Disengagement through Algorithms: How Traditional Organizations Aim for Experts' Satisfaction

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Abstract

This study examines the use of algorithmic tools in traditional organizational decision-making processes. Through forty semi-structured interviews with managers, engineers, and (expert) users across six European projects, we suggest that initiators deploy algorithms not to automate actions or replace users, but to disengage themselves from prescriptive decision-making. Consequently, the responsibility to choose, select, and decide falls upon the users; they become engaged. Therefore, algorithm evaluation is oriented towards utility, interpretability, and, more broadly, user satisfaction. Further research is encouraged to analyze the advent of a 'satisfaction regime', from platforms to traditional organizations.

Where Are the Management Algorithms?

"Management algorithms" are known to be deployed by online platforms to organize the activities of workers (Jarrahi and Sutherland 2019; Lee et al. 2015). When we began this research in 2019, we hoped to gain access to traditional organizations that utilized algorithms not only to orchestrate the activities of employees or independent workers but also applied this "algorithmic management" to themselves for decisions precisely related to management and business administration. After approximately 75 informal interviews across ten sectors (human resources, public service, finance, law, media, retail, customer service, transportation, logistics, and delivery), the consensus among respondents was clear: these strategic decisions cannot and should not be delegated to algorithms. The majority of those surveyed were not familiar with examples of algorithmic management, and some had never even heard the term before.

Although organizations have "explicitly become places for the creation, aggregation, and analysis of data" (Denis 2016), it is reasonable to perceive the vast majority of them as being at the early stages of developing a data culture. We mean by this that algorithmic management, as defined by the authors of the *Data&Society* report, Mateescu and Nguyen (2019), remains primarily confined to digital platforms:

> "It is a diverse set of tools and techniques for remotely managing the workforce, relying on data collection and worker surveillance to enable automated or semi-automated decision-making".

Despite numerous interviews, we have not encountered a traditional organization – one whose activities are not solely based on online connections between workers and clients – that engages in such extensive data collection and deploys algorithms, in lieu of managers, to direct workers. In other words, surveillance and information asymmetry are not exclusively mediated through management algorithms.

However, many decisions are based on data, and this trend is expected to grow. Some researchers argue that algorithmic management is gradually spreading within traditional organizations and influencing power dynamics as well as existing social structures (Jarrahi et al. 2021). Unlike Heinrich, Vu, and Vysochyna (2022), who consider algorithmic management and control to be synonymous, we prefer the term algorithmic control for one main reason: in traditional organizations, managers are rarely replaced by algorithms but rather equip themselves with tools to exercise increased control over workers. Algorithms now assist in directing, evaluating, and disciplining workers (Kellogg, Valentine, and Christin 2020). Just as platforms benefit from an asymmetric information-sharing relationship, managers and executives in traditional organizations benefit from greater transparency from workers (e.g., real-time evaluation of conversations in call centers), while making their decisions more opaque (Ajunwa 2020).

Control *via* Algorithms

Schafheitle et al. (2020) propose a typology of various control technologies, refraining from using the terms artificial intelligence or algorithms. Instead, they prefer to discuss the "datafication" of control within organizations. The authors operate under the assumption that control is not new but is influenced by data – although the specific manner and extent of this influence remain underexplored in the literature. Examples of "datafication" technologies include employee tracking devices (GPS, RFID tags), predicting absenteeism risk (Qomariyah and Sucahyo 2014), identifying periods of peak productivity, and implementing evaluation systems among employees to encourage knowledge sharing.

From this perspective, the algorithmic management of platforms is seen as an extension of "algocracy" (Aneesh 2009). Algorithmic control transforms the activities of both workers and managers alike. Aneesh demonstrates that algorithms are not necessary for monitoring workers; control can be exerted through interfaces or tracking tools. For instance, Indian developers are evaluated based on the number of errors in their code. Algorithms – or more broadly, tools – are not responsible for inadequate compensation, managerial harassment, or work pace: "To understand how work relations within capitalism persist, one must explore the 'hidden abodes' and open the 'black boxes"' (Moore and Joyce 2020).

However, it would be reductionist to approach algorithms and other decision-support tools solely through the prism of worker and employee control. The configurations and actors involved are diverse; some are compelled to use tools, while others choose to do so. Some delegate part of their tasks to algorithms, while others prefer occasional assistance. In addition to management algorithms and control support algorithms, we have discovered in the literature the existence of countless decision-support tools, ranging from less to more complex and varying degrees of visibility to researchers. As a result, "decision-support algorithm" could be classified into three categories (Parent-Rocheleau and Parker 2022):

1. Descriptive algorithms primarily record past events to analyze their effects on the present;
2. Predictive algorithms estimate the likelihood of an event occurring in the future:
3. Prescriptive algorithms have the ability to recommend (or directly implement) the solution estimated as the best – similar to algorithmic management.

Decision-Making *Facilitated* by Algorithms

The literature presents two general characteristics that distinguish decision-support algorithms from control and management algorithms. Initial studies indicate that decision-support algorithms do not replace decision-makers (Madhavan and Wiegmann 2007; Wong and Wang 2003; Pomerol and Adam 2006) and provide less alarmist conclusions compared to studies focusing on the other two types of algorithms (Lee et al. 2015; Burrell and Fourcade 2021; Rosenblat and Stark 2016). One reason for this non-replacement is that algorithms "can never make a decision". They make choices, filter information, but decision-making is a purely human practice (Dwyer 2020). The way algorithms calculate the world should thus be a supplementary source of information for decision-makers. For instance, algorithms could be allowed to make decisions only when their operation is more transparent and their results fairer than those of humans (Bolander 2019). If this requirement is not met, algorithms can still be used in a complementary relationship with decision-makers. This was concluded by Shestakofsky (2017) during participant observation within a digital platform, particularly in engineering departments. Initially, he observed that automation of development was impractical due to the rapid evolution of the company's environment and product. Consequently, managers did not deploy algorithms that could have replaced developers but rather sought to build an "assembly" between humans and algorithms. The author demonstrates that this complementarity is more beneficial for innovation than human replacement; "smart machines" can "enhance" decision-making (Jarrahi 2018).

The second group of studies examines this complementarity through the lens of the interaction loop between decision-support algorithms and decision-makers. While complementarity should serve a decision ultimately made by a human, the main "actor" of the loop is either the algorithm (human-in-the-loop) or a human (algorithm-in-the-loop). The human-in-the-loop is a recurring concept in the literature (Jones 2017; Grønsund and Aanestad 2020), particularly to emphasize the necessity of not leaving algorithms unattended by humans (to avoid errors) or the importance of having human final validation, even if the entire process is algorithmic (for example, granting social assistance). In contrast, Green and Chen (2020) advocate for the concept of algorithm-in-the-loop. In this configuration, humans retain control over the most productive tasks (data analysis) and delegate to algorithms the preparation of this analysis. The responsibility for the decision is therefore necessarily human, and importantly, individuals appear to have more freedom in how they use decision-support algorithms. Algorithms aimed at "enhancing" decisions can combine human judgment and technical regularity (Binns 2020).

(The) Organization *Through* Algorithms?

The studies cited throughout this introduction allow us to better understand how actors interact with control or decision-support algorithms. However, there is often a lack of perspective regarding the profile of the actors, the diversity of situations, and the organizational stakes that sometimes transcend these very actors. Experts (or "knowledge workers") can exhibit highly diverse behaviors towards these algorithms, ranging from enthusiastic adoption to skeptical refusal (Anthony 2021). Thus, they rarely rely exclusively on the algorithm to make a decision; rather, it is a hybrid approach of their judgment combined with the algorithm's results (referred to as "artificing") that is primarily at work (Snow 2021).

Moreover, the use of decision-support algorithms depends on a multitude of factors and is not solely in the hands of users (Bader and Kaiser 2019). In other words, beyond a question of result quality or trust in the tools, the deployment of decision-support algorithms is a matter of strategic choice within the purview of initiators – specifically, an organizational question (Marabelli, Newell, and Handunge 2021). In this regard, rather than referring to decision-support algorithms, we prefer the concept of *organizational algorithms*: they contribute to the "organization of the organization", not just to the organization of work.

Consequently, our study contributes to the extensive body of research focused on the transparency and explainability of artificial intelligence and algorithms (Langer et al. 2021; Bhatt et al. 2020; Cellard 2022). More importantly, it builds on research that emphasizes the transparency of stakeholders' intentions (Miller 2022), contrasting with users' needs, which may lead to mistrust (Bach et al. 2022; Kaplan et al. 2023) and value conflicts (Park et al. 2022).

A Qualitative Study

In early 2020, we began conducting semi-directed interviews with stakeholders involved in the design process (initiators and engineers) and users of organizational algorithms. By July 2021, we had conducted 92 interviews in approximately 40 organizations across 10 sectors (public service including defense and police, cultural industries including media, finance, humanitarian work, transportation, law, human resources, delivery, and maintenance) in eight different countries (France, the United States, Germany, Austria, Denmark, Switzerland, the Netherlands, and India). To maintain the benefits of a traditional field, we prioritized organizations for which we had a significant number of interviews with stakeholders involved in the design process, and ideally, users as well. This article is therefore based on the analysis of transcribed interviews with 43 anonymized respondents[1] from these six European case studies – 21 of them being featured in this article:

- Case A is a (small = 10 to 249 employees) media organization interested in standardizing and evaluating journalistic production (7 interviews);
- Case B comprises a (small) private research institute providing a risk assessment tool to evaluate domestic violence, here called *Risiko*, a (small) public social center and the (small) developer agency of the tool (6 interviews);
- Case C is the human resources department of a (large = over 5000 employees) corporation that implemented an algorithm for talent detection and turnover prediction (4 interviews);
- Case D is a (large) food delivery platform actively automating (prediction, allocation, routing) certain tasks in managing delivery schedules (9 interviews);
- Case E involves a (middle-sized = between 250 and 4999 employees) maritime affairs department that developed a risk prediction and targeting tool, here called *Nef*, to comply with new regulations (12 interviews);
- Lastly, Case F comprises three (large) criminal investigation departments that deployed a burglary prediction tool (5 interviews).

The users we encountered are exclusively experts, some of whom have decades of experience in their field and are engaged in discussions about the integration of organizational algorithms into their work. Organizational algorithms are not specifically designed to control these users but rather to assist them in decision-making – and in some cases, it is the users who control through the algorithms. Furthermore, we consider that depending on whether the algorithms have a descriptive, predictive, or prescriptive function (Parent-Rocheleau and Parker 2022), they serve different organizational objectives and mobilize user expertise in various ways. This leads us to question:

- to what extent does the level of engagement of user expertise influence the design of organizational algorithms?
- conversely, how do initiators manage the tension between organizational objectives and user objectives?

[1]The interviews were carried out between 2020 and 2021 and were selected from a pool of 92 interviews based on the following criterion: each interview had to accompany at least three others conducted within the same organization. Whether through its size, the heterogeneity of profiles among the 43 respondents, or the diversity of organizations, this panel illustrates the variety of situations in which organizational algorithms are deployed. The average duration of interviews was 65 minutes. Of the respondents, 34 were male and nine were female. The average age was 39 years old. While it is challenging to compare backgrounds and positions held, we can identify that five respondents studied law and five others studied computer science. Twenty-eight of them hold positions of responsibility. On average, they have 16 years of experience, with 12 years in their current organization.

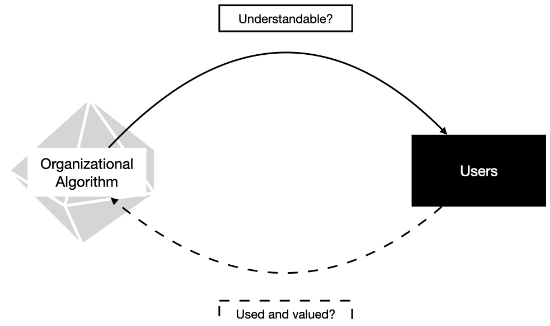

Figure 1: A schematic view of section ”User engagement with algorithms”.

User Engagement With Algorithms

We analyze organizational algorithms as objects whose value depends on user choice and their participation in diversifying sources of information. We then explain why users do not fear algorithms; instead, they value their expertise. However, for this to occur, algorithms must be understandable (Figure 1).

User Choice

The use of organizational algorithms appears to be seldom constrained. Our case studies demonstrate a certain freedom among users in choosing whether or not to utilize such tools, a choice also confirmed by design actors. We even encountered the opposite situation in Case D, where operators would like to use the tool for predicting the number of couriers needed for a given week. However, they feel “obliged” to perform the forecast “manually” using a spreadsheet because they do not trust the results of the organizational algorithm.

The two observed reasons for non-usage of a tool are:

- Fear of devaluation of their work:

> “The biggest distrust came from the analysts dealing with burglaries because there was a bit of fear that someone would come and say that the program is better than them.” (Tomi, NC, head of department, judicial police 2, case F)

- Perception of the tool's lack of utility due to incomprehensible results, perceived lower quality, or failure to fulfill its role as assistance:

> "If we have a fully automated process and the user doesn't trust it, and instead does their own calculations in a spreadsheet, it's pointless." (Victor, 30 yo., product manager, food delivery platform, case D)

Users seems to often have the ability to decide when or in what situations the algorithm may be relevant and can choose whether or not to follow the proposed recommendation. This situation arises when the recommendation must be sought by the user, as is the case for human resources managers (case C). They first have the choice to consult the recommendations and then to follow them. In the three regions that have implemented a predictive policing tool (case F), the freedom to follow these recommendations is present at three levels: that of the analyst (operator), the sector manager (at headquarters), and the patrol officers.

> "Basically, the patrol officer who notices a high-risk area can access it through their computer and tablet. They can look at the map and make a decision like 'today, we're going to increase our patrol'." (Aldric, 45 yo., head of "burglaries" department (local direction), judicial police 3, case F)

Less commonly, organizational algorithms even integrate a mechanism directly into the interface to override recommendations or modify results through manual input. It is not just about choosing to consider or disregard the results but rather the ability to supplement the tool with expert intuition. We particularly found this option for ship inspectors and judicial police operators.

> "If the system indicates a high-risk area, the evaluator can decide not to consider it. But if they are convinced that there is a risk of burglary in an area [not identified by the system], they can click a button: 'Yes, I see a risk here'." (Aldric, 45 yo., head of "burglaries" department (local direction), judicial police 3, case F)

Organizational algorithms appear to particularly satisfy both users and initiators when they complement existing practices. In this setup, the quality of results matters less than confirming intuitions or approving choices. The interest given to algorithmic results seems to always be met with some reservation. In other words, an organizational algorithm is not blindly "followed", as Rodolphe emphasizes:

> "Look at the HR guy from Mexico, he has 50 talents. If one day he takes out his list, he can jot down on a notepad, 'Hey, I should review Pablo Fernandez, I heard he's at risk of leaving. That's not silly. I'll grab a coffee with him to see if he's happy"'. (Rodolphe, 65 yo., career manager, large corporation, case C)

Lastly, we may mention cases where the actual use of the organizational algorithm cannot match the envisioned use, due to a lack of available data. For instance, the interest in predictive policing tools has diminished since the decline, after 2015, of the number of burglaries in Europe; the number of burglaries in a given area has become too low to allow for any statistical significance (Gerstner 2018). The relativization of the algorithm's utility is also evident in case C; since the tool is ideally used by human resources managers of often small-sized local subsidiaries, the number of executives is too low for the generated lists to lead to surprises, as Flore recalls:

> "These local HR people, they might have one or two each. It doesn't mean it's not super valuable information, but local HR have 90% non-talents, negotiations with social partners, etc., that's their daily grind. Talent management is very important for them, but it's once a year." (Flore, 40 yo., human resources manager, large corporation, case C)

User Selection

We have observed that users of organizational algorithms in our case studies seems to have the choice of mobilizing them or not, and then the choice of considering their results or not. This second dimension of choice is corroborated by other statements from our interviewees explaining what organizational algorithms bring to them. Firstly, we note that in our six case studies, users benefit from information that complements other decision-making aids. Specifically, algorithms help users better assess a situation rather than prescribing an action: which employees are most likely to be talents, which areas are more prone to burglaries than others, which individuals are at higher risk than others?

> "*Risiko* simply helps me prioritize cases, to see where I focus my energy. *Risiko* won't tell me, 'now, do this, that, and the other'." (Agnes, 40 yo., psychologist, private research institute, case B)

Users seem to appreciate the algorithms' ability to consider historical data over several years, which is more challenging for a ship inspector or a police analyst. In case E (*Nef*), the algorithm's function itself is legally limited to supporting the assessment of the situation, as explained by Maud:

> "I had written [in the decree] that these targeted visits were triggered by a targeting mechanism. And then everyone told me 'no, it shouldn't be stated like that' (...) If we say that the inspection is triggered by the targeting mechanism, there is a procedural flaw: it means that the system *has to* trigger the inspection." (Maud, 30 yo., legal counsel, maritime affairs, case E)

Diversifying sources of information. As a result, users regularly emphasize the various sources of information that help them make choices and decisions, in addition to organizational algorithms. Users are aware that algorithms cannot be omniscient about a situation and consider exclusive trust in their results problematic. Thus, the algorithm appears to hold as much significance as knowledge of the field and users' intuition. Interviews show that organizational algorithms may be part of a strategy to diversify sources of information to make better choices – these sources can be those described previously or other decision-support tools. The term "tool" is particularly appropriate here. Users benefit from the properties of multiple tools, according to their needs and situations (as recommended by Paul, designer of *Risiko*);

> "We call it a tool, but it doesn't replace their evaluation in any way. That's very important to us. And when two tools are available, it's actually quite good to use them." (Paul, 50 yo., founder, private research institute, case B)

Additionally, we observe that organizational algorithms are highly valued when they broaden the spectrum of knowledge, providing users with unknown information or a different perspective. This is evident in the case of social workers using *Risiko* to form an opinion on a case of violence, or when the algorithms confirm an intuition or initial choice made by the users. For instance, the list of ships to be inspected suggested by *Nef* should not surprise inspectors:

> "Providing me with a prioritized list of ships to visit is convenient. However, this list still needs to be consistent with our initial assessment of a vessel's criticality. If *Nef* is the supreme intelligence, we will defer to the supreme intelligence because maybe we are too foolish and cannot see the truth right in front of us." (Kilian, 50 yo., regional administrator, maritime affairs, case E)

Intelligibility of algorithms. For initiators, organizational algorithms, when they lack a prescriptive function, pose no threats to either themselves or the users. The primary reason cited is their intelligibility. As we have just discussed, the results most often reflect situations and phenomena in a manner familiar to users. This is the case with *Risiko*, designed according to the principles of "risk management" and patterns of violence. The results are also accompanied by explanations, benefiting both the initiators, who can more easily evaluate them, and the users. Finally, initiators like Tomi appear to rely on the fact that the more widespread the use of the algorithm, the more it is perceived for its true value, namely, as a tool for assistance:

> "If we also share it more broadly, I think people will see that the system isn't a black box. We'll tweak it a bit to suit our needs, and it'll be what it was originally meant to be; just another modest tool. A tool that's not overhyped, but not demonized either." (Tomi, NC, head of department, judicial police 2, case F)

When the model is not interpretable, the unintelligibility of organizational algorithms is also a reason why their threat is dismissed. Firstly, this type of algorithm, which relies on machine learning models does not seek to identify causal effects between certain values and the phenomenon under study – for example, between the configuration of a ship and the risk of receiving prescriptions during the next inspection:

> "When you're doing econometrics, you try to say 'this variable influences this characteristic in such a way'. With machine learning, you don't really care about that. What you want is just to predict your model well." (Hugo, 25 yo., data scientist, maritime affairs, case E)

Subsequently, if the decisions are not justified, users seem to have less confidence in the results and may, since they have the option, choose not to use the algorithm. This is precisely what occurs in case D, where the lack of transparency in the tool predicting the number of required delivery personnel prompts operators to make their own calculations on a spreadsheet:

> "If the number is 100% accurate or 99% accurate, but the user doesn't have an explanation of where it comes from, it's very likely that they will reject the number. Almost no one trusts the figures in the forecasting tool simply because there is no explanation." (Victor, 30 yo., product manager, food delivery platform, case D)

The situation recalls the work of Rouvroy (2013), who argues that the inability to articulate choices and justify decisions disconnects algorithms from the real world. The author's conclusions view this disconnection with concern. Our work, however, invites a more optimistic approach; users who can decide whether or not to deploy algorithms seem to turn this disconnection to their advantage, thereby increasing their choice capacity.

Our study shows that fears of being replaced affect only a small number of users. Their expertise is far from obsolete; on the contrary, to say so reveals a misunderstanding of what expertise entails; it is not merely the possession of certain knowledge and skills, but the ability to construct knowledge through various sources. We confirmed this by consistently finding a panel composed of tools, data, documents, and experience. In some cases (such as the food delivery platform), the organizational algorithm is even abandoned in favor of a more personal and informal method. In summary, an organizational algorithm only stands a chance when it complements other tools.

Defining Objectives and Their Evaluation

In this section, we first aim to establish a connection between the various objectives that initiators, engineers, and users might seek to achieve with organizational algorithms. We then illustrate how these objectives are evaluated, i) by employing scientific methods and ii) by collecting user feedback. We observe that in both cases, evaluation poses a significant challenge for both initiators and engineers (Figure 2).

Practical Objectives for General Goals

Objectives of initiators and users. Beyond the goals assigned to the organizational algorithm itself, such as accurately predicting a burglary, being utilized by inspectors, or aiding social workers in their duties, initiators have also articulated project objectives. Those are noteworthy as they reveal broader ambitions. Initiators design algorithms to achieve more general goals, such as economic and managerial objectives, or strategic purposes.

We encountered pragmatic project initiators, like Constantin, who set forth practical objectives:

> "The ideal scenario would be that during the start-of-shift briefings in the offices, they simply say: 'We

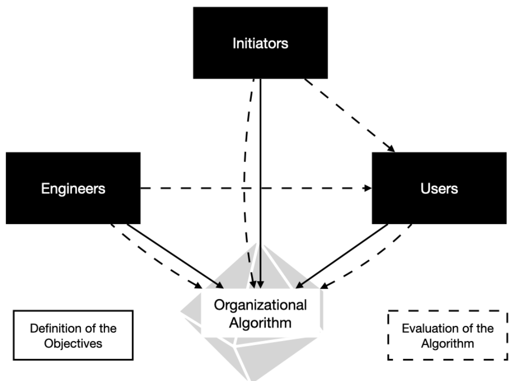

Figure 2: A schematic view of section "Defining objectives and their evaluation".

have two risk areas right now, and car A will go to one and car B will go to the other'." (Constantin, 50 yo., head of "research" department, judicial police 3, case F)

Like the initiators, users have managerial objectives (for example, having the algorithm provide an additional source of information). However, they also have goals specific to their activities. If these are met, the algorithm's results are considered good; it can be used. In the case of *Nef*, the goals include improving daily ship targeting as well as utilizing the tool to develop a targeting strategy at the regional management level. The objectives of users sometimes diverge from those of the initiators. On one hand, users may desire a tool they consider reliable, while initiators simply wish for the algorithm to be utilized. On the other hand, while initiators aim to deploy a tool to change the production process and emphasize economic imperatives, users may still be attached to old work habits and production evaluation methods, as would be the case with journalists:

> "Some journalists feel that if they don't have a very large audience, it's not as good. But what we want is to get as many subscribers as possible, and for these people to read as many articles as possible. There's a kind of conflict." (Anthony, NC, web editor, media, case A)

Objectives of engineers. The engineers we encountered primarily focus on two objectives: the ability to improve the model and to evaluate it statistically. This indicates that their activities are initially directed towards the quality of the prediction, before considering how it can be useful for the initiators and users. This stance is generally upheld by engineers who themselves highlight the discrepancy between how the model is programmed and the consideration of "real world" issues – for example, in the case of *Nef*, the criteria that seem most important to inspectors for targeting ships:

> "At first, they had an accident rate score that wasn't defined very rigorously, it was impossible to know if it was good or not since we didn't have criteria to evaluate it. (...) I based myself on 'does it improve the model or not', but I could have also asked the inspectors for their opinion." (Hugo, 25 yo., data scientist, maritime affairs, case E)

We observe efforts by engineers to translate the general objectives from initiators into scientific goals suitable for the development of organizational algorithms. Similarly, this occurs at the programming level and at a more strategic level, where engineers advocate for a more scientific approach. The case of *Nef* is particularly noteworthy because, despite the development of a new score that aligns more with the engineer's criteria, the old score was not abandoned as it serves the users (the inspectors); some of them believe that the new score is an insufficiently rigorous translation of their ship targeting needs.

A Conducted but Not Always Followed Evaluation

Scientific proof as a method of evaluation. Scientific evaluation allows the designers to verify and demonstrate the utility of the deployed organizational algorithms. However, only two of the six cases studied reveal an approach to scientific evaluation. In case B, the initiators support independent research that aims to evaluate the validity of the tool's results or its acceptance by users. Among the three judicial police departments, one conducted a project with a public research institute (Gerstner 2018) while another developed an internal protocol. It is interesting to note that the scientific evaluation corroborates a rational approach to resource allocation; the algorithm might be sound in itself, but if it does not provide (or no longer provides, in the case of predictive policing) significant aid relative to the financial investment, the initiators prefer other projects:

> "Based on scientific results, we can conclude that in some areas, implementing the predictive policing tool helps reduce the number of burglaries. (...) Currently, we believe we have other problems where we can achieve better results." (Julian, 35 yo., head of "analysis systems" department, judicial police 1, case F)

Collecting user feedback. Unlike the scientific evaluation reported in only two cases, the evaluation through user feedback appears to have been conducted for all six organizational algorithms. We note among the initiators an absence of hierarchy between the two methods, with the latter being used to assess reception, usage, and satisfaction of the algorithms, as well as to evaluate the quality of results. Except for case D (the food delivery platform) where evaluation is an integral part of the decision-making process, it typically occurs during a test phase with a more or less defined protocol. Interviews with our subjects reveal the informal nature of user-based evaluation; they did not report elements indicating a need for systematization. On the contrary, we align with the observation of Kluttz and Mulligan (2019) on the lack of standards and methods of evaluation both before and during the deployment of an organizational algorithm. With the exception of one of the judicial police departments, the only indicators that seem to have significant weight are the validation of results by users and/or their satisfaction. Cases C (the large corporation) and E (the maritime affairs department) are illustrative in this respect. In case C, the algorithm was evaluated during test phases. Lists of "overlooked talents" generated by the tool were sent to the human resources managers of subsidiaries who would then potentially forward them to local managers:

> "I regularly received lists from Rodolphe saying 'this person that the algorithm has identified as a potential talent, we confirm or not?"' (Flore, 40 yo., human resources manager, large corporation, case C)

The evaluation reports a moderate quality: according to user feedback, half of the managers identified by the algorithm were "overlooked talents". The other half of the list was not relevant. It is noteworthy that user evaluations also help to understand some results of the organizational algorithm – as in the case of the algorithm for detecting the risk of resignation:

> "It caught our attention when we realized that the departure probability for someone who hadn't received a raise was slightly lower than for someone who had received a very small raise. HR then explained to us that there is often a reason for not giving a raise, whereas for very small raises, maybe the person is just disappointing." (Lorenzo, 45 yo., data scientist, large corporation, case C)

The tests were conducted in a similar manner in the case of *Nef*. The design team asked the inspectors to provide feedback on the list generated by the algorithm, accompanied by a comment. It might seem surprising that users did not take advantage of this opportunity to provide feedback – especially since they seem to have a clear idea of what the list should look like; it should align with their knowledge of the ships:

> "Personally, I didn't spend much time on the *Nef* test; I opened it and tried to find ships that are in our scope." (Richard, 30 yo., inspector, maritime affairs, case E)

Initiators and users seem to agree that an organizational algorithm with satisfying results (which are valid according to the users) is more useful than an algorithm with valid results (according to engineers) but which fail to convince the users. This leads us to introduce the notion of satisfaction, which we will explore further below. Evaluating satisfaction can take several forms, but the most common seems to be the questionnaire through which users can express their opinions about the organizational algorithm.

A challenging implementation of evaluation and its results. One reason why user satisfaction is so paramount seems to lie in the difficulty that design actors (initiators and engineers) have in comprehensively evaluating organizational algorithms. In case C, for example, how can one assess the impact of losing a talent for the business (or other indicators)? In predictive policing (case F), the very activity of deterring burglaries is unassessable; how can one determine the causes of a burglary that did not occur?:

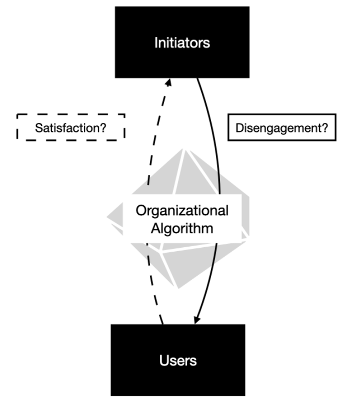

Figure 3: A schematic view of section "User satisfaction as the key to disengagement".

> "I calculate a probability, then send colleagues to the location. They might just deter the burglaries or spot suspicious activities, etc. If no burglary occurs, there are two possibilities: either the measures were incredibly effective, meaning the perpetrators were deterred, or the system is simply bad and predicted the wrong location." (Tomi, NC, head of department, judicial police 2, case F)

In their paper, Kluttz and Mulligan (2019) argue that in addition to being subject to higher quality evaluation, decision support tools must be interpretable and configurable. We prefer the reverse formulation; the use of tools primarily depends on user satisfaction, which involves the ability to grasp, interpret (understand), and configure them (either directly via the interface or by being in contact with the design actors). Studies that cover both statistical validity and user acceptance are still rare. Among our six cases, only one judicial police department has initiated such a research effort. In other cases, the evaluation of validity is disconnected from that of acceptance, reinforcing the divide between initiators, engineers, and users. In the rational game of prioritization, it is the evaluation of satisfaction that unites initiators and users:

> "[State X] did not conduct an impact assessment and placed more importance on the satisfaction of the police officers. We focused more on the effects. All the judicial police we spoke with noticed that the tools seem to have some effect, but it's hard to say exactly what." (Julian, 35 yo., head of "analysis systems" department, judicial police 1, case F)

User Satisfaction as the Key to Disengagement

In this final section, we delve deeper into the analysis of evaluation by satisfaction and then present how initiators disengage on users through recommendation algorithms (Figure 3). We conclude with the preferences of actors regarding algorithms with descriptive, predictive, or prescriptive functions.

Evaluation by Satisfaction

Let us revisit the conundrum discussed in the previous pages; why deploy or retain an algorithm whose effectiveness is questioned by various actors, primarily the users? We now understand that the first element of the answer lies in the differing interpretations of what constitutes effectiveness, as seen from the engineers' perspective (the validity of the model) and from the users' (the utility). Our findings corroborate the work of Benbouzid (2019), who wrote about *PredPol* stating that:

> "the statistical reality of the tool does not matter much – which is why, incidentally, the effectiveness of the *PredPol* algorithm has not been overseen by independent organizations" (Benbouzid 2016).

What matters is what can be done with the algorithm – its utility – and how it meets user expectations – the maximization of their satisfaction:

> "for a district manager, *PredPol* appears as a good tool to ensure that officers are indeed performing their preventive duties (...) The challenge of predictive policing is to manage, according to managerial criteria, the public offer of daily vigilance" (Benbouzid 2016).

A drive to satisfy users. Initiators evaluate organizational algorithms through the lenses of return on investment and user satisfaction. If the investment is profitable in any way, initiators are satisfied and willingly keep the algorithm in production for the simple reason that its use is not counterproductive. Again, they prefer the acceptance of the algorithm and its action-triggering capacity – the ability to initiate actions based on a quantitative basis – over the scientific validity of that same quantitative basis:

> "I could imagine that even scientists might wonder if we really have significance here. [But] the tool hasn't required much effort from us. We're pretty sure we're now directing patrols in a more sensible way than before." (Tomi, NC, head of department, judicial police 2, case F)

The satisfaction of initiators also depends on the satisfaction of users. This connection, though seemingly mundane, is significant as it is the only link that appears to bind the interests of both parties. Interviews show that despite ambitious goals, the expectations of initiators are confined to the utility of the algorithm for users and their satisfaction. To enhance this satisfaction, efforts are primarily focused on improving the intelligibility of the tools, whether through the interface and visual aids or by enabling the algorithm to evolve to produce clearer results:

> "I don't know how much the inspectors were worried about the fact that we initially had an algorithm that was hard to evaluate. In any case, when Hugo presented them with the alternative, it suited them, and they understood how this new algorithm worked." (Alex, 30 yo., developer, maritime affairs, case E)

User interest. For users, an organizational algorithm is satisfactory when its results align with their expertise and confirm what they know about the situation:

> "I know scientists don't really like it, but there's this notion of a comprehensive professional judgment of the ship that's very important." (Brice, NC, center manager, maritime affairs, case E)

In other words, an algorithm whose results are unexpected will hardly be positively surprising to users; it will be questioned, criticized, and most importantly, it may not be used. An organizational algorithm stands a good chance of being adopted by users if it supports and confirms their intuitions. This means that even if the system is not directly useful for achieving a general objective but serves the daily needs of the users, it will be appreciated. Conversely, if the utility of the algorithm is unclear, the users may not be satisfied.

> "In reality, *Risiko* raises all the questions that we already ask ourselves in our work anyway. Because we know that these aren't new risk factors. What we appreciate about *Risiko* is that it also looks at cases from a different perspective." (Angelina, NC, legal counsel, public social center, case B)

Beyond confirming users' intuitions, organizational algorithms are perceived as satisfactory when their role extends beyond aiding everyday decision-making. Particularly, several of our respondents highlighted the importance of the risk assurance role of organizational algorithms, which allows them to both bolster their intuitions with qualitative arguments and demonstrate that some situations are riskier than others – an insight that is then utilized by people other than the users. All three social workers from the center for the protection of domestic violence victims mentioned this aspect during the interview:

> "Throughout our collaboration, the courts have realized that our requests are very well-founded, not impulsive decisions, but supported by a solid basis. And that's where *Risiko* is a wonderful argument. (...) The police or the public prosecutor's office intervene very differently when we have something solid in the background." (Veronika, 50 yo., social worker (manager), public social center, case B)

Disengagement From Decision-Makers

The literature on automation and the deployment of decision-support algorithms, as discussed in this paper, often mentions the fear that users might offload their responsibilities as experts and decision-makers onto algorithms (Jarrahi 2018; Firlej and Taeihagh 2021; de Fine Licht and de Fine Licht 2020). Our survey shows that this is not always the case. Our respondents emphasize the importance of "human" responsibility and condemn practices where the decision, especially when its implications are significant (such as a resignation in case C), is relinquished to a tool:

> "'I commit to a decision at some point', and it's not just the machine that made the decision. If things go wrong and we can blame the machine, then there's no responsibility left in the organization at all." (Flore, 40 yo., human resources manager, large corporation, case C)

A disengagement chain. Our main finding is undoubtedly that organizational algorithms may enable disengagement by initiators and consequently, engagement by users. Our cases show that users often find themselves alone with a tool they did not deploy, they do not always understand, and master. However, through organizational algorithms, initiators have individually tasked them with making choices that were previously decided collectively (in case E), by hierarchical superiors (in cases C, D, and F), or even by the initiators themselves (in case A). We could say that under the guise of offering decision support, initiators shift (intentionally or unintentionally) the decision-making burden onto users. Furthermore, the analysis of interviews allows us to account for a disengagement chain that echoes the work of O'Malley and Hutchinson (2007). According to them, crime prevention techniques reveal the deployment of a liberal governance in the police. Shedding light on the disengagement chain can also be analyzed through this lens: algorithms enable traditionally decision-making individuals to offload responsibilities onto those closest to the field, the users. In case F (judicial police), predictive policing tools notably allow central police forces (equivalent to police stations or central precincts) to engage patrol officers:

> "Our hope was indeed that the information would come from headquarters; it's certainly more engaging when it comes from a colleague who knows their stuff. Unfortunately, this rarely happened. They always relied on the tablet displaying everything." (Constantin, 50 years old, head of "research" department, judicial police 3, case F)

Exceptionally, the disengagement chain can extend beyond the initiator-user couple, as is the case at the maritime affairs (case E). Here too, we confirm the statements of O'Malley and Hutchinson (2007); the deployment of organizational algorithms reflects a well-known State desire to disengage from a portion of its support and protection activities to refocus on its sovereign activities. In a sense, *Nef* betrays both the administrative objectives of reducing staff numbers and those of empowering shipowners – one not necessarily being the consequence of the other. On one hand, inspectors, who are fewer in number, are given additional missions. On the other hand, shipowners are subjected to less scrutiny regarding the safety of their vessels; it is up to them to ensure that their vessels is in good condition:

> "The trust agreement [with shipowners] will rely on this declaration obligation. 'Today, you declare haphazardly, because we know we'll see you every year. Tomorrow, the primary guarantor of compliance and monitoring of regulatory changes and your vessel will be you, gentlemen.'" (Florent, 45 yo., deputy office manager, maritime affairs, case E)

User resistance. The disengagement chain sometimes exists only in theory. Users may not be concerned about their work being replaced by machines but rather about the increased responsibility and the amount of decision-making compared to their role. While users generally perceive empowerment positively, they believe that the tasks assigned are not part of their job. Interviews with journalists from case A are particularly revealing in this regard. For the initiators of the journalistic production tracking tool, it serves to connect economic imperatives with editorial work. In other words, we could say that the newspaper's management is disengaging and seeking to offload some of their decision-making responsibilities onto journalists. As mentioned, journalists acknowledge the value of connecting economic and editorial goals. However, it is also evident to them that it is not their responsibility to assign objectives to each of their articles, either because they do not consider themselves competent to do so or because their job specifically entails the production (rather than the monetization) of journalistic content:

> "I told the editor-in-chief, I don't get involved. Not because I'm against it, but simply because I think it's logical for the editor-in-chief or the site manager to make that decision." (Gregory, 50 yo., section editor, media, case A)

The same logic is found in case D, where the operations managers' duties do not include forecasting the number of delivery personnel; in case E, where inspectors would prefer their duties to be limited to conducting ship inspections; and in case F, where the duties of police officers are to patrol rather than decide which areas to patrol. In summary, users are trying to resist – and sometimes succeed – in the disengagement by initiators. Users prefer that initiators take on the responsibility of decision-makers and provide clear directions rather than finding themselves in situations where they must understand what the algorithm can offer them and how to use it. From their perspective, an organizational algorithm should ideally limit the discretionary nature of their decisions, as Kilian points out:

> "The targeting will not be done by the inspectors. It won't be 'I decided to do this one', otherwise, it doesn't make sense anymore. If we want to use *Nef* (...) we must disregard everyone's individual judgment." (Kilian, 50 yo., regional administrator, maritime affairs, case E)

A preference for description over prediction. The concept of disengagement may be one of the keys to understanding the common interest of initiators and users in organizational algorithms with a descriptive function. One might imagine that predictive and prescriptive algorithms would be favored and even deployed despite user reluctance. However, we observe that despite the ambitions of initiators and the desires of engineers, organizational algorithms maintain a primarily descriptive function: they are understandable by engineers and interpretable by users. Consequently, the results are not extraordinary, and as we have seen, they mostly validate users' intuitions or knowledge. In case C, the project initiator, Rodolphe, expresses being "disappointed" with the main variable determining the prediction and would have hoped for the inclusion of less obvious variables in his view:

> "So, the algorithm disappoints me a bit because in predicting the risk of departure, it mainly focuses on 'did this person have their salary reviewed this year'."

(Rodolphe, 65 yo., career manager, large corporation, case C)

Furthermore, we observe that the prescriptive and predictive functions of tools have been neglected in favor of descriptive functions. This might be a significant finding for research in the field, as organizational algorithms are often criticized for their potential contribution to reinforcing certain phenomena – which, for example, could be the cause of discrimination. In the case of predictive policing, officers still rely heavily on maps that provide a snapshot of the current situation (hotspot policing) and overlook predictions that they sometimes cannot comprehend. In this scenario, it is challenging to blame a blind algorithm based on sociodemographic data (it only knows the history of burglaries):

> "Minds needed to change: transitioning from hotspot policing to predictive policing. For many police officers, it was difficult to accept that there might be risk areas where nothing has happened yet." (Constantin, 50 yo., head of "research" department, judicial police 3, case F)

In the majority of our cases, algorithms ultimately serve a descriptive function, even if the initial project goal was prediction or prescription. When they fail to design intelligible and satisfactory tools for users, initiators prefer to deploy algorithms with a descriptive function rather than unused tools. This latter situation may pose a high risk for initiators, as it could compromise the disengagement chain and thereby either limit user accountability (initiators must continue to make decisions, as evident in case D) or increase user autonomy (under the guise of a tool, they do as they please, as seen in case E).

Discussion

This study underscores the important role of user engagement. For an organizational algorithm to be effective, it must earn users' trust and acknowledge their expertise. In this regard, an organizational algorithm does not have sole decision-making authority and thus does not inherently pose a threat to users. Instead, it offers a valuable addition to the information available to users, similar to recommendation algorithms in music streaming. Consequently, the choice to adopt an organizational algorithm and the manner in which it is implemented ultimately lies with the users. Additionally, we note a tendency towards disengagement initiated or represented by initiators, particularly evident in the evaluation of organizational algorithms. Initiators and engineers mainly aim to gauge users' practical satisfaction.

In this context, system auditing, often recommended for evaluating and monitoring algorithms, appears to be inadequate. There is a noticeable gap between the intentions of the initiators, focused on prediction techniques, and the actual implementation – primarily descriptive techniques. Auditing should thus focus on the underlying principles of the algorithms, which can be particularly insightful in cases such as B (*Risiko*) and F (judicial police). Moreover, if the main contribution of an organizational algorithm is descriptive, it raises questions about why the initiators remain so insistent, especially in the face of limited user satisfaction.

Are they influenced by the inherent nature of algorithmization? We suggest that deploying an organizational algorithm serves as a practical way to avoid prescriptive decision-making. For initiators, if predictive methods prove ineffective, it may be more pragmatic to describe the situation – using the users' existing categories – rather than prescribing specific choices, which could imply a need for greater engagement or re-engagement.

Future Work

Despite the extensive number of interviews conducted (and case studies) that offer a comprehensive insight into the inner workings of organizational algorithms, the study may exhibit a lack of consistency. To address the potential contingency of the presented results, we invite other scholars to replicate similar studies across different cases, particularly in diverse cultural contexts and over regular intervals. To facilitate this, we propose three avenues for future research. We suggest scholars to delve more deeply into the goals of initiators, particularly the theories upon which algorithms are based, as exemplified perfectly by the case of predictive policing: without the "near-repeat" principle (Townsley, Homel, and Chaseling 2003), the tool as it is designed would not exist. Then, we call for collaborations with researchers in computer science and psychology to study, in a tri-disciplinary approach, the intentions of initiators, the selection and evaluation of the model by engineers, and the users' acceptability of algorithms. Finally, we recommend to assert the socio-philosophical approach, by studying in situ how actors instantiate their respective ethics – for example, the computer ethics of engineers and the public service ethics of users – and how these ethics come into tension.

Last but not least, we encourage initiators and engineers to shift their focus towards transparency and explainability concerning their intentions, evaluation methods, and indicators of satisfaction and success.

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