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Technological Transparency in the Workplace: Black Box Algorithmic Culture in the Warehousing Industry

Abstract: Algorithms in information technology influence changes in contemporary organizations. They monitor business processes, support decision-making, and help to increase efficiency. The literature has described extensively the applications of algorithmic technology in new models of organizations but few studies have addressed the relationship between algorithms and organizational culture. This paper fills that niche by concentrating on black boxing to address the technological transparency in the algorithmic workplace. This paper uses the case study of the Amazon POZ 1 warehouse near Poznań, Poland. The findings show that algorithmic culture has a profound effect on how employees interact, how they see themselves at work, and how they perform their job responsibilities. As we show, algorithmic transparency influences not only employees' worklife but also the general positionality of the workforce in the wider political economy. We conclude by arguing in favor of greater algorithmic regulation.

Keywords: workplace, Amazon, algorithm, warehouse, transparency, black box

Introduction

Nearly all professions use information technology in the workplace, changing the way we work and reshaping organizations. In recent decades, this technological shift has moved towards the adoption of workplace technologies, based on the usage of software and hardware, relying on advanced methods of data analysis. These methods, often falling under the umbrella of artificial intelligence, comprise a variety of procedures of algorithmic computation, including big data analysis, the Internet of Things, industry 4.0, and the integration and monitoring of numerous aspects of organizations, such as employees, vehicles, products and inventory (Acciarini et al. 2023; Tseng et al. 2023; Clarysse et al. 2022; Gupta et al. 2022; Adensamer et al. 2021). While timing has played a central role in managerial innovations since Taylorism, algorithmic technology has reduced the time spent on decision-making made by workers, managers, and employers. Contemporary algorithms are ubiquitous in the workplace, and their impact extends beyond simply automating tasks (Mahmud et al 2022; Willems & Hafermalz 2021). They are designed not only to optimize certain metrics or objectives, but also to influence how decisions are made, expediting those decisions and supporting real-time analysis of data from a variety of sources.

In addition, algorithms influence the behavior and attitudes that shape organizational culture.

This article describes an Amazon warehouse, where algorithmic computations support who gets hired, promoted or terminated; how daily work is done, and how resources are allocated (Langer & Landers 2021; Zanoni & Miszczyński 2023). These computations are linked to customer orders placed on e-commerce websites and inventory lists in hundreds of the company's warehouses. The implementation of algorithmic technology is based on millions of processes, all orchestrated and linked in a complex analytical orchestra (Polzer 2022). In this paper we show how algorithmic decisions go beyond workplace control, deeply influencing the social fabric of the warehouse workforce and generating a specific algorithmic workplace culture. Technology is used to manage inventory and to establish benchmarks for productivity and quality, but it also shapes employers' position in the workplace through quantified norms, rules, customs, and manners that govern the behavior and actions of employees. However, adding to the extensive list of ethical issues surrounding artificial intelligence (McDaid et al. 2023), this can have unintended consequences, which stem here from the lack of technological transparency.

The Amazon warehouse studied here is located in Poznań (POZ1), Poland. Computer technology is used to monitor its inventory and control the work of its employees (own reference). In this case, algorithmic technology relies on live computation based on recursive and persistent analysis of employee's actions, and their consequences and correlations with customer orders, deliveries, and shelving of items (de Assis Vilela et al. 2023). In the traditional, non-algorithmic, warehouse model of work, items were either sorted by numbers or categories which workers typically followed to recover different items. Algorithmic technology permitted the implementation of new computer-based heuristics where workers stow items in a random order (tracking them with technology) and other workers retrieve them, using computer availability (Hatton 2017; Danaher 2016). Additionally the system produces new processes relevant to time and efficiency of work of employees—and as a consequence rates their performance.

This paper theorizes the model of algorithmic culture and provides a view into the organizational dynamics shaped by the algorithmically fostered model of management. It is based on employee accounts and outlines the perspective of workplace participants, who are socialized to and interact with the technology. In our analysis we treat warehousing algorithms as computer programs that make decisions or recommendations for tasks such as hiring, performance evaluation, promotion, compensation, and termination. These algorithms can have significant impacts on the lives and careers of workers, but they are often opaque and inaccessible to the people affected by them. This is the premise of the black box theory: complex systems or processes are hidden from view and difficult to understand or explain (Christin 2020). Black box theory poses several challenges for workplace algorithms (Langer & König 2023; Lorente 2023; Bujold et al. 2022; Shin & Park 2019). For example, workers may wonder if the algorithms are fair, accurate, and unbiased, and whether they should trust them. Workers may also struggle to challenge or appeal the algorithmic outcomes if they disagree with them or suspect errors. Workers may find it hard to learn from the algorithms and improve their skills or performance. Workers may feel powerless and vulnerable in relation to the algorithms and their rights and interests may be compromised. These challenges highlight the rationale behind our analysis: addressing transparency, accountability, and participation in the design and use of workplace algorithms. In our theoretical description of this model of workplace culture, we concentrate on transparency, stemming from the nature and construction of algorithms. We show its consequences by outlining the threefold aspects of algorithmic transparency: its relationship to the labor process, especially in the domain of control, where workers predict and speculate about algorithmic measures; its relationship to privacy at work—generating algorithmic awareness; and finally, acceptance of hidden rules and implicit subordination to those rules. We conclude by incorporating these findings into the wider discussion on the political economy of workplace technology and its regulation.

Algorithmic Culture and Technological Transparency

In a workplace that relies on algorithms, human relationships are shaped by the technology and systems used to manage and control work processes. The usage of algorithms can create new forms of social interaction and power dynamics among employees, managers, and the technology itself. On the one hand, algorithms can provide structure and guidance for decision-making, leading to increased efficiency and productivity (Bader and Kaiser 2019; Hall, Horton, & Knoepfle 2019; Lix et al. 2019; Halavais 2018; Liu, Brynjolfsson, & Dowlatabadi 2018; Puranam 2018; Jharver et al. 2018; Leonardi & Contractor 2018; Davis 2016; Davis 2015; Levy 2015: 164). On the other hand, there are challenges in how algorithms affect human relationships (Schwartz 2018; Shestakofsky 2017; Gray et al. 2016). For example, algorithms may be biased or reinforce inequalities, leading to preferential treatment of some employees (Beunza 2019; Rosenblat et al. 2017; Rosenblat & Stark 2016). Additionally, the usage of algorithms can lead to a sense of surveillance and mistrust among employees (Anteby & Chan 2018; Eubanks 2018; Levy & Barocas 2018; Noble 2018; Davidson 2016; O'Neil 2016), creating a toxic workplace culture (Beunza 2019; Wood et al. 2019; Lebovitz, Lifshitz-Assaf, & Levina 2019; Danaher 2016). There is also the concern that the use of algorithms can dehumanize work processes, reducing the importance of interpersonal relationships and making work less fulfilling (Beane 2019; Graham et al. 2017; Shestakofsky 2017). Thus, it is crucial to consider organizations from the perspective of the role of algorithms and, consequently, organizations are finding it increasingly necessary to implement policies and practices that promote fairness, transparency, and collaboration among employees (Lix et al. 2019; Mitchell et al. 2019; Zhou, Valentine, & Bernstein 2018; Gebru et al. 2017; Scholz 2016).

We understand the algorithmic workplace culture as the management and control of various aspects of work in an organization based on algorithms. In this situation, decisions are the result of algorithmic calculations with possible human participation in this process. In practice, organizations most often rely on algorithms to manage the work process to improve operations, increase efficiency, and reduce costs (Puranam 2018; Davidson 2016), meaning that the main emphasis is placed on work efficiency and productivity. However, there are concerns about the potential for algorithms to reinforce biases or perpetuate inequalities (Angwin, Larson, Mattu, & Kirchner 2016; O'Neil 2016), as well as the impact on employee autonomy (Griesbach et al. 2019; Wood et al. 2019; Marabelli et al. 2018; Ekbia & Nardi 2017), relationships and job satisfaction (Meisner et al. 2022). As a result, organizations face a technological shift that is grounded in the usage of algorithms in the workplace. The challenge remains to make employers and employees aware of the role of algorithms in shaping their culture, and ensuring that they align with their values and goals (Bader and Kaiser 2019; Bucher 2017).

The literature contains few accounts of how technology is understood by the workforce, its significance to it, and how workers consequently interact with it—given its limited transparency and high level of secrecy. The literature places an important emphasis on work secrecy, but often overlooking its outcome on workplace realities. There is, however, a preliminary agreement that workplace algorithms are impenetrable (Meisner et al. 2022; Rahman 2019; Weld & Bansal 2018; Hatton 2017; Burrell 2016). Moreover, the literature notes that hidden rules of engagement with algorithms prevail in all low-skilled professions (Wood, Graham, Lehdonvirta, & Hjorth 2019). The literature additionally indicates that both workers and middle managers rarely know how to decode algorithms (Danaher 2016), sometimes even leading to doubt or low trust in algorithmic decisions (Lebovitz et al. 2019; Burrell 2016).

Algorithmic computation at work can contribute to bias in several ways. First, the information technology literature notes that algorithms are only as good as the data they are trained on, and if the training data is biased, the algorithms will be biased as well (Cunha & Carugati 2018; Brayne 2017; Barocas & Selbst 2016; Angwin et al. 2016; O'Neil 2016). For example, if an algorithm is trained on data that is predominantly from one gender, racial, or age group, it may be inherently biased against other groups. This can lead to discrimination against workers who belong to underrepresented groups (Angwin et al. 2016; O'Neil 2016). Additionally, even if the training data is not biased, the way that algorithms are used can contribute to bias. For example, if an algorithm is used to make decisions about promotions or pay raises, and the algorithm is not designed to take into account factors such as diversity and inclusion, it may place workers who belong to underrepresented groups at an unfair disadvantage. Furthermore, even if an algorithm is designed to be fair, it can still be misused if the people using it are themselves biased.

This discussion leads us to the consideration about the work culture that algorithms foster. In our study we rely on the stream of the literature that considers algorithms as "black boxes": devices that can be only understood in terms of their inputs and outputs, without any knowledge of their internal workings (Mols 2017). The black box approach stems from the fact that users of algorithms find them profoundly opaque and impenetrable, for instance in assigning tasks or processing their user data in unknown ways and in unknown datasets (Rosenblat 2018; Ticona & Mateescu 2018; Rosenblat & Stark 2016). As stated by Burrell, algorithms are opaque for the following reasons: (1) data and codes are kept secret by companies or administrations that guard them as valuable intellectual property; (2) they consist of code written in programming languages that only some people understand; (3) they evolve over time in the ways that are usually incomprehensible to humans and due to the sheer size of most algorithmic systems (2016). Users also develop their own representations and models for how these complex systems operate, thus relying on "algorithmic imaginaries" that shape how they interact with algorithms (Bucher 2017;

Baym 2018). As a result of these interactions, systems are reconfigured as people position themselves in relation to algorithms and try to register them with their institutionalized ways of doing things.

So far, the transparency of algorithmic technology has mainly been addressed by scholars considering their role in the reproduction of inequalities. Since algorithms rely in their decisions on historical data (Barocas & Selbst 2016), it often leads to "inequality automation" (Eubanks 2018). The input data needed by algorithms to function is constantly (and often secretly) extracted through multiple channels: from big data analysis of mailboxes, through online and hardware tracking. Many of these sources of data are unknown to their owners. Since 2010, the literature reported technological tracking by the authorities that went along the lines with racial profiling and class discrimination (Browne 2015). The dominant discourse of technological wizardry and algorithmic unintelligibility often points to analyses of social systems, pointing to their role in the reproduction of important social processes such as discrimination, surveillance, and standardization (Christin 2020: 902). The capabilities of algorithmic software are, however, often overestimated, especially its ability to scale flawlessly and hide the degree of involvement of human workers who do some of the work that algorithms are supposed to do (Shestakofsky 2017; Sachs 2019). The surveillance regime is thus part of the cultural and political institutionalization of the current economic model (Terranova 2000; Scholz 2013).

Methodology

This project focuses on the relationship between the use of algorithmic technology in the workplace and its effects on work and employment. The research is based on interpretative principles and consists of an industry case study of Amazon's POZ 1 warehouse near Poznań. The findings of this text are based on the first author's 85 in-depth interviews with workers (in Polish), conducted in 2017. In the interviews we asked questions about how they coped with work enhanced by the algorithmic process, the outcomes of algorithmic control and their adaptation to working with the algorithm over time. The sample of respondents was selected through purposive sampling (Teddlie & Yu 2007). Each interview was fully recorded, transcribed verbatim in Polish and coded using qualitative analysis software. All analyses were conducted using MaxQDA analysis software and qualitative and inductive techniques to recursively code and identify patterns in the data concerning work relationships (Coffey & Atkinson 1996). In the first cycle we inductively read through the data and assigned codes that captured the essence of each segment, concentrating on descriptions of the workplace. In the second cycle, we refined and reorganized codes into broader themes, following the procedure of thematic analysis. In the third cycle, we used narrative analysis to synthesize and interpret the themes and contrasted them across different workers, groups, and contexts. Based on this analysis, we developed a comprehensive and nuanced answer to our research question of how warehouse workers experience algorithmic technology. We identified the main themes and subthemes that captured the diversity and complexity of their experiences. We also discussed the implications and contributions of our findings for theory and practice in our field of study.

Findings

Algorithmic Forecasting

Amazon's organization relies on the Associate Development and Performance Tracker (ADAPT), which controls and organizes workers' tasks. ADAPT's function is to register performance and store data about the workforce. Warehouse workers, however, do not have the access to that system and often struggle to understand its functions. Data fed into the system occurs through workplace activity and while workers fully consent to the usage of technology, quite often they are not fully aware of how they are being monitored and what types of data are being collected about them (Bolin & Schwarz 2015). Below a worker describes his limited knowledge of ADAPT.

> Well, in general, this ADAPT system works in a way that there is a summary of the whole week and gives a current number but it is far from simple. Because, for example, someone is on four different processes during the week, so then it has to check each process separately (…), well there are some tables that show some number, targets and so on and so forth, and this ADAPT is typically for evaluating staff. I think the percentage pops up, to the minimum, to the target but as you see, I don't know much about it. (#19)

The passage describes workers' commonsense understanding of ADAPT, also pointing out the issues of transparency. The workers in this study have extensively commented on its secretive character, especially the unknown methods and criteria of computation, and as a result, of worker performance evaluation.

There were multiple aspects of ADAPT that were commented on by our interviewees. One of the main questions touched upon the ways in which warehouse work is monitored and how this evaluation affects worker assessment. One theme was the issue of item categorization, which according to the workers, was the central criterion of productivity assessment. For instance:

> Some workers don't know that the items that they pick have different weight [in the system]. Let's say half the people don't know that it influences their productivity rating. (#32)

> I don't know how it [worker assessment] works; I never found out. But it's not that every item is the same. Of course, you have a heavy duty drill and it is counted differently from a small plastic cutting board, for example. (#1)

> I see some items in this compartment; I don't know if they are small items or large ones. Only the computer knows, the database actually knows—the system out there on a server in Seattle. Everything is generally in America, yes. (#43)

These passages reflect workers' interpretations of how the assessment works. The informants depict the system as the black box, to which they do not have access, and which organizes their work and is the only and irrevocable criterion.

The same lack of knowledge about the rules spreads to middle management. The informants claimed that their line managers could not explain to them how algorithmic operations and machine learning occur at Amazon, and how, as a result, work was assessed. The common conclusion of these descriptions was that managers also work with the black box, being only given the effects of the computations. For example:

> Managers and leaders themselves are not fully able to say whether the object you are holding is small or large and how it counts toward the norm. But in general, there is a percentage factor that comes out of it later. And the

system can judge that you need to work faster or that it's good. And every week the system is taking the average from the weekly results, and if you get 100% or more, that's good, you met the criteria. (#21)

Lack of knowledge generates a sense of injustice, for instance, visible in situations where workers, while monitored, face issues connected to workplace stopovers independent from technology. As a result, superiors are focused solely on work efficiency, at the expense of empathy for their employees.

It depends on how many workers there are, because sometimes people who deliver the goods to us are late. (…), well, it's hard for them to do it quickly. And, for example, suddenly you have nothing on the table and you wait, let's say 10–15 minutes, half an hour, until someone brings you something, and at this point your numbers fall. So it's like you know the managers and the top know about the delay, but on the other hand they are also constantly pressured for numbers and it puts everybody under stress because the norm is calculated. (#33)

If we can't really find the product, or it's not there, we have to press a button on the scanner that the product is missing. And every single product in that container we need to scan as the proof that that product isn't there. Everything is fine, but if, for example, there is a drawer full of contact lenses that are so, full to the brim, so to scan all the lenses and prove that there is no product, it takes us 15 minutes. And this influences the norm (…). (#62)

In both situations, workers experienced delays that were not their fault—they were either tied to the slowdowns in the warehouse or objects that were missing from the shelves. In both cases, the delays created anxiety caused by the persistent monitoring by the algorithm.

A consequence of similar experiences generates reflections about the rules inside the black box. It is based on an estimation by workers trying to determine how heavy a workload they could handle. As they do not have the access to algorithm and systems that dictate the work processes, they need to rely on their own experience and intuition. The most important question is how much work they could handle within a given time frame to meet the minimum. For example, they estimated how much inventory they needed to pick in a certain amount of time, or how many orders they needed to pack in a day. They often considered factors such as the size and weight of the items or the distance between locations. One worker explained how she confirmed her performance with a line manager, who had access to the system, knowing if she was meeting the expected standard of productivity.

You constantly feel you have to work because you never know what speed you are actually working at. For example, you will go to the so-called pallets, where you have to pick up, say, ten kilos of cat food, ten cans of 1 kilo. (…). And you don't know how it's going to mess up your score in system: look in the tote and see that you have few items. So in situations like that I approach my leader: "How much do I have in ADAPT?" She says, "One hundred and ten." I ask "So… Is that a sacred oracle?" She says, "Yes, that's already a sacred oracle." And this is how I cope with it. (#22)

Another worker described how he tried to learn the rhythm of work so that he always met the system criteria.

There is a guy who is a bit crazy, a permanent employee and every day reaches 150% of the norm, (…) once just out of curiosity, I wanted to be as ambitious and I achieved 130% of the norm, or something like that. (…) With time I learned how to do the 100%, well, you need not to talk and you actually do it, you just have to act logically, make sure that you are looking for these products, you just go to this shelf, find the product and you go to the next one and you make this norm, but you need to use intuition; the system won't give you the number live as you go. (#29)

This worker explains how estimating the workload ensures that work is completed efficiently and within the desired time frame. If workers take on too much work, they may not be able to complete it on schedule. Conversely, if they underestimate it, they may not meet expectations, which in Amazon's organization model, might result in a formal warning, or even dismissal. One worker explained why this lack of transparency is beneficial for the employer.

But it's also part of social engineering that you never know what speed you're working at, no. (…) It would be great if for example, you clicked on the scanner and when the light is green, it means you're doing a good job, and read would mean that something is wrong. Everyone would immediately take advantage of it. (…) Yes, so it's good for Amazon, because you never know how fast you work. (#40)

Forecasting the expectations dictated by the black box is the first element of the algorithmic work culture at Amazon; learning to do it effectively is part of the shop floor culture. It is about the awareness of the implementation of tasks based on the guidelines of the algorithm, which focuses on results and minimizes efficiency losses.

Algorithmic Awareness

The relationship between algorithmic technology and the workforce goes beyond labour process. Our study has shown that a specific awareness of the algorithm is an important part of the culture is . Its first aspect is surveillance. As workers scan each item and move it to its designated location, the scanner records their actions and provides recursive feedback on the next step in the process—for instance, the next item to be picked from the shelf. This feedback is based on the algorithm's understanding of the warehouse layout and inventory locations, as well as each worker's movements and progress. Being aware of the monitoring, workers feel that they are being surveilled. One informant shared his experience of panopticon.

Actually, there's something about Amazon that makes people feel like there's an eye watching you. That they are always controlled. It seems to me that there you are left more to yourself. That your results, your logs from your scanner say more about you. (#17)

Relying on scanners, warehouse workers develop spatial awareness, as their key task is based on quick finding of locations displayed on the scanner. They also becomeconscious of their own movements and progress, and can adjust their actions to optimize their workflow and efficiency. This awareness means that, for instance, workers at any time can be easily found by their managers, because scanners are tied to the locations of items, and relay real-time feedback on their movement and progress to the management.

These scanners know what you are doing and where you are. If you have scanned, for example, one location, it means that now you will be going to the next location. And your leader will know that you will be walking from here to there. (#4)

There is tracking. Suddenly my manager shows up and how did he know where I was? "Oh, you know, well, I passed by." No, he knows perfectly well that you are here and in a moment you will be there, because he sees your path of collecting products, and he can transfer you to another path in his computer. (#27)

Experiencing this awareness, workers believe that the procedures are aimed at controlling them, leaving them very little autonomy in decision-making. Employees become aware of being an element of the process controlled by an algorithm, which means that workers are being treated without subjectivity.

There is a procedure called fast start. You need to start work by logging in and scanning five items, for example. This is to monitor if someone went to the bathroom after the start of the shift. If you don't do five items they come and give a warning that you should first pack five items, or pick, and then go to the bathroom. It is done so that the norm starts calculating. But if I, for example, go to the bathroom and I don't log in, they also know and then someone comes along and tries to find out why I didn't log in. (#45)

Even though technology of supervision is not directly aimed at surveillance (as in the case of cameras or metal detectors), our interviewees have stated that part of their daily work is coupled with the permanent sense of being observed and monitored, which is generally shared and embedded in Amazon's organizational culture. As a result, the employees themselves control the implementation of processes by other employees.

Algorithmic Subordination

The decisions and monitoring processes take place inside the black box. Organizational culture not only requires workers to follow instructions but also to agree with the decisions based on the unknown criteria by the unknown technology. We label this aspect of worker culture *algorithmic subordination*. In this case the algorithms and computer systems that govern the warehouse operations are designed and implemented with no input or feedback from workers, their managers or local offices. This subordination is tied to Amazon's employment policy. Our interviewees have described how Amazon relies on a large pool of workers who can easily replace any underperforming employee. This creates a dynamic of forced obsolescence among the workforce, as workers may fear that they are at risk of being replaced if they do not consistently meet their employers' expectations. For instance:

[At Amazon] you generally feel like nobody cares about you. And you are a kind of a record in Excel. If you become visible, get flagged in the system, and get [negative] feedback [from the manager] then you can really tell that the person who comes to talk to you does not care; they are just doing that to have it done. It is the same with instructors and managers on all levels in the warehouse. The system decides, they just follow the procedure. (#7)

The informant remarks on multiple aspects of the algorithmic culture. He describes his position, which according to him is only based on the numeric score. He also speaks about line management, which according to his experience has limited authority and decision-making power, as most decisions are made by the computer systems that dictate the workflow of the warehouse. Another informant described line management as only responsible for delivery of printouts, based on the output of the warehouse system:

If you have less than 100%, you get the so-called feedback. In a sense, they put a piece of paper in front of you, sign here and it's official. We're really sorry, but there's no time to read it either, because it has two pages, yeah. They only show. The person who brings it also does not fully understand it. You can see that this is a person who comes to bring you a reprimand, but does not fully understand what this is based on, it is simply. You just don't have 100%, sign here and I am going to the next one. (#51)

Another informant emphasizes worker management's algorithmic subordination by emphasizing that line managers rely on the system rather than on their own judgment or experience. This means that the result of the algorithmic calculations is more important than the reflections and experiences of the line manager:

And when, for example, you are having a bad day, you are doing poorly, you are not meeting the norm—meaning you are below 100%, the manager or leader comes to you, gives you a piece of paper to sign. It says that you generally did not meet standards that it was bad and so on. And it is no longer important that, let's say, for a month you were doing great and you were working above the norm, this one card simply means that with the next card, the next, the next you can just go to dismissal. And that's why people are just super tense to just have this norm met. (#33)

Our case study has shown that this subordination was embedded in the culture and omnipresent to the degree that workers were unsure if communication from the management was computer-based.

An illustration of another aspect of algorithmic black box is sending messages about the performance to the scanner by line managers. The following passage describes workers' thoughts on this process. All three of them attribute the message to different levels of human decision making.

Once logged in, we get a message, someone in the system will write that we have to work faster. A message for example, "speed up," and signed by the manager. (#7)

[Talking about messaging] From, I don't know, let's say [name of the manager] to [login of the worker]. Like, please work a little faster, or, please don't be too slow, something like that. Something like just to increase the pace of the movements, that's it about the messaging in a nutshell. (interview_7, Pos. 15–19)

Surely, it is automated [the messaging on scanner], for situations such as a break, right? Employees are grouped and the leader doesn't even write a message by hand, but this message is generated all the time at a given time, for a given group. Because it's almost the same every day. They either copy-paste and send, or it's automatic. And, for example, when you are below your norm, you first get a message that you are missing some percentage to meet the norm. And it seems to me that this is also automatically generated. That it's not like they're worried and look: "Oh, we'll rush him because he's 73," but it's 12:00 so the computer sends it. (#51)

While it is impossible to determine the source of the message, workers subject to their content, wanting to meet the quota set by the machine. This type of subordination can create a sense of powerlessness, widely accepted by the warehouse workers, who feel that their input and expertise is not valued or utilized in the decision-making process.

Discussion and Conclusion

This paper shows the direction in which workplace cultures evolve due to digitalization. The described warehouse is organized by the algorithmic system, which controls operations and automates decisions. Our description of limited transparency of this system helps to understand the positionality of the worker. The algorithmic system structures the organization and informs warehouse culture. Subjection and subordination to this technology by all workers informs how workers interact with each other, how they see themselves at work and how they perform their duties. As we show, warehouse employees' tasks are highly fragmented, strictly defined and based on specialization, and controlled by the algorithm, leaving them almost no decision-making. At the same time, the workforce operates according to the black box: unknown rules of the algorithm; with insufficient information; often projecting systems' computations; but always subordinating to its decisions.

This organization generates a flat organizational hierarchy, removing collaborative and cooperative relationships, and replacing them with registering and analysis of work performance. The computations made by the algorithm inform performance and, as a result of further computations, reward outcomes. The workforce follows the strategy of satisfying key benchmarks, and tries to optimize their actions according to the algorithm. In that context, lack of transparency and accountability of the algorithm creates a situation where employees rely only on their predictions. The blackboxing also applies to lower-level management, present at the shop floor, whose actions are also guided by the algorithm. For them, the black box is also an algorithmic boss, whose power is difficult to challenge and decisions are rarely appealed. A culture based on a shared experience of the black box, emerges as the consequence.

In the wider context, the black box translates into progressing inequality, experienced by all members of the organization. The most disadvantaged group consists of employees who are behind the black box and work with it. They engage with the black box with insufficient information about the rules and a deep sense of insecurity, both regarding their job performance and duration of the employment. In that sense technology orchestrates not only swift execution of the logistic processes but also responds to the waves of seasonal demand. There is also a smaller fraction of employees (including office workers, HR staff, middle and upper management), whose job is not directly based on algorithmic performance, yet, their control and knowledge of the algorithmic system is still highly limited. The black box's development and design occur out of their sight, in an unknown way and in an unknown geography. The algorithmic system establishes an organization impenetrable and understand.

It is impossible to determine if the complexity and opacity of algorithms is an intentional strategy to increase the productivity and efficiency of employees. However their result is clear and blackboxing them makes the workforce highly dependent upon and compliant with the algorithm (and critical of it at the same time). This exemplifies a form of labor exploitation, aimed to optimize and control every aspect of work. In that sense, the findings of this paper exemplify digital Taylorism based on algorithmic management. In that sense the algorithmic culture is a tool of increasing work efficiency and reducing costs of labour.

This study of algorithmic transparency provides arguments for the regulation of algorithmic control and decision making in the workplace. Workplace algorithms call for systematic regulation to protect the rights and interests of workers and to ensure accountability and fairness in the algorithmic decision-making process. The case study presented in this paper shows very low extent to which the logic and functioning of algorithms are understandable and explainable to the workers and outside stakeholders. Workers should have access to information about how the algorithms work, what data they use, and what criteria they apply. Workers should also have opportunities to provide feedback, voice concerns, and seek redress if they experience harm or injustice due to the algorithms. By opening up the black box of workplace algorithms, workers can benefit from their potential advantages while safeguarding their dignity and autonomy.

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