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THE LIFECYCLE OF ALGORITHMIC DECISION-MAKING SYSTEMS: ORGANIZATIONAL CHOICES AND ETHICAL CHALLENGES

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Abstract – in this viewpoint article we discuss algorithmic decision-making systems (ADMS), which we view as organizational sociotechnical systems with their use in practice having consequences within and beyond organizational boundaries. We build a framework that revolves around the ADMS lifecycle and propose that each phase challenges organizations with "choices" related to technical and processual characteristics – ways to design, implement and use these systems in practice. We argue that it is important that organizations make these strategic choices with awareness and responsibly, as ADMS' consequences affect a broad array of stakeholders (the workforce, suppliers, customers and society at-large) and involve ethical considerations. With this article we make two main contributions. First, we identify key choices associated with the design, implementation and use in practice of ADMS in organizations, that build on past literature and are tied to timely industry-related examples. Second, we provide IS scholars with a broad research agenda that will promote the generation of new knowledge and original theorizing within the domain of the strategic applications of ADMS in organizations.

Keywords: algorithmic decision-making systems (ADMS); strategic choices; ethical implications; IS strategizing; automatic systems.

INTRODUCTION

Strategic decision-making is an ongoing process in organizations (Eisenhardt and Zbaracki 1992). Such decision-making has always included data (internal and external) but today the data that is employed is often algorithmically processed to support or even automatically make decisions by algorithmic decision-making systems (ADMS) (Newell and Marabelli 2015). While these systems support strategic decisions, whether and *how* to design, implement and use ADMS are strategic decisions in their own right. In this respect, ADMS can help to make timely and accurate assessments on various key aspects of organizations and organizing (Davenport and Bean 2018; Leonardi and Contractor 2018; von Krogh 2018) but can also become problematic because they can involve discriminations, privacy issues and other legal and ethical considerations (Loebbecke and Picot 2015; Markus 2017).

Five years ago, we wrote a viewpoint article for the *Journal of Strategic Information Systems* (*JSIS*) where we noted the relatively limited IS (information systems) research addressing the ethical implications of ADMS (Newell and Marabelli 2015). To lay out our concerns, our call for action included the identification of organizational tradeoffs affecting algorithmic systems and the use of big data: privacy vs. security; control vs. freedom; and dependence vs. independence. We suggested that IS scholars should join the discussion on the problematic use of these systems by taking advantage of the interdisciplinary background of our community. Since then, IS scholarship has showcased a growing interest in these problems associated with algorithmic decision-making, *JSIS* being a good example of related articles (cf. Gable 2020; Galliers et al. 2017; Grønsund and Aanestad 2020; Günther et al. 2017; Loebbecke and Picot 2015; Marjanovic and Cecez-Kecmanovic 2017; Markus 2017; Newell and Marabelli 2015).

In this viewpoint article we aim to build on past work, including our own (not just our *JSIS* viewpoint, but also several related studies that we have conducted in recent times) to further discuss issues associated with ADMS. We examine the issues from a "choice" perspective because organizations need to develop awareness of how choices associated with using ADMS will affect their employees, customers, suppliers and the whole society (Bailey et al. 2019; Kellogg et al. 2020). To wit, managers (and researchers) need to recognize and learn to navigate choices consciously and responsibly, because they are highly consequential for many.

Social scientists have long discussed the notion of strategic choices in organizations, and have highlighted that these choices involve ethical problems that are affected by external and internal environments, including political considerations (Child 1972; Peng 2003). Choices concerning ADMS, as we will demonstrate, follow suit; as previously noted by the strategic choice literature, when technologies come into play ethical issues proliferate (Sarathy and Robertson 2003). These issue, we argue, are even more acute when discussing algorithmic systems, since their use may involve lack of transparency and accountability of the underlying decision-making processes (Lepri et al. 2018). For the purpose of our paper, we therefore define strategic choices associated with ADMS as conscious managerial decisions on how to employ such systems. Such decisions include considerations of technical characteristics of the artifact at hand and take into account internal (policy, culture), external (institutions, law/regulations, markets and customers), political and ethical aspects.

In the reminder of the paper, having briefly discussed strategic choices of ADMS, we provide examples of choices related to the "ADMS lifecycle" (design, implementation and use in practice) and account for ethical considerations. We then present a framework that summarizes choices and ethical challenges and build a broad research agenda that leverages our (IS) sociotechnical background for exploring novel nuances on how to employ ADMS strategically, yet responsibly in organizations and beyond.

ADMS LIFECYCLE: A SOCIOTECHNICAL APPROACH

Historically, making strategic choices has been a relevant topic in the management domain (Child 1972; Hambrick and Mason 1984; Peng 2003; Pfeffer and Salancik 2003), including in the IS literature, for instance with respect to inter/intra-organizational systems adoption (Brown and Vessey 1999; Holland and Light 1999), IT investment and outsourcing (Schermann et al. 2016; Shin 2001), alignment tactics (Chan and Reich 2007; Henderson and Venkatraman 1989) and the use of decision support systems (DSS) (Agarwal et al. 1992; Hong and Vogel 1991). The "big data era" (Goes 2014) has unveiled incredible opportunities for improving decision-making processes and how to design, implement and use these systems has become even more strategic (McAfee and Brynjolfsson 2012).

Today, decision-making processes are streamlined by powerful analytics systems, involving AI (artificial intelligence) technologies that leverage big data, cutting-edge algorithms and computing capabilities (Borges et al. 2021). Yet, despite the potential of ADMS, their realization – or use in practice efficiently, yet wisely – is not an easy task, because of the profound organizational and societal implications of using these systems improperly.

ADMS represent a holistic and interdisciplinary phenomenon and should not be studied in silos but rather require a joint technical and human/organizational perspective (cf. Markus and Rowe 2018). Existing silos, however, have led to two main perspectives on the topic at hand. One – led by computer scientists – focuses on technical aspects of algorithms, implicitly privileges business interests and celebrates the *power of the artifact*. Related research suggests that algorithmic systems in general create economic benefits that substantially exceed the potential concerns and ethical implications (Jarrahi and Sutherland 2019; Priami 2009). The other viewpoint – mainly led by sociologists and lawyers – is overly pessimistic. Often these scholars argue for the ban of most ADMS because unfair, unethical or otherwise inappropriate decisions can be unleashed in society (Shin and Park 2019; Veale et al. 2018). Taking a sociotechnical approach, in this paper we aim to celebrate the potential of ADMS while accounting for the potential pitfalls, therefore discussing technical as well as processual and behavioral aspects of the phenomenon, following the IS tradition (Sarker et al. 2019). The focus of our study is on organizations and their *algorithmic* decision-making, yet the blurry boundaries and widespread effects of these systems means we also discuss other actors such as customers, suppliers, institutions and society more broadly.

We focus on “choices”, which organizations need to make at various stages of the lifecycle of the ADMS (design, implementation and use in practice). We argue that these choices should be responsibly managed with awareness. We observe that strategic choices are highly context-dependent; a choice made in one setting may be totally inappropriate (or unethical) if translated into a different setting, or made at a different point in time. Also, choices generally tend to focus on exploiting ADMS’ efficiency (to control or improve existing processes) at the expense of considering the need for flexibility. For instance, using automatic systems to triage COVID patients was (a choice) adopted in many hospitals able to do so with AI – never mind if these systems were less effective with particular populations of patients (e.g., people of color) (Obermeyer et al. 2019).

These choices not only concern how an ADMS is applied to a specific situation but for instance concern the way these systems are designed and implemented. In the above example, the ethical implications of ADMS relate to a data issue (minorities, historically, were poorly involved in clinical trials (George et al. 2014)), which therefore limits the design of the algorithm. An implementation issue involves the wide-scale of the rollout of these systems during the COVID pandemic, where human intervention is weakly included in the process (triaging) of assisting people who cannot benefit from automatic diagnosis. And a use in practice issue becomes evident because, over time, using these ADMS that work better with particular categories of people can perpetuate longstanding injustices. This example clarifies the need to be always open-minded and conceive the ADMS lifecycle as “circular”, where design and implementation should be seen as dynamic and never-ending processes, based on emergent issues associated with use in practice.

We next deconstruct the ADMS lifecycle – broken down only for analytical purposes – and provide examples of choices and how the associated negative consequences, can be mitigated through specific practices that we name “supporting mechanisms.”

ADMS Design

The design of ADMS includes building the “engine” (the algorithm), deciding on the (more or less dynamic) data it will be fed with (the “fuel”) and creating various visualization systems (dashboards etc.) that are then used in practice and are made available to managers and executives. Design is a key phase of the ADMS lifecycle as flaws in design can subsequently show up in these systems’ implementation and use in practice. One example often used by related literature (cf. Elish 2019) is that of the tragedy of the AirFrance Airbus A330 Flight 447. The AI system running the onboard autopilot was designed for one person at a time to be in control (captain or copilot), yet it did not provide any warning when the other pilot was taking control – this happened automatically, by simply pulling the yoke. In the moments prior to the crash, the confusion in the cockpit increased as the system was showing inconsistent readings (increased speed while pitching the airplane's nose – the opposite should happen). The system was neither designed to inform pilots of who was in charge; nor was it designed to turn the decision to the human, should systems provide inconsistent readings.

Even more importantly, one feature (or flaw) of the Airbus A330 autopilot was that stall warnings stop once the aircraft's angle of ascent is too steep, therefore considered by the system as invalid (i.e., "unreal"). This was the case of flight 447, where the angle of ascent reached 41 degrees (note that stall in commercial airliners normally occurs at 10 to 15 degrees, at cruising altitude and speed). The result was that during the attempts to recover from the stall, flight 447's pilots could hear the autopilot's warning "STALL" until the angle exceeded normal parameters. This led the pilots to believe that the plane was no longer stalling. Every time one of the pilots would lower the aircraft's nose to reduce the angle, the reading would fall back into the acceptable range, and a warning was heard again, leading the pilots to behave in a way opposite to that appropriate to regain control of the plane (BEA 2012). All these design flaws contributed to the pilots not being able to recover from a stall, resulting in the plane crashing into the Atlantic Ocean, killing 228.

Common problems in the design phase are associated with the use (or mis-use) of datasets. Datasets may be incomplete, biased or even incorrect, when for instance data labeling is performed in a shallow manner (Schwemmer et al. 2020). It is therefore important that algorithm design focuses on preventing or minimizing dataset issues (for instance, in the AirFrance case, the autopilot was not trained on how to deal with problematic airspeed readings). Because design can be approached in various ways, organizations need to make choices – some of them potentially raising ethical issues. We next provide two examples of these choices.

Choice between designing transparent vs. blackboxed algorithms*:* This choice involves technical aspects of ADMS and concerns whether organizations should create static and transparent algorithms (e.g., traditional AI) or dynamic and blackboxed ones (e.g., machine learning (ML), a subset of AI). The benefits deriving from ML are immense; these systems are continuously trained with "real world" data, can process more variables than traditional AI systems and do not need to be reconfigured every time a scenario changes. For these reasons they are widely adopted (Asatiani et al. 2020). However, the underlying explanatory power when ML is used is limited, decreases over time and is difficult to understand even by the creators of the algorithms (Hosanagar and Jair 2018). The outcome of this design choice is that ML algorithms become extremely cryptic and thus it is problematic to assess their fairness (Lepri et al. 2018).

Organizations can make this strategic choice, taking into consideration the context in which a system will be used (Selbst et al. 2019). For instance, ADMS employed to hire individuals may become problematic if the underlying algorithm is too obscure. This happens for two main reasons. One is ethical; it might be difficult to spot potential biases, which might be funneled into the algorithms in the form of historical data/past hiring practices (perhaps discriminatory) (Barocas and Selbst 2016) – despite companies continuously highlighting the (opportunistic) benefits of the utilization of these systems (Finocchiaro et al. 2021). The other reason is more strategic and to some extent convenient because it involves organizational liability; companies employing algorithmic systems are increasingly at high risk of being sued by candidates whose applications were turned down by an ADMS (Raub 2018). Being able to show, in a transparent manner, that the algorithm managing the final decision was not biased becomes of paramount importance.

Other contexts can be viewed as less "risky", if they do not involve specifically human beings. This was recently recognized by the EU, with a proposal that aims to create stricter regulations on how to use AI if dealing with humans rather than goods/products (European Union 2021). It follows that algorithms designed to make decisions on purchasing materials, managing operations in a supply chain and other non-human-related decisions, can be more autonomous in their ongoing learning because the consequences of design flaws do not directly affect humans. This said, most if not any use of AI in real world contexts ultimately holds consequences for humans. An example relates to AI systems managing supply chains of large-scale distributors such as Amazon in the early days of the COVID pandemic (spring 2020). When COVID hit, distributors quickly ran out of items such as toilet paper, cleaning wipes, face masks etc. The shift was sudden and not predicted by automatic systems, as documented by a study by Nozzle, the London-based consultancy company specialized in algorithmic advertising for Amazon sellers (Heaven 2020).

It is also worth noting that organizations do not always make choices concerning algorithmic transparency on the basis of whether algorithms affect people more or less directly. It is therefore important to highlight the relevance of making this choice wisely and exploiting the opportunity to blackbox algorithms only when needed. Finally, we need to bear in mind that the lack of traceability of how algorithms come to a certain outcome may slow down a possibly required redesign.

Choice between slow and careful and expedited and timely design: The second choice concerns *processes* underlying design, and is associated with what we call "design-to-market speed", defined as the organizational need to turn R&D (research and development) projects into working ADMS systems. While the timely delivery of an innovative algorithm is key, poor testing and fast-track to production can magnify unintended consequences. Technologies released in a timely way can have a strategic impact on competitive advantage (Peppard and Ward 2004). Yet, making savvy decisions responsibly can be extremely strategic in the long run. This means that while releasing beta versions could be acceptable for "non intelligent" software such as Microsoft Office, in the realm of human-related ADMS the consequences of an algorithm that does not include a sufficient number of variables for assessing people fairly can be immense.

Similar to the previous choice on the extent to which an ADMS should be blackboxed, the context of application seems to be an important issue to consider. Yet, it is often not possible to test algorithms thoughtfully before deployment. In the case of the AirFrance disaster, flight simulators clearly did not cover extreme situations that would have prevented a stall system working once the angle of ascent becomes too steep. This brings to the surface another ADMS issue of commercial airliners that emerged with the two Boeing 737 MAX crashes in 2018 and 2019. In these cases, a design flaw of the autopilot was exacerbated by the pilots' lack of training; most airlines provided pilots solely with video training once the Maneuvering Characteristics Augmentation System (MCAS) component was embedded in the aircraft's autopilot system. This allowed Boeing to release the new MCAS systems quickly, yet with little testing (APA 2020).

In other fast-changing settings, such as social media, algorithm testing by platform owners, even on a small proportion of their users (Kramer et al. 2014), have been heavily criticized by the press for having performed covert research on their users without proper debriefing, as was the case of the so-called Facebook mood experiment (Shaw 2016). More recently, flawed design of ADMS in social media in relation to political debates worldwide have come to the fore (Seneca 2020). One case in point is the design of Facebook's algorithm during the 2020 US presidential elections. Initially, some accused the platform's algorithms of promoting the sharing of radical posts and therefore conditioning the electorate. Now it is clear that Facebook's algorithm "supports" radical groups simply because it encourages connections between people sharing the same beliefs, therefore reinforcing conversations within toxic siloes – the so called filter bubble (Pariser 2011). Facebook's algorithm polarizes the electorate, which becomes more and more radical. Obviously, this was not the initial goal of Facebook's algorithmic design; its goal was to keep users engaged in what they are interested in. Yet, this is another example of a company's algorithm unleashed to the public with poor testing, to meet the demand of a very dynamic competitive environment. This example also raises the problem of how certain algorithms can be effectively lab-tested, thereby potentially limiting companies' ability to make choices, in specific settings and industries.

Supporting Mechanism: Team diversity

One emerging issue, which can be seen as a supporting mechanism in making design choices, relates to how teams of ADMS developers are created. It is important that data scientists involved in design are constantly interacting with various actors from different fields and backgrounds (interdisciplinary teams) and are diverse in gender and ethnicity. There is strong evidence that diverse teams, especially with respect to gender and ethnicity, are more attentive and emphatic to potential unfairness and discriminations of algorithms (Barocas and Selbst 2016; Cobb-Payton and Berki 2019). The 2016 Interagency Policy workgroup under the Obama

Administration released a broad report illustrating how increasing diversity in the STEM workforce[1] will drastically reduce the impact of algorithmic biases (OSTP 2016).

Team diversity brings in a multitude of perspectives that come from the varied communities and cultural systems in which people live (Howard and Borenstein 2018). For instance, airbags kill more women and children, why does it happen? It is probably because someone wasn't in the room to say "why don't we test the airbags on women in the front seat", Ayanna Howard suggested in a recent interview[2]. Also, diverse teams may develop more awareness and prevent ADMS from being released too soon (mitigating the design-to-market speed) thereby avoiding potential issues associated with poor/shallow testing.

Yet, high-tech companies that develop algorithms and AI for various purposes (e.g., Amazon, Apple and Google) are not particularly sensitive to diversity issue (Duranton et al. 2020). For instance, with respect to gender and ethnicity, an example is the so-called "Gebru case": On December 2nd Timnit Gebru was abruptly fired by Google (she was one of the lead AI ethicists at the company) for refusing to retract a paper that pointed out weaknesses and potential ethical concerns associated with the design of natural-language processing AI systems (for fairness of perspectives: Google asserted that the firing came because Dr. Gebru's paper did not meet the high standard of research papers that Google employees should publish, yet she refused to pull the paper from a prestigious conference) (Hao 2020). Note that Gegbru was one of the few black women working in a leadership role at Google, which, similar to other Silicon Valley companies, still have gender and diversity issues (Wynn 2019).

[1] Because throughout the paper we use examples of workers who are not employees (e.g., Uber drivers) we use the term workforce rather than employees unless we specifically refer to a context where, e.g., an employee supposedly hired with a permanent contract was fired, as per the Gebru case that follows.
[2] https://www.technologyreview.com/2021/05/13/1024874/ai-ayanna-howard-trust-robots/

In conclusion, diverse teams may be better placed to identify future problems stemming from algorithm design and to advise organizations on how to navigate often difficult choices, for example between the need to generate efficient ADMS in the short-term while making sure that adverse consequences do not affect employees, customers or other stakeholders in the long run.

System Implementation

The problem of implementing systems effectively – e.g., whether people actually *use* ES (enterprise systems) as intended once they are rolled out (Elbanna 2006; Marabelli and Newell 2019) applies also to ADMS (Chen et al. 2017; Gartner 2014; Schüritz and Satzger 2016). In fact, being able to effectively use analytics and understand the benefits and challenges of ADMS involves cultural changes (Davenport and Bean 2018), issues that IS scholars are very much familiar with (Grant 2003; Lee and Myers 2004; Robey et al. 2002). For instance, using analytics systems in silos leads to what some call the deployment gap (Wiener et al. 2020), when organizations can't figure out how to fully exploit ADMS capabilities at the organizational level.

Nevertheless, it is unlikely that ADMS are designed and developed with much user involvement. Often these systems are purchased off the shelf and interface mainly with executives, so the employees become either the controlled party or are provided with the outputs of analytics (i.e., dashboards) with poor explanations of the underlying processes. It is therefore extremely important to reflect on implementation choices, which will affect employees in the short and long-term.

Choice between passive and active approaches to implementation: implementing ADMS to monitor/improve internal processes – so-called people analytics (Tursunbayeva et al. 2018) – can be done either by simply configuring these systems to passively capture data on employees, for instance through ES; or it can be done with the active cooperation of the people being “analyzed.” One example of the former approach is Amazon’s surveillance system, which controls picking, packing and shipping processes that the workforce undertakes in large warehouses, using digital cameras and sensors (Delfanti and Frey 2020). This type of employee monitoring is very efficient, yet evidence suggests it may led to negative (angry) feelings towards the employer (Greene 2020). In the period 2011-2017 Amazon warehouse turnover has increased from 38% to 100%, according to a National Employment Law Project report. Nevertheless, in the same timeframe its revenue has grown exponentially (Gawer 2020).

One example of the latter happens when data is collected via voluntary surveys instead of automatically through cameras and sensors. For instance, Leonardi and Contractor (2018) found that it is possible to collect skills and behavioral characteristics of organizational actors through surveys and to algorithmically set up “ideal” teams where people can work together effectively in the long term. The voluntary basis of the participation in these initiatives promotes engagement. Yet, it, partially compromises the reliability of the data collected (sampling issues and biases).

Clearly the choice between “passive” – and at times subtle (cf. Kellogg et al. 2020) – and “active” but potentially flawed ways to collect data to feed ADMS is extremely strategic. It determines short-term employee feelings (in passive settings) but also potential errors due to incomplete datasets (in active settings). This strategic choice, we argue, should be influenced by the work being done, within a specific organizational form. In machine bureaucracies (cf. Mintzberg 1980) where most employees are task workers such as at Amazon, implementing surveillance-based analytics can be an efficient strategy – albeit debatable from an ethical standpoint; high turnover of unhappy employees may not affect organizational performance, because training of task workers is minimal. In professional bureaucracies (cf. Mintzberg 1980) instead, a more collaborative way to collect and use data on the workforce may be better – knowledge workers may refrain from being "told" what to do by an algorithm (cf. Anthony 2021), because of their professional identity (Abbott 2014).

For instance, a study of sepsis spread at the ER unit of Duke University Health System showcases the effectiveness of AI in identifying specific risks (patients, conditions, environment) that could be mitigated in hospitals. Yet, because mainly nurses were trained on how to use the AI, when it was time to address issues (i.e., the AI flagged a patient as high risk) a nurse would have to tell a doctor to take care of the potential problem. This subverted the typical processes at a hospital where it is doctors alerting nurses that a task needs to be performed – in fact several nurses reported being afraid of doing so (Sendak et al. 2020). This example is illustrative of challenges associated with the implementation of ADMS in particular settings where established professional practices may generate implementation issues.

Choice between obscure and open ADMS implementation: This strategic choice is between ADMS being implemented without disclosing the key variables used by algorithms, in contrast with what we call an "open implementation" where the system is made transparent and is explained to the end users (employees or customers). One risk of the latter choice is that people may attempt to game the underlying algorithm (Lee et al. 2017). When organizations hide the logic behind an algorithm, however, they implicitly prevent others from filing lawsuits, should user data be employed unproperly – for instance for purposes that deviate from the reason the data was collected in the first place. The Cambridge Analytica scandal started a conversation among scholars on the extent to which data (and what data) that is more or less publicly available on the web can be used for research of various kind (Bruns 2019).

One example of ADMS obscure to customers concerns automotive insurance companies' use of monitoring systems (onboard devices) able to record and examine one's driving style. Accepting monitoring could help the insured person lower the monthly premium, should she/he demonstrate "good" driving behavior, according to the algorithms that process the recorded data from the onboard devices. However, should the parameters upon which the algorithm is making decisions (frequency of using brakes, extent of deceleration, driving at night) be made public, some insured people may start to drive in ways that would meet the algorithm's expectations regardless of safety –potentially leading to reckless driving, e.g., when not using brakes too often (Marabelli et al. 2017).

Supporting Mechanism: Human in the Loop

Almost a decade ago, when big data-based ADMS started to be used for HiPPOs (the highest paid people in companies), these high profile powerful organizational actors did not like to be overruled by these systems, believing that their gut decisions were more valuable (McAfee and Brynjolfsson 2012). More recently, however, the opposite problem has started to emerge – that of the human too often taken out of the loop (Grønsund and Aanestad 2020). This happens either voluntarily, when managers are afraid to override an automatic decision because "the algorithm is always right", or because organizational processes prevent people from overriding these systems (Markus 2017). Without the human in the loop, managers will not be able to tweak an employee's performance (people analytics); nor will an insurer be able to spot cases where drivers are gaming the algorithm but as a consequence having frequent accidents.

Overall, implementing processes so that ADMS keep humans in the loop will help manage exceptions and account for localized issues that narrow algorithms cannot capture (Luca et al. 2016). Given our sociotechnical tradition, IS scholars are well- equipped for tackling and effectively addressing this important issue requiring a balance between what ADMS can do on they own and when and how they need to be supervised. Here, the implementation concerns are about keeping (some) human decision-making in the loop, for instance to spot design issues once the system is being implemented. For example, where AI-based ADMS hiring systems are implemented, humans may be required to systematically vet algorithmic decisions when the AI identifies unusual behaviors in a candidate's interview. This may help prevent a situation where a candidate has disabilities that trigger an AI system reject, yet the candidate can be perfectly capable of doing the job (Sánchez-Monedero et al. 2020).

Use in Practice

ADMS use in practice refers to the long-term use of these technologies – i.e., once they are fully embedded and used in an organization. Technologies carefully designed and successfully implemented may still have issues in the long-term because of emerging characteristics of the technology at hand. With ADMS, we argue, this happens when they become imbued in cultural mechanisms and power dynamics in organizations. And it is only by observing their use in practice that we are able to identify (and hopefully address) potential misuses with ethical implications (Scott and Orlikowski 2014). Here too it is crucial for organizations to make wise and informed choices on how to craft long-term strategies associated with ADMS. Two examples of these choices follow.

***Choice between compliance and risk taking**:* This choice refers to decisions about whether an organization wants to "control" the workforce (that needs to be compliant) or whether they want to grant workers a certain degree of flexibility, which may promote innovation and individual initiative. This choice is different than the people analytics example from the implementation phase, which is about how the system is "set up" at the outset (implementation/configuration), for instance with respect to workforce satisfaction. Here we still discuss control and performance management but the focus shifts to consequences related to how, over time, the configuration of a particular ADMS determines the degree of freedom of the workforce.

Organizations establish standards and policies that are then incorporated into ADMS which, consequently, make recommendations on how employees should behave. Not following these recommendations may have consequences for the employees' paycheck and beyond. Think of Uber drivers, who need to follow specific routes to pick-up and drop-off customers according to an algorithm that makes decisions on their behalf. Deviating from its prescriptions has consequences that include a lower rating, loss of income and ultimately being laid off (Page et al. 2017). Yet, the long-term use of these algorithms has demonstrated that drivers cannot sever customers effectively if they follow the (rigid) algorithm blindly (Möhlmann et al. 2020). Clearly the Uber algorithm wasn't designed or rolled out to upset customers (or make drivers uncomfortable) but its use in practice unveiled these issues. Uber's choice (compliance) may well stem from the fact that drivers are not employees and therefore control can be less enforceable. Yet this may have led to drivers not being able to accommodate various requests from riders, possibly at the expense of customer satisfaction (Möhlmann and Henfridsson 2019).

The implications of using algorithms instead of traditional performance management systems are immense. For instance, with a traditional ES, a sales manager consults the (ES) reports related to salespeople and decides who deserves bonuses, on the basis of productivity and other information gained through working with employees on a daily basis. When automated decisions come into play, salespeople are rewarded or punished automatically based on performance data captured by analytics systems (Hancock et al. 2018). This may leave out important contextual factors such as that a salesperson's productivity decreased for a quarter because he had a baby and took paternity leave. A manager making the decision would probably be more flexible and understanding, being aware of the personal issue. This is an example where the human in the loop was not implemented with the ADMS – therefore the emergent use of ADMS in practice may suggest going back to implementation, illustrative of the circularity of the lifecycle.

Choice between contextual vs. standardized use of ADMS*:* This strategic choice emerges when a decision needs to be made concerning the extent to which an algorithm (that makes decisions, often automatically) should be used locally or across settings. Localized use of algorithms involves continuous redesign for specific contexts which is expensive, yet effective as the algorithms are set up for specific situations (Luca et al. 2016). Unleashing algorithms across contexts is more cost-efficient, yet can be problematic, as illustrated by an example from the judicial system.

In 2018 an algorithm (called COMPAS) was created that supports several US court decisions for bailing out (or not) suspects awaiting trial charged with minor crimes (Courtland 2018). The algorithm was meant to speed up judicial decisions so that people eligible for bail could benefit from it and detention centers could become less overpopulated (this being a longstanding US issue). In most cases, the algorithm – based on the "best practice" of examining people's background, along with other metrics – was successful.

However, it was demonstrated that in some instances the algorithm had substantially penalized people of color for various reasons including, e.g., the fact that statistics on criminals at risk of fleeing before the trial include considering the area in which they live (zip code was the variable used). But neighborhoods are often ethnically characterized. Put simply, black applicants for bail were penalized because they lived in particular neighborhoods and therefore, according to the algorithm, were more at risk of not showing up for trial or were more prone to commit a(nother) crime before being tried. While making decisions on the basis of race is illegal in the US, proxying it via zip code is not – or at least it represents a very sneaky way to circumvent laws and ethics.

Another example comes from the UK education system where, in 2020, an algorithm was deployed to grade students automatically (because of the COVID situation) on the basis of a teacher assessment of individual students, and other information concerning the school. Since final grades were calculated including the schools' historical performance, students from poorer areas were twice as likely to have their results downgraded than those from richer areas (Mowat 2020). While in general, students do worse in less affluent schools, including historical school data in the algorithm in this way meant it was impossible to account for individuals or small groups of students who might have been better than their historic school-peers.

This example is therefore illustrative of how supposedly carefully designed and successfully implemented ADMS then fall short once used in practice if the choice is made to spread localized algorithms blindly. Clearly some ADMS can and should be standardized across contexts. For instance, an ADMS in charge of determining COVID vaccination priorities based on health conditions and age should apply to different regions of a country (e.g., regardless of the prevalent ethnicity of a specific are, the opposite would be unfair and discriminatory). But here our point is that often it is convenient to translate ADMS across contexts, yet organizations need to try and make sense of potential adverse long-term consequences of these choices.

Supporting Mechanism: Constant Monitoring for Unforeseen Uses of ADMS

Research has shown that one can never fully predict technology use from design – since there will always be affordance in use (Leonardi 2011). While design can be useful to look at the big picture ahead of a careful implementation, we still need to focus on affordances in practice and recognize that there will be a continuous need for adaptation in the post implementation period (Costa 2018; Orlikowski and Scott 2008). This relates to the need to understand to what extent design can predict technology use and how far affordances can be addressed through organizational policies, codes of ethics and the like (Marabelli and Markus 2017).

While some argue that it is difficult to incorporate ethics into the design of automated systems (Manders-Huits 2011) other propose methodologies to at least mitigate algorithmic biases (d'Aquin et al. 2018; Martin 2018). Yet, scholarship generally agrees with the idea that technology use needs to be at least ad-hoc revised after being implemented, for ethical considerations. Therefore, it is important to put processes and rules in place that constantly vet and scrutinize ADMS. This is especially true when ADMS are ML-based and therefore evolve over time and when ADMS are used across contexts.

STRATEGIC CHOICES: A COMPREHENSIVE FRAMEWORK

How organizations design, implement and use ADMS is highly consequential for a number of stakeholders, including organizational actors, customers, suppliers etc. (Boone et al. 2019). The associated key strategic choices are heavily influenced by goals of efficiency vs. flexibility (Adler et al. 1999) and considerations related to short vs. long-term perspectives (Kaplan 2009) – where the long-term perspective is often only evident when ADMS is used in practice. We noted that ADMS' strategic choices can be supported by ensuring team diversity in the design phase, making use of the human in the loop during the implementation phase and monitoring emerging uses of these systems during the (never ending) use in practice phase.

Figure 1 summarizes the ADMS lifecycle with respect to strategic choices and supporting mechanisms, while next we provide a research agenda related to this lifecycle analysis.

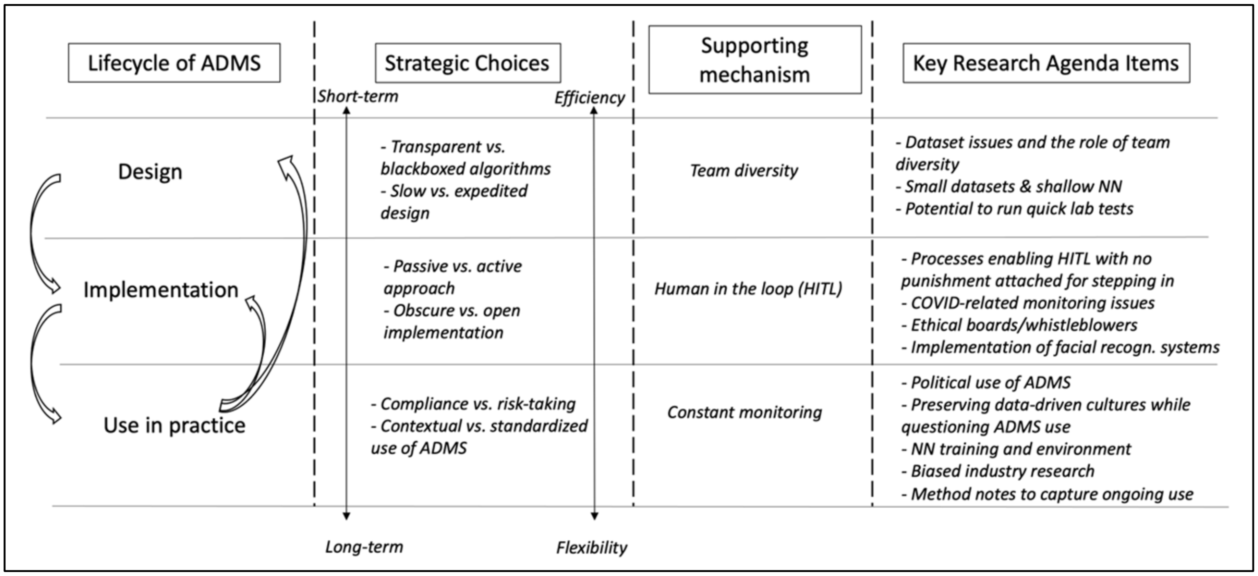

Figure 1. Managing Strategic Choices

A RESEARCH AGENDA FOR IS SCHOLARSHIP ENGAGED IN ADMS

In this paper, we specifically focus on ADMS and organizational choices concerning how these systems are designed, implemented and used in practice. We next identify some specific areas of future research that concern each phase of the ADMS lifecycle.

In particular, in the design phase a key focus is on team diversity and its influence on how data and datasets may support wise choices. Implementation concentrates more on how organizational processes are set-up, for instance with respect to surveillance (or more active/collaborative control) and how the human in the loop can be “embedded” in such processes. The use in practice focuses on long-term consequences, or problems that emerge only when ADMS are used over time. In the agenda of the use in practice we go beyond issues related to the previously discussed choices and discuss ADMS’ impact on the environment, data sharing policies at the national level, the extent to which grants promote academic research and conclude with a short methodological note.

Design

One aspect of design that we think should be further investigated by IS scholars is about data, the *fuel* of ADMS, which also relates to the way developers identify and use data to train systems to learn how to behave in the real world. First off, team diversity can serve as a balancing factor when datasets are selected for training purposes, potentially limiting biased outcomes if selected carefully (cf. the example of women and children poorly tested in crash tests). However, other problems emerge that relate to how the dataset itself is being generated. Even when data seem to be comprehensive there might be problems that are associated with how the data is "prepared", before it is processed by ADMS. One case in point is about systems able to recognize (or not) photos (and their meaning) that stems from problematic labeling, as a recent MIT study illustrates (Northcutt et al. 2021).

Most photo labelers are crowdworkers (e.g., Mechanical Turkers at Amazon) who are notoriously underpaid. Labeling photos may seem a trivial task – it is just a matter of using keywords that describe a photo. Yet, crowdworkers do not undergo unconscious bias training. A recent EU/US study (Schwemmer et al. 2020) found that most crowdworkers are biased against women. Photos of males (politicians) were labeled using tags such as "power", "suit", "business", "official." The counterpart female photos were labelled with tags such as "smile", "hairstyle", "chin", "television presenter" and so on. Here IS scholarship should reflect first on the ethical implications of using low-cost (for some, exploited) workers to undertake such key tasks that are highly consequential for other ADMS phases (in particular, use in practice). Some, in our community, suggest that crowdworkers should be rewarded with additional compensation provided by researchers directly (e.g., Deng et al. 2016). One may wonder whether it is at all ethical for researchers to use crowdworkers for most data-related collection, and analysis/computation.

Second, a more substantial problem related to the cost of labeling or other kinds of work relate to creating a data set, involves the professionality and preparedness of the people doing the work. What incentives would lead companies to invest more in data accuracy? Would diverse teams of developer address these issues? One interesting insight that should drive future research comes from Andrew Ng, one of the pioneers of AI. He suggests that, in ML contexts that are well-studied, it is possible to shrink datasets to as few as 10,000 examples, "a sort of threshold where the engineer can basically look at every example and design it themselves and then make a decision" (Hao 2021). Ng's intuition is backed by research suggesting that, in circumstances where outcomes are known, training data of neural networks – (NN, a subset of AI – computer system modeled on the human brain and nervous system) can be minimal. They call them shallow NN, defined as small NN with only a few layers in which calculations take place (Vanian 2021).

But what are the pitfalls and risks of adopting shallow AI? What are the implications for small organizations who are currently outsourcing (or purchasing off the shelf and standard) ADMS products because of their inability to manage large datasets in-house? Will the design of ADMS shift from (only) large companies capable of collecting and using vast amounts of data to smaller but skilled companies able to use very small datasets, accurately cleaned for use? Clearly this topic touches several IS interests such as design strategizing, outsourcing and system development.

Implementation

ADMS implementation issues can be partially addressed by the human (kept) in the loop, even if this is in implicit contrast with the "spirit" of these systems, which is to minimize human intervention. However, even with the human in the loop, implementation may not work as expected. For instance, how can organizations design processes that "protect" humans stepping in and overriding algorithmic decisions without risking paying a high price for disrupting automatic processes? This relates to research that suggests that humans are often "in the loop" but are also discouraged from stepping in, because if the algorithm is then proven right they risk being fired (Markus 2017). We believe that IS scholarship can successfully expand on research on organizational contexts where efficiency-led policies subtly discourage humans stepping in when ADMS make the wrong call.

Relatedly, having most knowledge workers moved online during the COVID pandemic, several companies have created performance systems that collect data on online meetings and interactions (Leonardi 2020). We wonder: what will be the ethical implications of constant surveillance related to novel and emerging organizational dynamics associated with remote work, and what will be the role of ADMS? For instance, what will be the role of the human in the loop in assessing information deriving from ADMS that log employees' online/remote activities and interactions?

Building on the literature on algorithmic opacity cf. Burrell (2016), focusing on the implementation phase of ADMS we identified an important nuance of transparency (or the lack thereof – opacity); that of companies willing to obscure logic underlying algorithms because of potential gaming issues (Kellogg et al. 2020). Examining this issue relates to much sociotechnical IS research. We have the knowledge and business-related background on how the workforce should (or should not) be managed. This would also add to (and build on) the growing

(IS) body of literature on algorithms at work, for instance in Uber contexts (Möhlmann et al. 2020; Page et al. 2017). This would help addressing questions such as: how is it possible to incorporate human vetting of ADMS in novel and emergent surveillance settings? How can organizations assess the extent to which this type of surveillance is too invasive?

It is also important to note that implementing obscure algorithms may lead to ambiguous profiling activities by analyzing data on, e.g., a small group of social media users and inferring more information for non-users – mechanisms known as information externalities (Choi et al. 2019). For instance, Google owns FitBit and by collecting data on a few users who shared their data, Google is able to predict health outcomes for much larger groups with similar characteristics and thus target a much wider array of consumers via its platform, thus generating invasive advertisement and potentially creating discriminations. For instance, genetic information is considered sensitive information that can lead to job and healthcare discriminations. Yet, only 2% of a country's population needs to have done a DNA test to identify nearly everyone else (Erlich et al. 2018). Learning more about how algorithms work and how the underlying inferences and decision-making processes operate is of paramount importance. Yet, how organizations make (or should make) choices related to the extent to which algorithms should remain obscure to most remains an under-researched area in our community. What should companies do to minimize information externalities leading to potential discriminations, while being able to leverage the potential of information externalities, for marketing and advertising purposes?

To this end, another issue worth researching relates to whether we should reasonably expect that laws and regulations will provide guidelines, or whether organizations should instead consider developing their own oversight systems. Facebook, for instance has recently created an external oversight board (https://www.oversightboard.com) formed by academics and industry experts on ethics matters. It is supposed to help the company make difficult ethical decisions with respect to freedom of speech and online safety. Yet, precisely because this is an external board, Facebook does not have to follow its recommendations (Marabelli et al. 2021). Alternatives are represented by boards not specifically associated with companies, such as the Ada Lovelace Institute in London that suggests independent, legal oversight be implemented to supervise applications of biometric technologies (http://go.nature.com/3cejmtk).

Some however advocate for increased regulation of ADMS (Erdélyi and Goldsmith 2018). Given the slow pace at which laws have addressed technological issues in the past, for instance with respect to privacy (Sweeney 2016), we suggest that more research is needed that explores the possibility of organization-based approaches to address the implementation of algorithmic systems. Should companies create their own oversight ethical committees, what are the power considerations arising from having in house whistleblowers advocating for ethical principles, which may contrast with organizational efficiency?

Kate Crawford in a recent book (Crawford 2021) fleshes out several power-related issues associated with ADMS in organizations. Her point is that algorithmic systems risk perpetuating longstanding social injustices; they rely on historical data and are in the hands of powerful people. This recalls our own IS research on power and organizational systems (cf. Markus 1983) and builds on more recent viewpoints related to the unequal distribution of power because of ADMS. Cathy O'Neil (O'Neil 2016) calls them "weapons of math destruction". Others point to the need to figure out ways to involve end users in the implementation of ADMS, to mitigate power unbalances (Kalluri 2020). What are key political considerations concerning decisions on who controls and vets algorithm's outputs, for instance in the area of performance management of remote workers?

Managing ADMS issues *from inside* (i.e., with oversight boards that enforce the human in the loop) may address ADMS implementations that are clearly unethical, yet their use is perpetuated by (some) organizations because of the lack of legal consequences. In fact, regulations concerning the implementation of emerging technologies often come too late to prevent adverse consequences, even if they are well-known to most. This reflects the history of technology use, whereby issues emerge first and then regulations attempt to catch up (Sweeney 2016). For instance, AI regulations are now picking up. Yet, the lag between, e.g., the discriminatory damages deriving from using facial recognition systems are still happening in several countries.

One case in point is about the use of this technology for predictive policing purposes – widely used worldwide albeit shortcomings are widely documented in the literature (Browning and Arrigo 2021; Karppi 2018; Sheehey 2019). Two key issues of predictive policing concern the use of historical data that penalizes minorities and flawed facial recognition systems (Buolamwini and Gebru 2018) (the latter which takes us back to design problems). Yet, we wonder whether novel sociotechnical systems implementing the human in the loop before performing a (wrong) arrest (Ryan-Mosley 2020) can find room in police stations, public administrations and other institutions.

Also – and related to how AI enhances people who are already in power (Crawford 2021) – we wonder whether ADMS used in police departments should broaden in scope, to achieve more fairness. For instance, what if these predictive systems were used (also) to single out (or predict) police officers more likely than others to perform an arrest that is racially driven, on the basis of past arrests? There is plenty of evidence documenting that police officers that are found guilty of crimes associated with abuse of power that are racially-motivated have a history reflecting this behavior (complaints that were dismissed, charges dropped etc.). Wouldn't it be fairer to apply ADMS to both citizens and law enforcement? Doing this could help to restore power balances between those who now can use ADMS and those who are scrutinized. Would it be possible to apply what we call a "two-way scrutinization principle" also in business settings? People analytics initiatives could be implemented with various actions and behaviors of managers and executives being monitored and analyzed – actions and behaviors related to hiring policies that do not pay attention to gender and race diversity, number of complaints for alleged harassment at the workplace and the like.

One last implementation issue, again referring to image recognition, begs the question of whether it is ethical to capture and digitalize body details of people not wanting to give away this information. This is not (only) about policing – where these systems are used widely (Rezende 2020) – but relates also to business settings such as hiring/firing automatic systems (Sánchez-Monedero et al. 2020), social media scraping to train ML (Smith and Miller 2021). More generally, these are systems aimed at "learning more" about people for commercial/marketing purposes, never mind if these systems are able to extract more about a person than she chooses to reveal. They also include emotion-based facial recognition systems that are employed by governments to "control" citizens, as it is happening in Western China's autonomous region of Uyghur (Wakefield 2021).

What is more, systems aimed at understanding people's emotions from their facial expressions are largely flawed (Barrett et al. 2019). What are the privacy implications arising from using these systems with current or potential employees? What is the role of IS scholarship in investigating these themes of system implementation having to do with the use or mis-use of advanced technologies such as ADMS, which will provide organizations with decision-making tools based on questionable information – information obtained without explicit consent of their employees or other stakeholders?

Use in Practice (and Beyond)

Most if not all IT systems, when used in the long-term, may reveal characteristics not reflecting the intent of the system and, not surprisingly, these characteristics often stick with the system being used for opportunistic reasons. For instance, for over two decades (since 1999), the malfunction of a software system (Horizon) that manages the UK Post Office, has sent many individuals to jail. The software had a bug that meant employees were seen to be stealing from the Post Office's account (they were not). The Post Office accepted the decisions of the malfunctional software because they didn't want to admit that it was bugged – and for a decade they refused to acknowledge the software's errors and replace it, according to a BBC report[3].

This example of a system (not entirely based on algorithms) not being overruled over the years, for convenience and political reasons should be a stimulus for investigating the myriad of power-related ramifications of ADMS, more difficult to debug especially if blackboxed. We should therefore address questions such as: how can organizations promptly detect and address inappropriate use in practice of ADMS, without completely discrediting a system? In 2011, Proctor and Gamble (P&G) considered not overruling a forecasting ADMS even if its sales predictions were clearly not accurate because of "incomplete data." Because it had taken P&G's management almost a decade to create an organizational culture of trust in ADMS, they were

[3] https://www.bbc.com/news/business-56859357

afraid that allowing humans to override the sales predictions would undermine all the effort of instilling a data-driven approach (Davenport et al. 2012).

Here the human in the loop (implementation) emerges as an intervening factor after (long-term) use in practice. This also showcases the interwoven nature of the three phases of the ADMS lifecycle. It is however important to note that not considering emerging, yet unpredictable "behaviors" of these technologies may lead to organizations overlooking potential "side effects" of the long-term use of ADMS – one of them being that questioning these systems outputs may reverse an organization's data-driven culture. All this leads to questions such as: what is the role of organizational culture in the use in practice of ADMS? How can organizations address the competing demands of pursuing a "pure" data-driven culture while recognizing exceptions, flexibility and improvisation, such as those in our example of compliance vs. risk taking choices? How do these challenges fit in recent IS debates on ADMS deployment in the long-term? (cf. Wiener et al. 2020)

Another area of AMDS' use in practice that is understudied, at least by IS scholars, concerns data visualization, key to synthesizing findings, either with dashboards, for managers/executives; or with slides and graphs, for employees, or the general public if used by government bodies (Donalek et al. 2014). It is now clear that all the phases of ADMS can lead to power dynamics, often exercised by dominant coalitions (Hardy 1996). Examples proliferate and involve organizational actors who control the workforce in people analytics contexts, or other actors such as governments and institutions as we saw in the example of the juridical software COMPAS, which has been described as "racist" ADMS (Courtland 2018). In our view, the use in practice of data visualization features of ADMS is particularly prone to political manipulation, especially if we think of how these tools have the ability to influence the opinion of large masses.

This is done with so-called data “massaging” techniques – presenting data in ways that support a particular position (Marabelli et al. 2021). They can foster political interests and lead to the manipulation of the knowledge embedded in ADMS. Knowledge is highly political (Swan and Scarbrough 2005) and while it may be easy to present synthesis of algorithmic outputs in ways that are not faithful to the underlying analyses, this is also unethical. Examples of data visualization that were used to expose COVID data in various countries showcase how government policies can be supported by “customized” presentations of data about infections, hospitalization and deaths (Maglio et al. 2021).

Set apart political (and unethical) exploitation of data through visualization, it is worth pointing to the power of charts as they can be distributed to large masses – and to the damages that easy access to (visual) information holds. During the early period of the pandemic, countries and local administrations adopted inconsistent criteria related to how data was collected, processed and analyzed (Patel 2020). While this confusion is understandable – COVID is (we hope) a once in a century event – one consequence was that graphs presented by various countries/governments were not comparable, with the result that knowledge sharing on how to address problems and make sense of lessons learned were minimal. In this case, huge amounts of data were analyzed to provide projections and trends, for instance, on potential spreads by geographical area, or taking into consideration new rules such as the lifting of a stay-at-home mandate. However, if the data itself is skewed the underlying dashboards are misleading for decision-makers (governments and local administrations) and confusing for the general public.

For instance, in the US, states have used heterogenous criteria to collect COVID data on positives, infections, hospital beds, and deaths, making it impossible to do comparisons and assessments nationwide (Patel 2020). Similarly, in the UK data concerning tests and infections have been partially collected manually (paper and pen). As a results, comprehensive reports were inaccurate, and made it almost impossible to assess the real status of the progress of the disease in the country (Conway 2020). Incorrect data reporting the speed of COVID community spreads in China in January-March 2020 had potentially compromised other countries' ability to adopt quick countermeasures (Badker et al. 2021). India's COVID infections in 2020 were vastly underreported (Chatterjee 2020), and this may have been one of the factors that led to poor preventive measures (e.g., masking and physical distancing) and that caused a national catastrophe in spring 2021. The lack of preparedness of countries worldwide during the COVID pandemic should serve as an example of the relevance of "good" data, especially if we think of the power of visualization. This should also encourage IS scholarship to focus more on visualization aspects, their use in practice and the organizational and macroeconomic ramifications of data massage (with ethical implications) and data quality issues.

Other problems of ADMS's use in practice concerns the environment. These systems (especially ML and NN) require an incredible amount of resources (Dhar 2020). For instance, the emissions incurred in training an NN model can be easily compared to that of several jets carrying thousands of passengers for long-haul trips. Researchers based at the University of Massachusetts, Amherst, performed a life cycle assessment for training AI models. They found that the process of training a single NN can emit more than 626,000 pounds of carbon dioxide equivalent—nearly five times the lifetime emissions of an average automobile (Strubell et al. 2019). This effect of the employment of ADMS is clearly something that involves system design (how ML works with training data), implementation (the context in which it is used determines the type of training) but most importantly the system's use in practice. It is only by observing how ADMS develop and propagate in various settings that researchers will be able to assess the potential ethical threats – in this case related to sustainability. This begs the question of whether IS scholarship should broaden its focus and consider choices beyond the use of ADMS in a single organization and rather consider more holistic aspects such as science and progress more generally.

Related to the above, broad, macro-level research on the use of ADMS, for instance in relation to emissions, generally requires grant support because of lab costs etc. One consequence is that this research is often conducted by the private sector rather than academia, and this can compromise the relevance of the research questions, and potentially the reliability and impartiality of its findings. Various institutions are trying to address this issue. In May 2021 a new bill, the Social Media DATA Act[4] was introduced by a US lawmaker that calls for companies such as Facebook and Google to give researchers more access to platform/user data. A similar initiative is taking place in Europe with the Digital Service Act[5] that will give researchers access to data gathered by "very large platforms", otherwise protected by the EU General Data Protection Regulation (GDPR).

Meredith Whittaker, the faculty director of the AI Now Institute (https://ainowinstitute.org) stated that "At any moment a company can spike your work or shape it so it functions more as PR than as knowledge production in the public interest." (Simonite 2020). The Gebru case we mention earlier supports Whittaker's point that companies may drive opportunistic research while pointing to the importance of academic freedom. In fact, only one of the coauthors of the paper that cost Gebru her job disclosed her identity, fearless of repercussion; Emily M. Bender, a professor of computational linguistics at the University of Washington. She

[4] https://trahan.house.gov/uploadedfiles/social_media_data_act_two-pager.pdf
[5] https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=72148

acknowledged that she was able to identify herself as an author because, unlike company employees, she holds tenure status at a university.

It is however important to remember that tech companies provide huge grants to academics for conducting research. In turn, if most AI/ML research takes place in (or is influenced by) companies, how can we make sure that ADMS advances reflect ethical and deontological principles? What is the role of IS scholarship in investigating long-term consequences of the design, implementation and use in practice of these systems if the underlying research is conducted in affiliation with companies with dubious ethical standards? Is it possible to generate national and international policies that warrant independent research undertaken by various stakeholders, with the aim to create a "free market" of findings and discoveries that prevents conflicts of interest?

Social and computer scientists have already noticed that an impressive amount of data - in particular sensor data – were collected during the COVID pandemic, which has helped researchers trace the way people behave, for instance using GPS trackers on smartphones. This pandemic-related data is about natural experiments related to how people behave (whereabouts, social interactions), and researchers worldwide are now much more willing to collaborate and share finding (Aschwander 2021). For instance, European researchers focused on how people moved from/in rural and urban areas during the pandemic in France, Italy and the UK and singled out different patterns of mobility reflecting different infrastructures. This predicted economic resilience which has been helpful for policymakers to make decisions in case of future widespread disasters (Galeazzi et al. 2020).

These results are increasing the relevance of ADMS for social purposes, at the international level and, we argue, researchers should access these and more datasets. Yet, lessons learned from the COVID pandemic can be used and shared only if large data providers (social media, mobile phone providers etc.) are willing to share anonymous datasets outside their companies. We therefore ask: What is the role of IS scholarship in advancing data sharing strategies that promote "open research" while ensuring that citizens' privacy is protected?

Finally, a methodological note. The massive use of sensor data that feed ADMS systems and supports organizational and policy-based decisions rely almost exclusively on quantitative approaches. The established qualitative tradition of some IS scholarship should push us further in considering collaborations across different research philosophies and approaches and engage more in mixed-method research. Qualitative research on ADMS is still very scant – because it is difficult to ask questions to individuals that are not fully (or even partially) involved in the design and implementation of ADMS (contrary to what we have done with ES) because these decision-making systems are often invisible and available only to top management. Also researchers report how difficult it is to interview or observe the workforce (cf. Uber or Amazon), with companies threatening retaliation if the workforce speaks with the press or researchers (Rubin 2020).

However, recently the IS community has started to promote qualitative inquiries in the realm of digitalization (cf. the special issue Qualitative Research in the Age of Digitalization ongoing at *Information and Organization* (Galliers et al. 2020)). We hope that future research on how ADMS are used in practice (but also designed and implemented, in this case) will stem from these "signals" of interdisciplinary collaborations among the IS community and beyond.

CONCLUSIONS

The goal of this commentary was to take the conversation on ADMS further (Newell and Marabelli 2015) and push IS scholars to leverage our specific sociotechnical competences to make sense of several strategic choices related to design, implementation and use in practice of algorithms in organizations. Overall, it is naïve to think of algorithms that are perfectly designed and effectively implemented so that their use in practice allows better and more objective decision-making for all stakeholders involved. Like all technologies, these systems have emergent affordances and unintended consequences are always "around the corner." With our framework and our analysis of potential future avenues of research we hope to have laid the ground for novel, exciting studies in our domain that will address the problematic use of ADMS in organizations, institutions and society.

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