In the Age of the Smart Artificial Intelligence: AI's Dual Capacities for Automating and Informating Work

Mohammad Hossein Jarrahi
University of North Carolina, Chapel Hill
Chapel Hill, NC 27599 USA
jarrahi@unc.edu

Abstract

Recent developments in AI have generated tidal waves, which are shaking the foundation of organizations and businesses. Even though AI is considered an unprecedented disruptive force for work automation, much can be learned from current research on the computerization of work. Drawing on the seminal work of Shoshana Zuboff, this article provides a balanced perspective on the dual affordances of AI systems for automating and informating work. Whereas AI offers unique capacities for automating cognitive work that once required high-skill workers, it may be a source of unintended consequences such as cognitive complacency or deskilling workers. To overcome such effects, the informating capacities of AI systems can be invoked to augment work, generate a more comprehensive perspective on organization, and finally equip workers with new sets of intellectual skills.

Keywords: Artificial intelligence, intelligent machine, automating, informating, augmentation, algorithmic management

Background

Organizations around the globe consider AI the frontier for digital transformation and the most critical disruptive technological innovation, which has the potential to unleash the second machine age (Brynjolfsson and Mcafee, 2017). Excitement around the relationship between AI and work automation involves both fascination and trepidation -- aptly captured in the antithetical concepts of "automatopia" or "automageddon," which mirror unrealistic expectations about AI power for mass automation (Lacity and Willcocks, 2018).

A common fear is that AI, with unprecedented capacities for automating intelligence, will displace legions of workers as it starts to outperform humans in a rising number of task domains. Recent analyses contend half of today's work activities could be automated by 2055 (Manyika et al., 2017). Some predictions are even bolder: Ray Kurzweil, a co-founder of Singularity University predicts the "singularity" for AI to take place in 2029 when AI will virtually match humans in cognitive tasks (Rejcek, 2017). Such assertions regarding intelligent machines and their automating apparatus are not entirely new. Herbert Simon, lauded as a pioneer of artificial intelligence, maintained in 1960: "Within the very near future — much less than twenty–five years — we shall have the technical capability of substituting machines for any and all human functions in organizations" (Simon, 1960, p. 22).

Nonetheless, such pronouncements have proven inflated in the past, and predictions of rapid and radical organizational transformations in the wake of technological innovations have repeatedly manifested as unrealistically optimistic (King and Grudin, 2016, Tredinnick, 2017). Against this historical backdrop, some pundits consider that AI is reaching the peak of its hype cycle and that the aphorism of automation and human replacement will soon wither. While there is some evidence supporting this argument (Davenport, 2018), emergent AI algorithms seem to offer new foundations for work automation that may set them apart from previous waves of automating information technologies (IT) (Brynjolfsson and Mitchell, 2017, Phillips and Collins, 2019).

Earlier waves of intelligent IT (used, for example, in expert systems) functioned based on symbolic logic in domains with clear rules and definitions, and often drew on statistically based learning (Rouse and Spohrer, 2018). The advent of deep learning, which invokes the power of neural networks, presents groundbreaking opportunities for machines to learn and expand its intelligence outside pre-specified structures and instructions. Beyond the booming growth of new AI like deep learning, the utilization of big data and powerful computing capacity, such as quantum computing, further bolsters the power of smart technologies (Bean, 2018). These two factors have probably provided a boost to AI-driven approaches, which enable organizations to swiftly collect and process massive amounts of data, and then act upon it in making decisions.

As such, emergent algorithmic systems present qualitatively different capabilities for transforming work and organizations (Faraj et al., 2018), and may usher in a fundamental departure from the previous waves of IT applications in organizations (Brynjolfsson et al., 2018). For example, they may present unique capabilities through which automation does not only replace low-skill workers (which was primarily the case with the previous IT-enabled automation) but could also impinge upon knowledge-intensive tasks we once thought required high-skill workers (Manyika et al., 2017).

The current discourse around AI and the future of work is often skewed towards macro trends in the labor market, particularly the creation or elimination of jobs or unemployment (e.g., Bughin, 2018). These studies typically center around examinations of entire industries or occupations (e.g., Frey and Osborne, 2017), or investigate AI's potential impacts on productivity at an economic level (e.g., Brynjolfsson et al., 2018). This article adopts a somewhat different approach by focusing on the roles AI may play at an activity-level and how these systems may transform work practices. In doing so, it builds on the wealth of computerization research, and more specifically the work of Shoshana Zuboff (1988), a prominent labor ethnographer and business administration scholar.

Computerization Movement

Computerization research has emerged as a grounded research tradition to address the relationship between computerization (the use of IT systems in organizations), and automation (for more information, see Kling and Dunlop, 1993). Zuboff's scholarship – considered monumental in computerization research -- offers a cogent conception of IT characteristics (in comparison to the common understanding of the industrial machine) and how IT-based automation may foster unique changes in the workplace.

In this article, we build on and adapt the theoretical foundation offered by Shoshana Zuboff's inspiring work regarding the impact of smart IT. Specifically, the article focuses on the dual affordances of emergent AI capabilities for automating work practices. In doing so, a brief overview of Zuboff's theory is provided first, and then along the key dimensions of *automating* and *informating*, this article will examine the potential opportunities and challenges in the implementation of AI systems. Finally, the paper discusses some implications for managing AI-powered systems in organizations.

Zuboff's Theory of Computerization and Automation

In her 1988 widely-acclaimed book ("In the age of the smart machine: The future of work and power"), Zuboff offers a well-grounded account of how unique characteristics of IT shape workers and work in modern organizations. Using ethnographic approaches, Zuboff's detailed description of digital transformation illustrates how IT connects to daily work practices. This is a useful outlook for this article (which takes a more micro focus), and complements ubiquitous macro analyses of AI and digital transformation.

Despite rapid technological changes in the past decades, Zuboff's core argument relative to computerization, automation, and work dynamics remains largely relevant today; she delivers a versatile conceptual vocabulary for unpacking the social and organizational implications of smart machines (Kallinikos, 2010). Zuboff's thesis can explain current fundamental characteristics of IT, such as its informating capacities, and organizational dynamics, such as power differentials in organizations (Burton-Jones, 2014).

Zuboff postulates computer systems as "smart machines" and her conceptualization was among the first to explore the transformative nature of IT through the lens of informating and automating work (Burton-Jones, 2014), which are detailed below.

Automating

In simple terms, automation refers to employing technology to conduct work more quickly and efficiently. Zuboff sees automation as a defining element of IT and the computerization movement, comprising the explication of organizational tasks and then the transformation of this codified description of tasks into particular courses of actions and procedures to be automatically performed by computerized systems. In this process, "electronic texts" occupy a central position, through which workers experience and access the organizational concepts. IT-enabled automation often results in converting activity-oriented work into symbolic work. Subsequently, this abstraction process requires new forms of analytical skills (e.g., data-based reasoning). Therefore, the ever-evolving partnership between humans and machines is accompanied by the "intellectification of work," which then requires a new dynamic environment for learning and abstract thinking.

Automating work activities can have mixed results; it can simultaneously enrich people's work (e.g., by providing opportunities to develop new skills through interacting with the smart systems), while also relegating workers to uninspiring roles (Barrett et al., 2012). For example, automating capacities of IT can be harnessed to free up workers from mundane activities and to orient them towards a more comprehensive, holistic, and abstract perspective of their work (enabled by the 'informating' capacities of the same technology). Zuboff advocates for utilizing intelligent machines to 'informate,' which enables workers to enlarge the information content of their tasks rather than deskilling them.

Informating

The potential to informate distinguishes IT from other technologies, and is considered essential to modern computer systems. That is, IT offers capacities beyond automation, and can be used to generate a more comprehensive perspective on organizational reality (e.g., organizational tasks and operations). What Zuboff dubs an "information panopticon" facilitates total observation and visibility. This is achieved by the actualization of informating capacities of computer-based IT, and brings together many details of organizational records, and information across functions, and processes. Therefore, not only can IT transform operations into an abstract electronic system (automating) but it can also render these operations transparent potentially for both workers and managers.

Informating opportunities of smart technologies cannot be exploited unless the worker develops a new set of competencies. Zuboff calls these 'intellective skills,' which often involve new cognitive capacities related to abstraction, explicit inference, and procedural reasoning.

The remainder of this article is dedicated to exploring the dual roles played by AI in relation to automating and informating modern work practices (see Figure 1)

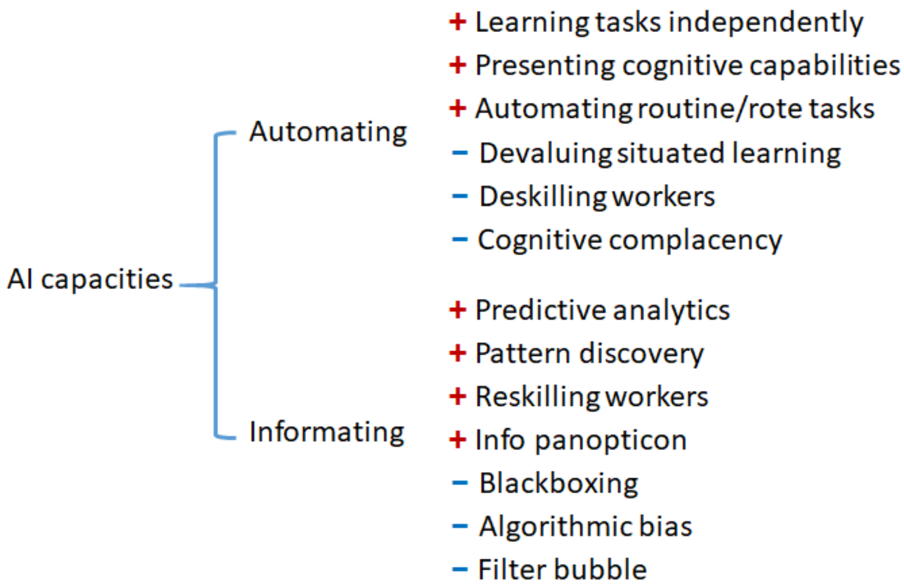

Figure 1: Potential affordances and downsides of AI for automating and informating work

AI and Automating Work

As noted, AI technologies are powerful levers for automating work. The positive affordances of AI as well as potential downsides relative to automation are broached below.

Positive Affordances for Automating

Machine learning techniques enable the computer program to learn progressively more independently based on examples and to develop its own evolving logic and outcomes rather than being pre-programmed (Tredinnick, 2017). Some go so far as to assign attributes of 'creativity' to AI when, for example, machine learning algorithms figure out new solutions to certain problems on their own (Brynjolfsson and Mitchell, 2017).

This opens up opportunities for superseding a human's performance in an expanding range of tasks and penetrating elements of work tasks that once required cognitive capabilities (e.g., classification and data-based prediction and sensing facets of humans emotions) (Manyika et al., 2017). Expressly, AI has made inroads into the realm of perception and cognition in recent years by offering unparalleled affordances for speech and image recognition as well problem solving and analytical thinking (Brynjolfsson and Mcafee, 2017). Moreover, machine learning algorithms are now able to learn aspects of tacit knowledge (Faraj et al., 2018). Humans typically develop tacit knowledge through continuous cycles of practice and experimentation. Yet, tacit knowledge is embedded in tasks that were previously deemed beyond the reach of existing IT systems due to the difficulty of explanation and articulation.

AI can automate aspects of tasks wherein it has a competitive edge. For example, AI's superior capacities can be used to help humans in pattern recognition. A fertile ground for this is medical diagnosis, in which AI will be able to support physicians (e.g., radiologists) and augment their diagnostic skills (Park and Han, 2018). In some cases, AI has rendered entire workflows more straightforward without necessarily displacing the human actor. For example, deep learning models now help insurance adjusters by streamlining the triage process and generating estimates for repair costs (reducing the need for manually scanning photos) (O'Reilly, 2016).

Routine and mundane tasks are most susceptible to this form of AI-based automation. The Economist (2016) suggests: "What determines vulnerability to automation is not so much whether the work is manual or white-collar but whether or not it is routine." Targeting routine tasks echoes a common logic in automation research (also ratified by Zuboff), which treats technology-based automation as a vehicle to free workers from mundane work and help them direct attention to more systematic knowledge of work and organization (what is implied by the concept of informating). To this end, rote tasks should be the first frontier for AI automation since human's engagement in these tasks does not typically enable learning or generate new knowledge.

It is important to note that the capabilities of emerging AI are often overestimated. Realistic estimates show we are far from the idea of 'general artificial intelligence,' as most machine and deep learning techniques only apply to specific, narrow task domains and may not easily transfer to other contexts (Rouse and Spohrer, 2018, Ekbia and Nardi, 2014, Brynjolfsson and Mitchell, 2017). To satisfactorily function, machine learning techniques also often require a large number of training examples, which are not readily available in many organizational domains.

Potential Side Effects

AI automating capacities can have negative unintended consequences. First, AI-based automation often requires rationalizing and standardizing activities and events so that they can be done programmatically and efficiently by the smart machine. The algorithms, however, may not carry the richness of the social and organizational milieu within which these practices are performed (Tredinnick, 2017). No matter how smart AI algorithms grow, they are unlikely to develop capabilities on par with humans' to dissect many facets of knowledge work's complex logic, particularly those that are not amenable to codification and explication (Pettersen, 2019). Therefore, AI systems may lack the situated logic of practice, and automating practices may deprive the organization from situated, context-aware, and informal learning opportunities that are profoundly human-centric and engrained in the social fabrics of the organization.

In addition, a common strategy for rationalizing work is breaking tasks into decomposable sub-tasks to be conducted through a partnership of micro-workers and AI systems. McAfee and Brynjolfsson (2017) predict new organizational forms to lie at the intersection of AI technologies, crowd contributions, and digital platforms that coordinate scores of crowd workers. Integration of AI into the organization of work (to decompose, distribute, and then integrate tasks) can introduce new forms of control while algorithms monitor and evaluate workers' outputs and work processes (Faraj et al., 2018). Some also argue that the use of algorithms in this way revives the traditional piecework systems and logic of scientific management, which are intertwined with the strict monitoring of workers (Irani, 2016).

While scientific management can improve work efficiency, it has been called into question for deskilling workers by exposing them to the narrow scope of micro tasks, inadvertently discouraging more innovative and holistic thinking and learning. If AI-based automation does not provide information richness, workers have little opportunity to exploit the system's capacity for conducting more complex activities that require a greater vision of one's work. Zuboff observed this could lower workers' commitment to and accountability for organization, as they increasingly see themselves as helpless bystanders in the face of automatic control. The history of computerization suggests that reducing human contributors into automated systems as "computational components" takes a heavy toll on humans' sense of fulfillment, affective rewards, and consequently their performance over time (Ekbia and Nardi, 2014).

Finally, negative byproducts of automation include workers falling into traps of 'cognitive complacency' by making themselves an 'appendage to the system' (Zuboff, 1988, p. 68). Cognitive complacency can riddle effective human-technology partnership. For example, people may assign more importance (and less bias) to advice given by automated aids compared to other sources of expertise (Parasuraman and Manzey, 2010). As another example, Shank et al. (2019) found that people may attribute less fault to AIs in partnership situations with smart machines compared to their partnership with other humans. Cognitive complacency can contribute to further deskilling as, for example, workers passively carry out a system's directives rather than exploiting its informating capacities and learning about its processes.

AI and Informating Work

AI systems are mixed blessings when it comes to informating work. As Zuboff points out, design assumption of algorithms can both encourage and extinguish learning opportunities and developing intellective skills. Both positive and potentially negative outcomes are discussed below.

Positive Affordances for Informating

Much of AI informating capability lies in its predictive power – in other words, "the ability to take information you have and generate information you didn't previously have" (Agrawal et al., 2017b). In particular, AI-enabled systems can be implemented to generate a bird's-eye view of the organization across different functions, integrating a variety of analytical efforts undertaken in different operations. Reid Hoffman (2016), the former CEO of LinkedIn, outlines 'corporate knowledge graphs' as prominent applications of AI, which comprehensively capture and render visible the relationships between all data and communication flows within an organization. Corporate knowledge graphs present a wide-ranging overview of information streams in an organizational dashboard, guiding decision making at different levels. Not only can such AI-powered systems embrace backward-looking metrics (e.g., revenue streams or payroll information), but they can also project powerful predictive intelligence on how these metrics may evolve in the future. Furthermore, AI provides unique informating capacities for both workers and organizations to conceptualize their sources of expertise and identity (Faraj et al., 2018). The social graph not only impacts managers' decision making, but it also visualizes the information panopticon by empowering other organizational members. For example, Hoffman suggests social graphs can facilitate the onboarding process of new employees by illuminating social networks and revealing key sources of informal expertise throughout the organization.

In addition, AI offers information and data management utility. In fact, many see these technologies as qualitative shifts in gathering, interpreting, and acting on information (Jarrahi, 2018). AI roles can include augmenting information selection, aggregation, and representation in real time across different information modalities within organizations. A clear case for human and AI partnership involves 'intent inferencing,' through which, smart agents learn and fine-tune their offerings based on the information needs of human decision makers. Through recurrent interactions and feedback, AI systems ascertain what workers intend to achieve, and regulate corresponding velocity and viscosity of information (Rouse and Spohrer, 2018).

As deep learning techniques follow non-deterministic logic, they are capable of self-learning, developing their own rules and criteria, and discerning patterns in the input data, previously unknown to human decision makers (Riemer, 2018). This capacity to sort through complex big data can yield new discoveries. As an example HubSpot, a developer of marketing and sales software, recently integrated machine learning features into its marketing tools to help users identify 'trigger events' in an organization: if an organization can be considered a sale prospect (Ha, 2017). Trigger events are moments of critical changes in an organization, discerned based on predictive analysis of data points such as job changes, news articles, or even government filings.

In this manner, AI fits the definition of informating technology offered by Zuboff as it contributes to the efficient delivery of products and services (automating) and proffers a dimension of reflexivity and transparency. It specifically helps the organizations and its members reflect back on the entirety of the organizational system of activities, people, events, processes, and environment. As such, automation does not have to be synonymous with deskilling workers, and it can serve as occasions for developing new sets of skills and insights. The informating power of AI can be invoked to reskill workers. Zuboff argues that a central benefit of IT manifests as a symbolic medium through which the worker is given opportunities to disengage from the physical context of work. Then, "a new playfulness becomes possible" when workers compare, contrast and connect surrounding events and processes (Zuboff, 1988, p. 180). AI can generate the same effect, enabling workers to develop declarative knowledge by raising new questions, finding unexplored connections between key variables, and taking different courses of action on the basis of a heightened understanding of their work and organization.

Potential Side Effects

Black-boxing

Neural network algorithms that serve as the bedrock for much of machine learning innovation may lack the capacity to explain why certain recommendations are made and how models driven by deep learning arrive at certain decisions or predictions (Chui et al., 2018). Systems' predictions that derive from hundreds of millions of connections in layers of deep neural networks may defy simple explanation and justification, keeping human decision makers in the dark. This means these AI systems often know more than they can explain in an intelligible way (Brynjolfsson and Mcafee, 2017), and hence emerge as a *black-box* to human decision makers (Sachs, 2019). Rabinowitz et al. (2018) argue: "Even if we have a complete description of their weights, it's hard to get a handle on what patterns they're exploiting, and where they might go wrong" (p. 1).

The nature of emerging deep learning techniques may contrast with explicit logic rules that underlie traditional intelligent systems (e.g., expert systems), which made it easier to ascertain and explicate the certainty and verifiability of system recommendations. Furthermore, unlike traditional systems, the algorithms used in emergent AI technologies do not build on pre-specified instructions; because of this and because of the immense quantity of data and the highly complex interactions of the data points fed into the algorithms, even the system developers themselves may not be able to fully unpick the ambiguity of the process and explain results (Riemer, 2018, Mackenzie, 2018). Acting as an opaque partner contradicts the informating power of AI and may have legal and business consequences where the rationales behind decisions cannot be made explicit.

As AI algorithms gradually penetrate more aspects of knowledge work, they can clash with knowledge workers and devalue workers' expertise due to their black-boxed performance. From the workers' perspective, algorithms can be seen as intruders that gradually take over their job while workers have little control and knowledge over how these systems learn and accomplish various tasks (Faraj et al., 2018). Opaque algorithmic performance, therefore, can contribute to deskilling workers. As Zuboff observed in financial institutions, if an information system turns into a black box imbedded with intelligence about banking procedures, workers who depend on the system are likely to grow less informed about much of the financial logic of their work and banking business.

Filter Bubble

AI presents paradoxical affordances for discovery of new information. As noted earlier, it can reveal new patterns in large quantities of data at the disposal of organization; however, integration of AI algorithms can simultaneously attenuate the serendipitous discovery of information, and access to innovative, fresh ideas. By identifying personal and organizational preferences, AI-powered systems typically customize the information flow and access to information sources, creating a so-called filter bubble, which is now considered a known characteristic of the digital world, particularly social media (Bozdag et al., 2014).

Take the example of autocompletion suggestions provided by search engines; these build from records of previous searches and project social biases or users' preferences. Other examples are recommendation algorithms that personalize outputs based on a user's prior choices or stated preferences. Recent studies indicate recommendation systems may fuel invisible biases and shape sales in ways not necessarily aligned with the interests of the end customers (Adomavicius et al., 2018). Such algorithmic performances adversely affect the quality of information supplied to decision makers. Filter bubbles, reinforced by the AI algorithms' proclivity to tailor results, run counter to the vision of an information panopticon; that is, rather than helping construct an all-encompassing perspective into an organization, the AI algorithm may filter and deliver information that organizational decision makers wish to see.

Algorithmic Bias

Algorithms are argued to carry less bias in their decision-making compared to their human counterparts (Miller, 2018). However, seldom are AI algorithms neutral and impartial. Zuboff puts this eloquently: "technology cannot be considered neutral. Technology is brimming with valence and specificity in that it both creates and forecloses avenues of experience" (p. 388). AI algorithms can project and buttress two types of biases that compromise the decision-making process: 1) biases derived from the developers' intention and value choices, and 2) biases hidden in the training data. First, designers' preferences—consciously or unconsciously—have an important bearing on which data points are integrated or disregarded in the machine learning model (Chui et al., 2018). Such important design decisions are not necessarily reached collectively and may not comprehensively reflect the interests of multiple organizational stakeholders.

Second, research suggests that smart systems and algorithms are not impartial as they reflect social biases embedded in the data they rely on for making decisions; this set of biases can result in implicit discrimination against certain groups of workers or clients. For example, Amazon recently shut down hiring AI tools because it reportedly discriminated against women by predominantly recommending male candidates; the system had trawled through male-dominated database of resumes to develop its model (Hamilton, 2018). As another example, a recent study found that algorithms of AI-driven lending programs discriminate against black and Latino borrowers by charging higher interest rates (UC Berkeley, 2018).

Implications for Organizing and Managing Work in the Age of AI

Informate Rather than Fully Automate

Focusing only on automating capacities of smart machines is inevitably mired in Frederick Taylor's ideals of scientific management, and puts technology rather than humans at center stage (Ekbia and Nardi, 2014). The prospect of fully automated systems in organizations is both implausible and unlikely. Brynjolfsson and Mcafee (2017) note: "machine learning systems hardly ever replace the entire job, process, or business model. Most often they complement human activities."

While much of the conversation on AI accentuates the smart agent and its potential for autonomous action and developing completely autonomous systems, the thrust of organizational approaches must instead shift towards the partnership between humans and AI in accomplishing work. In this sense, the work system must be perceived as sociotechnical, one that emerges from contributions of both workers and AI systems that augment work practices. The crux of 'human augmentation' can be captured in concepts such as 'augmented intelligence' (Zheng et al., 2017) or 'human-AI symbiosis' (Jarrahi, 2018), through which AI systems amplify intellectual and cognitive capacities of humans rather than replacing them.

AI can still play a key role not just by performing organizational tasks more efficiently, but also by empowering workers through symbiotic interactions with humans. This points to the needs for active engagement of workers (rather than taking a passive role as recipients of AI directives). Workers must be given the opportunity to dynamically participate in the analysis and interpretation of AI-generated results. It is only through this engagement that cognitive complacency can be overcome.

A vast majority of AI systems in organizations will still involve humans. Supervised learning, which underlies most current AI models, still requires contributions of humans to label and categorize the training datasets. However, these uses of human resources may not informate and empower workers. For example, mundane jobs are assigned to digital micro-workers to do cognitive piecework by producing training data for machine learning algorithm (Chui et al., 2018). This work is often presented as ‘janitor work’ or the menial, uninteresting labor of calibrating algorithms (Irani, 2016). Such a participation does not free workers from drudgery work while they continue to work “behind the AI curtain” without many opportunities for learning and professional growth (Gray and Suri, 2017).

Recognize and Nurture Intellective Skills

AI will yield a greater likelihood of changing the logic of work, creating new avenues for abstraction and procedural reasoning about work and organization. However, intellective skills are necessary competencies for taking advantage of these informating capacities. In dealing with AI, both workers and organizations continue to require many of the intellective skills that defined the knowledge-intensive work of the twenty-first century. Over the years, the computerization movement removed the embodied experience of concrete, action-centered labor, and introduced what Zuboff calls the ‘data interface’ to access the reality of organizations. AI systems will likely push this symbolic medium further, causing workers’ interactions with organizational events and processes to become more abstract. As highlighted by Zuboff, this emphasizes abstract thinking that enables manipulating ideas and relationships without immediate references to concrete objects and events in the real world and bring to the fore data-based inferential reasoning skills as the ability to make sense of data and discern meaningful patterns in them. A primary example of these competencies is analytical skills tied to data science. However, since AI is expected to permeate many processes, organizational roles and skills that will be redefined stretch well beyond analytical terrains. For example, the need for ‘conversational analysts’ is on the rise (McKendrick, 2018). The role oversees, analyzes, and facilitates interactions between AI agents with customers, inviting a new combination of soft and hard skills.

To fulfil a true “human in the loop” approach (Brynjolfsson and Mitchell, 2017), organizations must also appreciate the intellective skills that are exclusively provided by humans. The most valuable skill that managers contribute to AI-powered decision-making is critical judgement. Intelligent machines can contribute to predictions through their superior power in learning associations in (big) data, but judgment is a profound, implicit human-centered process. Judgment involves a contextual understanding against which various costs and benefits of predictions can be weighed. Moreover, judgment also necessitates making intuitive decisions about new situations without precedents (Agrawal et al., 2017a). Judgment also often draws on common sense or background knowledge that a machine is less capable of mastering (Brynjolfsson and Mitchell, 2017). For example, AI can inform legal practitioners by helping find and organize previous legal precedents for a case, but developing a holistic winning strategy lies beyond a machine’s capability (Remus and Levy, 2017).

Intelligent Interface Layer to Foster Mutual Learning

Deep learning systems are prone to error and can be fooled (Rouse and Spohrer, 2018). In contrast to traditional algorithms the system may have a hard time recognizing it has made mistakes, or if it has been fed with unknown or erroneous inputs (Riemer, 2018). For example, an AI system powered with deep neural networks recently made systematically incorrect predictions with high confidence for unrecognizable images (Nguyen et al., 2015). Such fundamental limitations of AI systems perpetuate the need for AI to augment humans’ intelligence rather than operating autonomously in most organizational processes. In these cases, decision responsibility eventually lies with humans, and their active participation ensures the accountability of decisions being made (Lupton and Jutel, 2015).

To avoid the pitfalls of cognitive complacency, human contributors need to have some sense of how their technological partners develop inferences, and so require a decision support system in the form of an 'intelligent interface layer' that facilitates interactions with the intelligent system. An intelligent interface sets in motion a process of mutual learning. AI learns about information needs, the intention of decision makers, and overall task environments; humans develop an understanding of what learning process AI is going through and is capable of at each point in time (Rouse and Spohrer, 2018).

Transparency of algorithms helps establish trust between the workers and AI. The unintelligible ways in which algorithms arrive at a decision is an inherent nature of machine learning algorithms empowered by deep learning. This inscrutability of algorithmic decision making can diminish workers' trust in their artificial partners (Fan, 2018). To redress this challenge, the intelligent interface layer can integrate recent developments in computer science. The first option is to apply experimental methods to articulate statistical models of input-output relationships; these models help explain AI recommendations to human decision makers (Rouse and Spohrer, 2018). Second, bourgeoning techniques such as local interpretable model agnostic explanations (LIME) and attention techniques help identify aspects of the input data that the model builds on most to make predictions (Chui et al., 2018). Finally, another possible strategy has its roots in 'theory of mind.' Recent experiments show promising results regarding the application of theory mind, which equips AI algorithms with a way to simulate the mind of its human partners and their needs, and more importantly determine effective strategies to communicate and justify the decisions the intelligent agent autonomously develops to humans before putting them into action (Rabinowitz et al., 2018).

The design of an intelligent interface layer can be mindful of filter bubbles. Developers and adapters of AI systems must strive to incorporate elements of serendipity into the design of the system, through which the organizational users are constantly exposed to alternative paths and data points (than those in the realm of familiar experience). An inspiring example is Gobo[1] (a social media aggregator developed in the MIT Media Lab), which systematically subjects users "to news and points of view from outside their usual orbit, as well as inviting them to explore what was filtered out by your current filter settings" (Bhargava, 2018).

Algorithmic Management and Transparency

There is little doubt that AI algorithms will bring about more profound organizational changes and infiltrate more managerial roles in the future. But recent surveys indicate managers are often too optimistic about the transformative power of AI systems (Davenport, 2018). AI presents novel capacities for automating and informating work, but as a technology it is only a catalyst in algorithmic management. Complementary investments in new sets of intellective skills, infrastructures, business models, organizational processes, and policies add true value and trigger cascades of organizational productivity and innovation (McAfee and Brynjolfsson, 2017). Before rolling out any AI-enabled

[1] https://gobo.social/

initiative, organizations need to ensure that managers and other stakeholders throughout the organization are adapting to the new reality of algorithmic management and proliferation of smart technologies in decision making.

Paying attention to potential impacts on workers' morale is even more critical in the utilization of AI in managing work. By reducing the sense of autonomy, AI algorithms can enforce Tayloristic work rules and standards, lower workers' negotiating power, and conceivably resulting in deskilling and demoralizing the workforce. Dwelling only on the automating power of AI harkens back to the premise of hierarchical control and suppresses nonhierarchical and panoptic forces of informating. Taylorism in the era of smart algorithms may manifest itself in the treatment of humans as programmable cogs in machines (Frischmann and Selinger, 2017).

AI's informating capacities have the potential to engender a more democratic organizational culture by creating more equal access to information. As Zuboff found years ago, informating power can upend dominant social and political orders and the hierarchical and positional power gleaned from them. A hierarchical mindset may therefore promulgate the opaqueness of algorithms to forgo the informating power of AI, and instead reproduce prevailing structural regimes and traditional hierarchical distance. For example, recent research demonstrates that algorithms that manage work on digital platforms implicitly (or sometimes explicitly and by design) withhold key information from gig workers, and therefore herald the information asymmetry between the platform and gig workers to sustain a power differential in the sharing economy (Rosenblat and Stark, 2016).

In contrast, Zuboff's vision of an information panopticon propagates transparency and underscores the intelligent agents' role in rendering these processes more visible and comprehensible to a broad range of stakeholders, not just organizational elites and managers. This disparages using the informating power of smart technologies just to create a "single omniscient overseer" at the apex of the organization. An information panopticon as articulated by Zuboff animates collectivism by advocating for both vertical and horizontal visibility in organizations. As a result, organizations must orient the application of AI towards appreciating and galvanizing comprehensibility of algorithmic management.

Finally, removing bias in data and consequently in AI algorithms remains one of the most crucial but daunting elements of algorithmic transparency (Chui et al., 2018). To harness the full informating power of AI and big data, organizations must regularly conduct algorithmic audits to first recognize sources of bias in data and then take the necessary steps to debias them. In addition to examining dimensions such as fairness, bias, consistency or accuracy, algorithmic audits help open up the black-box of AI algorithms, and raise trust between human and intelligent machines and accountability for algorithmic decision making (Diakopoulos, 2016).

Conclusion

Noticeable characteristics that define the recent rise of AI may be distinct from previous waves of smart technologies. However, the allure and anxiety surrounding the automating power of AI is anything but new. Computerization research, particularly the work of Zuboff helps us embrace the organizational dynamics of smart IT adoption and their capacity for augmenting and automating work. Changes in the automation and organization of work are sociotechnical, meaning that while technology is an indispensable driver, ultimate organizational outcomes of AI systems are shaped by the ways through which the informating and automating capacities are perceived and put into practice within an organization.

Automating and informating dimensions of AI are closely associated, but automation does not always result in a more abstract, comprehensive view of an organization or a higher quality understanding about one's work environment. As Zuboff (1988, p. 11) attests: "It is quite possible to proceed with automation without reference to how it will contribute to the technology's informating potential." Implementation of AI systems may not be automatically conducive to informating benefits wherein managers and system developers are predominantly driven by an automating logic. Therefore, without a more holistic perspective towards AI, its informatics logic and complementarity, as well as the centrality of organizational and social factors, it is likely that the hyperbole around new AI and its capabilities will give way to another underwhelming wave of outcomes, and consequently another big AI winter like those we have witnessed in the past.

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