aude explained that she could appeal to the quality of the user experience to shape algorithmic interventions. Presenting herself as the user advocate is what provided her with 'a veto right'.

> 'I can state my opinion, what is the best for the user. If that really disturbs the experience, I can veto. Sometimes we resist, for example recently, they [the marketing department] wanted that if a person was looking at iPhones 10, we should push them an iPhone 11 if it was currently on sale. If we think that it is too complex, we can say no [...] We are the user experience guarantor, so sometimes that allows us to say no.' (Aude, 28 y.o., UX designer, tech. corp.)

Aude calls it her 'veto right', rejecting the integration of what she deems too aggressive recommendations mandated by the marketing department, presented as responsible for the financial health of the company, in contrast with the design, responsible for user experience.

5.3. Organizational and meta-interventions

Finally, designers conducted interventions within their organization but not acting directly at a techno- nor design-centric level. We define these specific interventions as meta-interventions, aiming to influence the organization through advocacy, education, or appeal to shared values (like diversity).

5.3.1. *Implementing consensual values*

For designers working on content recommendation, a special focus was put on thinking about different ways to address diversity issues. If designers were presenting the situation rather than actually defining how to practically address such issues, their position was important enough to go beyond aspirations. For example, Victoria was very aware of the balance between recommending more of the same or trying to push users to watch different content.

> 'So that's trying to balance between what seems to be an intervention that is not negative, if not positive, because, of course it's horrible to judge like this but watching "temptation island" the whole night, ouch. To recommend something, it's to catch attention, and you do not want to catch attention about things that could have negative effects.' (Victoria, 31 y.o., designer, recommender engine)

In the music industry too, Dora thought that it was important to take into account the diversity of the different recommendations that are given to the users, in terms of gender as well as geographical regions.

As a way to have a more global impact, three designers (Aude, Sara and Dora) mentioned trying to advocate for having ethics and bias taken into account when designing algorithms, thus needing to collaborate with managers and other decision-makers.

> 'Unfortunately, we are working for big and very business oriented companies. I think that, as a designer, we need to bring up questions of bias and ethics. As the guarantor of the user experience, I think that we tend to have this long term focus.' (Aude, 28 y.o., UX designer, tech. corp.)

5.3.2. *Educating designers and organizations about algorithms*

One of the informants, Nathan, who was very interested in algorithms and is working in a team of engineers, has recently been involved in the creation of education material for designers about machine learning and set up an internal event about the topic.

> 'I have been helping to develop some of those materials and get consultants from outside, on how we should be approaching machine learning from a design point of view.' (Nathan, 40 y.o., senior product designer, music streaming (C))

In this case, his effort was not focused on impacting a specific algorithm, but rather on trying to develop a culture and strengthen skills for more designers within the company to be able to understand and participate in defining future recommendation algorithms.

Nathan also leveraged his visual design skills to represent internally the decisions that have been made, communicating about what exactly the algorithm did: 'what is the product and how does it work? And going into as much detail as is necessary for non-technical people to fully understand how this product might be making decisions on behalf of a user or not, so just enough information to be technical without getting into complex pipelined diagrams.' (Nathan) This goes beyond educating designers, it focuses on translating algorithm into processes that are intelligible by various stakeholders across the organization.

5.4. Non interventions with algorithmic systems

In contrast with efforts to actively influence the design of algorithmic systems, informants also described how they sometimes chose not to engage with algorithms, deliberately or not. Sara demonstrated a passive resistance to algorithmic push coming from upper management levels. She explained her resistance was because she thought the algorithm was not valuable for users.

> 'It's more for ethical reasons. What drives me crazy is that we take this from the wrong end. You see, the thing with integrating this [ML algorithm], where is the need? [...] We are told that it's for the clients. But I have never seen a client... Well, I have been working on this product for a long time and they complain. If they complain, it's not because there is no AI. [...] Nobody, never ever, from all the users with whom I have talked told me "oh, we would love to have some AI in our products". That's why it's driving me nuts.' (Sara, 42 y.o., UX designer, tech. corp.)

Justine, a design consultant, only had little time to offer her assistance to a start-up. For her, trying to improve the algorithm was not the priority. She criticized the significant gap between how much effort goes into developing an algorithm that identifies and recommends which companies are at risk of bankruptcy and how little human means were planned to actually carry the prevention work. So she decided to focus her intervention on trying to make 'the service as useful as possible' by bringing the different stakeholders aligned on a shared goal.

> 'So yes, I didn't work too much on [the algorithm] because for me, what's crucial is the first step. It is really to get everyone to agree about how will this service work, what is the service we are creating.' (Justine, 38 y.o., transverse designer, public admin. (A))

This was not because of a lack of interest or knowledge, but rather because organizational or structural constraints gave these designers little agency or time. Leading them to focus on product issues they considered more important than the algorithms. Daniel who worked for a media company in which he thinks design is not yet as integrated as it should be, considered that UX designers should ideally be involved in the design of algorithms, including the recommendation algorithm included in his company's product. But he explicitly noted that he does not currently have time to do it and has other priorities, such as improving the interface of a search feature.

6. Discussion

Stepping back, we now reflect on what can be learned from the modes of interventions we identified in the previous section. We first discuss one question that guided our interviews: whether or not values and attitudes would shape positions and interventions. Then we reflect on what it means to 'design' algorithms, and how to scope 'algorithmic systems'. Following up on this, we question the centrality of machine learning in common discourses, discuss the power that designers can yield in actual products. Finally we identify opportunities for expanding design education especially by addressing strategic and political work within organizations.

6.1. Do opinions and attitudes regarding algorithms influence designers' interventions?

We have chosen to categorize designers' interventions according to their focus within the algorithmic system: techno and data-centric; interface and user-centric; and organizational and meta-interventions (see figure 1). We discuss in this section how designers interventions correlate or not with their personal attitude towards algorithms and their position within the organization.

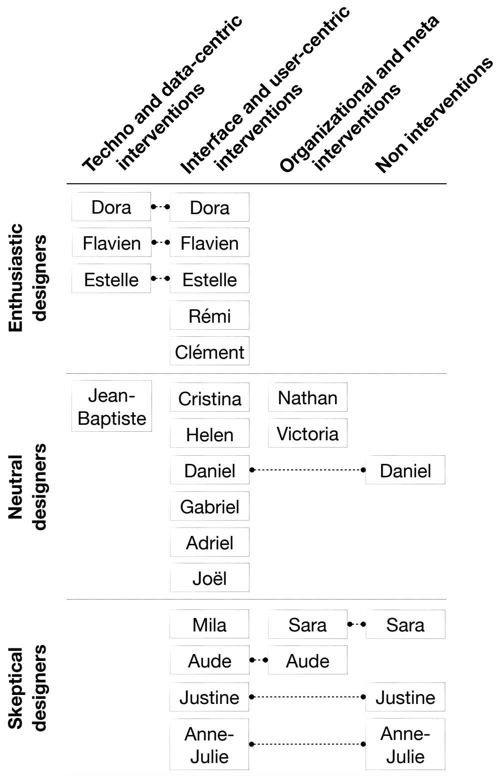

Figure 2. Designers interventions w.r.t. their attitudes.

During interviews, most of the informants expressed their opinions and attitude about algorithms. Interestingly, designers held an homogeneous user-centered discourse that led to both enthusiastic or skeptical opinions and stances regarding algorithms and how they should be incorporated into products. Skepticism reflects degrees of doubt regarding the value of including sophisticated algorithms in the product if they don't serve users. 'I did interviews in the context of the application redesign and, actually, there are people for whom it is not interesting at all to have a personalized feed as we are a local media company.' (Adrien, 28 y.o., UX designer, media group (A)). Conversely, algorithm enthusiasts think that advances in artificial intelligence are beneficial and their relevance, for example in music recommendation, far surpass that of human curators. Flavien is certainly the designer who expressed the most positive attitude regarding algorithms, which, in turn, negatively affected his vision of human content curation in musical streaming services:

> 'For me, algorithmic recommendation has ten times the potential and relevance of editorial work, you can discover new music your whole life. The algorithmic content is always personalized whereas editorial content will never be.' (Flavien, 34 y.o., head of design Ops, music streaming (A))

We tried to identify correlations between informants' opinion regarding algorithm and how close they were from the technical team in charge of implementing the algorithms. We noticed that designers who tended to be the most negative were also the one that were the most distant from algorithm's technical implementation in the company. For example, Sara had a strongly negative opinion that pushed her to stay as far as possible from algorithmic systems in her company: '[...] In general, AI raises my hackles. So I'm not trying to include any.' (Sara, 42 y.o., UX designer, tech. corp.). When they were not part of the implementation team but did try to intervene, skeptical designers engaged primarily in meta-interventions but also in interface and especially user-centric work. On the other end of the spectrum, unsurprisingly, enthusiasts explained that they learned about and were interested in the technical aspects of algorithms.

In between these two attitudes, a third of the designers had an ambiguous relationship with algorithms, recognizing their potentially innovative power but also seeing how they could lead to important issues. Aude, for example, thought that algorithms should prove that they can provide tangible benefits to the users before being implemented.

> 'I often try to resist what is more of an "algorithmic push": personalization, recommendation that are pushed by the marketing department. I think that it will sometimes hinder the user experience. But there are cases where I sincerely believe that a search

engine or an algorithm does answer the real user needs to find information in a fast and efficient way.' (Aude, 28 y.o., UX designer, tech. corp.)

This could be perceived as a seemingly neutral attitude. It reflects a certain image of user-centricity: designers would have employed their tools and methods so well that users' needs would align perfectly with technical answers, possibly leaving designers themselves outside of a self-supported loop. This view is also supported by Helen: 'As good researcher [...] if we get to the point where we set up all of the processes so that they happen almost by themselves, then we're almost not needed...' (Helen, 32 y.o., UX researcher, food delivery).

Skeptical and neutral designers criticized the lack of reflection and the decisions taken only to reach financial goals. In terms of actions, these designers also invested time in the promotion of values that could be described as uncontroversial, such as the limitation of discrimination and bias that could affect users. Designers who were closest to the team in charge of the implementation tended to integrate ethical issues at the margin, by correcting things rather than trying to oppose them. It should be noted that although almost all the respondents spoke of promoting ethical values that are independent of financial objectives, few of them presented an articulated view of the organizational challenges involved, and even fewer presented a project in which these values were explicitly taken into account. In that sense, we perceived a strong ethical discourse from designers but that discourse seldom translated into concrete interventions. Further longitudinal on-site studies would be welcome to investigate how designers' values and attitudes are mobilized in practice, whether they are mainly discursive stances or translate in concrete actions and transformation of products.

6.2. Broadening the scope of what it means to design algorithms

6.2.1. *Designing Algorithmic systems*

In our work, we have considered algorithms as systems, following the evolution in academic understanding of algorithms as socio-technical systems (Bijker, 1997; Lee et al., 2019; Kitchin, 2017; Green, 2021). This trend moves away from a code-centric vision of algorithms, which would be only an object consisting of computer code, data and mathematical formulas. The socio-technical approach considers algorithms as the result of interactions between the algorithm and the users, but also between the different actors involved in the design of the algorithm; engineers of course, but also designers, product managers, sales and marketing professionals, decision makers and so on. Understanding algorithms in a systemic way makes it possible to shift the focus from the code in itself, and look at how the various forces shape the construction, deployment and use of algorithms.

Not restricting our interviews and analysis to the implementation of algorithms, but rather looking at the construction of algorithmic systems, we were able to uncover a wider range of design interventions than anticipated. A majority of the interventions did not explicitly target nor impact coded implementations by the engineering team but involved other means, i.e interface and meta-interventions. However, in the literature, understanding of algorithms as algorithmic systems hardly breaks with the centrality of its computational properties; the role of the interface and the interactions in recommendation is seldom studied or acknowledged (Shin, 2020), whereas they often are decisive in terms of visibility and performance (Maasø and Spilker, 2022). Online content recommendation is implicitly understood as a matter of algorithms, while it covers a multitude of strategies and tools, among them positioning choices in interface design, timing and frequency at which recommendations are made, how data is gathered through interface and interaction work, human curation or more technical constraints such as available products or legal restrictions.

6.2.2. *Acknowledging the variety of modes of design intervention*

Our findings show the heterogeneity of designers interventions, stances and agency regarding algorithmic systems. We could not identify a shared agreement or understanding on what should their role be in designing algorithmic systems. Nor did we observe established practices and tools for this purpose. However, the heterogeneity of practices should not necessarily be considered an issue or the reflection of an immature relationship of designers with algorithms. Rather, it calls for more attention to the variety of ways in which designers are already influencing algorithmic systems. Indeed, designers intervened and managed to have an impact by shaping information architecture, setting defaults, sometimes by vetoing some algorithmic outputs, and in many other designerly ways. This shows that even in positions where they do not have a full understanding of algorithms inner-workings or direct influence on their implementation, designers managed to have an impact, however indirect.

These findings call for reconsidering and extending what designing algorithmic systems means. In the result section, we as authors, reflecting the language of our informants, talked about designing algorithms, but this term encompassed very diverse activities, from defining filtering criteria to drawing the interface of various features. We usually have a narrow technical perception of what designing algorithms mean: implementing them using code. Our results show that the technical work on the algorithm cannot be reduced to their implementation through code. Interface and interaction work are very technical interventions that we argue should count as what designing algorithmic systems means. Designing algorithmic systems does not necessarily require locating design interventions as close as possible to their implementation into code. Designers already manage to impact algorithmic systems in many ways, often using means that are neither data nor code centric. Being close from a technological point of view does not necessarily mean a greater impact on the algorithm, despite a better understanding. In fact, closeness may mean stickiness to the technical framework, thus only allowing designers marginal changes like improving the usability of the algorithmic-based product, rather defining its existence, its goals, or the way it is integrated in a product.

6.2.3. *The unconsidered impact of Design on algorithmic systems*
Designers themselves, however, did not really share this broader conception of algorithms. As Aude explained, designers do not generally perceive algorithms as being part of their landscape: ‘As designers, we don’t think in terms of algorithms, that we are going to create things that will result in algorithms. We rather think in terms of user journeys, diagrams with branching paths, personalization, etc. [. . .] So we are not going to think in terms of algorithms even if this will have an algorithm as a consequence.’ (Aude, 28 y.o., UX designer, tech. corp.). Algorithms tend to be obscured or held at a distance with traditional design tooling such as user journeys or information architecture, and this discourse resonates with previous studies on the topics (Yang et al., 2018a; Dove et al., 2017).

One implication is that we collectively need to transform the perception of what designing algorithmic systems means, even for designers. Yang et al. together with Dove et al. argue for developing the algorithmic literacy (or mastery) of designers (Dove et al., 2017), which focuses on the code and mathematical aspects of algorithms. On top of this approach, our results call for spreading a broader understanding of algorithms as algorithmic systems. We see here an opportunity to develop what we call a design-centric approach of algorithms. This entails mapping precisely how algorithmic systems come in contact with traditional design work and the ways design tools and methods already impact them. This paper is a first step in that direction but more focused and longitudinal studies are needed to deepen our understanding.

6.3. Design tools for Algorithmic systems

6.3.1. *Leveraging existing tools*

One of the most efficient way for designers to impact algorithmic systems was to use information architecture and interface zoning, which can greatly affect the promotion and appeal of functionalities, be they algorithmic or not. Authors such as Yang (2017) indeed argue that ML and UX ideally exist in a symbiotic relationship with one another.

However, it seems that for most designers in our study interface work was not explicitly perceived or recognized as a possible way to impact algorithms. In fact, algorithmic and UX work were generally perceived as mutually exclusive (Maudet, 2019), even when, as Clément showed, they generally work hand in hand, and information architecture can have a strong impact on whether algorithmic features may be used at all. As we have seen in how designers position themselves regarding algorithms, the belief that algorithms have strong impact on people's experience and even lives is pervasive. However, the same cannot be said of the perception of interface and UX work, which tends not to be problematized in the same way in the press nor by academics (even if counter examples exist, e.g. dark patterns (Gray et al., 2018)).

An avenue for research is to explore and recognize more clearly the impact of interface and interaction on algorithmic systems. This type of intervention has an untapped potential and is already part of the designers toolbox. Research could in turn be used to develop dedicated representations, tools and methods that can support designers interventions through interfaces. Another avenue for research is to more systematically inquire into the various ways interface work can impact algorithmic systems. For example, in their study on folk theories regarding curation algorithms, Eslami et al. experimented with different ways of representing a feed algorithms through seamful interface design, i.e 'adding visibility into system operation by designing "seams" into technologically-mediated experiences' (Eslami et al., 2016). They showed that this design intervention impacted how users were able to form folk theories regarding the Facebook feed curation algorithm. In that case, the design intervention was meant to help users reflect on the underlying algorithmic system. Cristina's will to display some of the limitations of the algorithm through a pop-up, for example, certainly fits within this type of interface intervention.

6.3.2. *Developing new tools and representations*

The under-acknowledged interplay between interfaces and algorithmic systems can be partly explained by a lack of representation. Although we inquired about the materiality (Jung and Stolterman, 2012) of practices in regard to algorithms, the informants remained very elusive about material productions. For instance, they did not discuss wireframes, UI mockups, or user journey maps as relevant tools that would be shared with developers, managers, or other collaborators in order to impact algorithms. Although they worked on such UX/UI materials but did not consider them appropriate when we talked about their practices regarding algorithms.

The issue may not be one of understanding or technical mastery, but rather one of tooling and representation. As Joël stated, it is their intangibility that make algorithms difficult to integrate in the conversation:

> 'And on the topic of algorithms, it's even less obvious because when we talk about interface, it is tangible, we can see it, but when we talk about algorithms, we are touching upon a topic where, at the beginning, there is nothing tangible.' (Joël, 40 y.o., lead UX designer, retail)

This aligns with previous work showing that designers currently lack the means to represent algorithms in their work (Françoise et al., 2021). On top of current efforts focusing on providing ways to capture the technicality of algorithms, an open question relates to the type of support designers need to represent algorithmic systems and their connections to interface, user journeys, information architecture and other concerns they may have. This necessitates shared representations that help designers and other stakeholders to consider algorithmic systems while taking into account their complexity and multiple implications. Benqué's speculative work on diagrams and representations of algorithmic prediction could hint at some directions (Benqué, 2020).

6.4. The strategic and political work of designers

6.4.1. *Beyond design tools: negotiation work*

In contrast to the informants elusive material productions, meetings and advocacy appeared as central to designers' work with algorithmic systems, both in terms of impact but also time spent. Meetings and other forms of oral (or written in the form of Slack/Teams exchanges) communication were mobilized as ways to shape the design of algorithms, by influencing engineers or decision-makers directly. Participation to meetings especially seemed to have a central role in the activity of many informants.

Although it was not the initial focus of our work, the strategic and political work of designers in organizations seems of significant importance. Studies of negociation work with end-users (McDonnell, 2009), collaborative conversations in the design studio (Kleinsmann et al., 2012), or during design critiques (Gray, 2014) all emphasize the importance of negociation and the 'integrative' role of designers in balancing multiple design constraints. Here we would like to call for attention on a complementary aspect: political work, in the form of advocacy, consensus building, or other strategies in which the question of power should be explicitly studied.

Better understanding these dynamics would require deeper ethnographic site-centric work (Christin, 2017), conversational analysis (Reeves, 2019), or empirical studies of material artifact mobilized in negociations (Lee, 2005). Which could then be useful for design education, i.e., training designers to have a better political literacy of organizations and understand strategic and tactical means of interventions to wield influence.

6.4.2. *User-centricity as a mean of reframing*

In practice, user-centricity, i.e., presenting oneself as bearing the voice of the user, was among the most efficient way for designers to seize influence and control on algorithms. All informants shared a view of themselves as users advocates: they justified their actions that had impacts on the algorithms with the idea that they were for the users' sake. However, they exhibited strong valence in their opinions and actions regarding algorithms. This begs the question of what is the concrete purpose this user-centric value, since it is mobilized both to reject or to push the adoption of algorithms? It seems that positioning oneself as the user advocate was less about concrete actions or results but rather a strategy to be able to get a say or even to override decisions from other professions, i.e. engineering or marketing departments. Designers used it to shift the focus, from algorithm to product. In that sense, designers were doing a reframing, finding a new productive frame for subsequent activities (Paton and Dorst, 2011) and a way to legitimize their interventions.

Yang et al. discuss the importance of developing a data-centric culture for designers if they want to be heard on product decisions (Yang et al., 2018a) regarding algorithms. Some informants indeed leveraged metrics to influence decisions, but the consensus among the informants on user-centricity suggests an other engagement for design-centric values. It may well be that designers should be more fluent in discussing the technical details of algorithms and using them as design material, but user-centricity shall foremost spread across the whole organization. This is what what Dora was arguing for:

> '[...] I really think that everyone should be focusing on the user. If you're business driven or if you are product driven, you need to focus on the user. So to me, I know people say that the designer is the voice of the user, but I think that's a little bit outdated. [...]

I think that everyone needs to be user driven.' (Dora, 26 y.o., senior product designer, music streaming (B))

The more designers turn design concerns into shared concerns for management, engineering, or marketing, the more agency they may acquire.

7. Conclusion

We investigated the agency designers when they design products that include algorithmic features, i.e., how they intervene in such projects, including but not limited to ML-based systems. Through 19 in-depth interviews with designers working in small to large international companies with very different organizational structures, we tried to shed light on how they form their perceptions and opinions of algorithmic systems; and how this interacts with their ability to shape or negotiate algorithm-based features.

We found interventions at various locations of algorithmic systems, from techno-centric ones related to parametrization and data, to more designerly ones involving interface work, to more political ones, involving strategic interventions. This depends on work conditions, design practices and levels of agency. While some designers were in position to define the outcomes of the algorithms, others were pushed to integrate externally defined algorithms into their design. Paradoxically, designers shared an homogeneous user-centered discourse, but held both enthusiastic or skeptical opinions and stances regarding algorithms and how they should be included in products.

We argue that the wide diversity of designers' interventions should be nurtured. Beyond helping designers develop a technical understanding of complex algorithmic systems, we should also support them in developing various design-centric strategies to broaden the diversity of the ways in which they shape algorithmic systems. These strategies range from sharpening classical design tools and methods, developing stronger algorithmic and organizational literacy to embracing the power of interfaces and information architecture.

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9. Declaration of Interest

The author(s) declared that they have no conflict of interest.

Appendix

A. A note on our coding method

While we mainly relied on thematic analysis to analyze our data, we also used Activity Theory in preliminary stages. As we were familiarizing with the data, we became interested in the conflicts described by designers and temporarily turned towards Engeström's activity system model (Engeström, 2001; Kaptelinin and Nardi, 2006). His model identifies conflicts within an organization as a motor of changes (and hence designers' impact) and provided a structured framework to compare informants' highly varied accounts. Early on, our codes reflected our work with activity system model categories (Engeström, 2001), taking a deductive approach. For instance, we had codes related to 'dividing labor' to describe how the informant presented situations in which work of implementing a new feature was attributed. However, we found this approach difficult to implement due to the lack of multiple perspectives within each company that could better enable to track internal conflicts and how they led to change. This led us to go back to a more inductive approach following the thematic analysis described in the method section.

B. Interview guide

1. **Factual questions** to set the framework, about the organization, the personal situation within the company and the team

2. **Overview of the algorithms**
   What is a recommendation algorithm in your company? What algorithms (recommendation, filtering, search, classification) exist within your product?

3. Which ones do you use, which ones do you have 'contact' with, which ones do you think you have an impact on?

4. Are there any algorithms you are not working on? Why not?
5. Have you participated in the creation/implementation of a new algorithm? How and with whom?
6. How did you become aware of this algorithm (code, via discussion with the developers, etc.)?
7. Have you, at any time, seen problems emerge with one of these algorithms (or a product using an algorithm)?
8. If so, in this particular example, what exactly was the issue?
9. How did you become aware of this problem (tests with users, external audit, personal awareness, etc.)?
10. Do you know what the background of this algorithm was? Who implemented it and why?
11. What is your technical or logical knowledge of this algorithm?
12. What was your reaction? Were you able to solve this problem? If so, how, and if not, why?
13. Did you work with somebody to solve this problem and if so, with whom? What is your relationship with the engineers? Are you in regular contact?
14. Did this event changed the way you test algorithms now? On the way you work with algorithms?
15. If not, how do you make sure the algorithms work the way you want them to?
16. Do you conduct tests? If so, can you tell us more about their implementation?
17. Who are your users? Do you mobilize data, statistics, etc.? What is your relationship with the users?
18. **General questions to conclude the interview**
    Does this type of 'algorithmic' project reflect the progress of other projects you may have been working on recently? To what extent? In your opinion, how much control should designers have over algorithms? What is the specificity of their contribution (compared to that of marketing for example)? What space do you give to your values and personal ethics in your design work? And what place do you give to the values of the users?

19. **Personal questions** about the organization of the team, the methods of intervention on projects, the background, the experience in design and in the organization, the familiarity with programming.

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