Abstract

In recent years, artificial intelligence (AI) systems have been deployed and implemented in a variety of economic sectors. These developments have contributed to increasing fears of worker replacement by machines. However, instead of completely replacing workers, in most cases, they have led to the transformation of existing jobs and cooperation relations—frequently conflicting—between workers and machines. In this chapter, we explore three types of relations between workers and AI in the workplace: human-to-machine communication, human-with-machine communication, and machine-to-human communication. We argue that these relationships and the need for human-machine communication in the constant development of artificial intelligence have blurred the boundaries between the development, customization, and deployment of AI. We conclude that, while the cooperation between humans and AI will remain essential in productive activities, the quality of these relationships—and especially the power relations between these actors—will be a fundamental object of study.

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Keywords

Artificial intelligence, Labour Process, Automation, Data Work, AI-as-a-service

Labour, Automation, and Human-Machine Communication

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Introduction

In 1779, an English weaver called Ned Ludd allegedly smashed two stocking frames in a fit of rage. Decades later, a movement of workshop artisans eponymously named *the Luddites* targeted the machinery of the First Industrial Revolution, fearing their replacement and the impoverishment of their living conditions (Smith, 2021). Throughout the centuries, automation anxiety has occurred in waves as new technologies threaten to replace workers and 'disrupt' labour markets. Research has indeed shown that people overwhelmingly fear widescale job displacement by robots and other machines, even if they do not perceive their own occupations to be susceptible (Taipale & Fortunati, 2018). Yet, while emerging technologies continue to reshape both labour markets and labour processes (Acemoglu & Restrepo, 2019), they have not yet led to the replacement of workers since employment levels have remained stable for centuries (Autor, 2015).

Although often simplistic, antagonistic, or even affectionate, workers have always developed communicative relationships with the machines they use at work, as well as with those used to control them. An artisan's tools, for instance, or a chef's knives, are often conceptualised as an extension of the self in an organisational setting; they are spoken to lovingly and cared for, or perhaps shouted at in annoyance when something goes wrong. As the prominent 'Computers Are Social Actors' (CASA) paradigm relates, even early computing technologies were imbued with a social agency and treated mindlessly as either a team-mate or an adversary (Nass & Moon, 2000). However, imbued with more complex communicative affordances, contemporary Artificial Intelligence (AI) based technologies offer more active and social communication forms vis-à-vis their human counterparts (Chui & Malhotra, 2018; Fox & McEwan, 2017). AI both facilitates and automates forms of communication that have historically been limited only to human interactants (Reeves, 2016; Guzman & Lewis, 2020). Natural language processing, for instance, enables AI-based technologies to interact in a broader variety of social settings (Gambino et al., 2020). As Westerman et al. (2020) explain 'developments in AI have led to new communication contexts in which people talk not only through technologies, but also to and with them as if they were legitimate partners' (p.395).

The way that intelligent technologies are interpreted and viewed, ontologically, is important for creating meaning and expectations (Gibbs et al., 2021). As Guzman (2018) explains, 'Human-machine communication is the creation of meaning among humans and machines' (p.17). Yet, despite its more than half-century development as a field of inquiry, AI has remained challenging to define. In general terms, the study of AI concerns itself with the development and understanding of 'intelligent' machines (Russell & Norvig, 2020). However, there is no consensus on what constitutes 'intelligent'. Today's 'second wave' of AI, as opposed to the early developments in the field, has been primarily due to advancements in machine learning (ML) (Alpaydin, 2020). While ML research has existed for decades, its development—and financial investment—skyrocketed in the recent decade due to the availability of vast amounts of data thanks to internet connectivity and pervasive data collection methods (Zuboff, 2019). In this chapter, we use the generic term 'AI', while acknowledging that most current applications do utilize ML, natural language processing, and other specific techniques. Our focus will therefore be on ML-based technologies that learn from data interpretation, which are the main applications in the AI-as-a-Service (AIaaS) sector (Newlands, 2021b). Moreover, although there are a panoply of embodied workplace robots, most of the AI applications in the workplace are predominantly disembodied and communicative (Guzman, 2020), such as chatbots, workforce management tools, or HR systems.

With some exceptions, such as Gibbs et al.'s (2021) work on automated journalism, research around HMC in organisations or at work has remained scarce. As they succinctly explain, 'the notion of HMC as an organizational process has not yet been adequately theorized' (Gibbs et al., 2021, p.155). Nevertheless, it is crucial to explore the interplay of AI, HMC, and work since AI applications can transform organisations (Fortunati & Edwards, 2021) and the replacement of decision-making functions means that AI applications are often viewed more as social agents than as tools (Banks & de Graaf, 2020; Jarrahi et al., 2021). With the current implementation of AI applications in the workplace, we now observe what Shestakofsky (2017) calls 'human-software complementarity' in the human labour that supports algorithms and helps the adaptation to these systems by their users. Since AI systems are continuously produced and reproduced through human actions at work (Gibbs et al., 2021), there is a blurring of boundaries between the human and machinic elements (Edwards et al., 2019).

As we will explain in this chapter, this human-AI complementarity also shapes how the full life-cycle of AI systems emerges, whereby there is an ongoing, dynamic conversation occurring between the human and the AI across each AI application's development, customization, and deployment. This life-cycle perspective presents a unique opportunity for Human-Machine Communication scholars to study meaning-making processes that emerge from ongoing communicative processes between human workers and AI systems. In this chapter, we therefore explore and describe three moments in the relationship between workers and AI, namely *human-to-machine communication* in AI development with a special focus on the production of training data, *human-with-machine communication* in processes of AI customization, and *machine-to-human communication* in AI deployment at the workplace. As Fortunati and Edwards (2020) explain, 'people have passed from acceptance of talking to machines to talking with machines' (p. 12). Accordingly, the directionality and hierarchy of communication between the human worker and the AI is highly dependent on the particular phase of the AI's development. Whereas workers in the generative, developmental phase far more often are speaking to the machine, imbuing it with communicative capacity and a voice, workers in the later stages are often merely passive audiences to a top-down machinic voice. We thus focus on the meaning-making processes present at each stage to argue that the three communicative instances are complementary and the boundaries between them are blurry. As we will argue in the next section, meaning is created in the interaction of workers and algorithmic models in training, customisation, and deployment instances.

This extended approach also allows a view into the power dynamics at the core of meaning-making processes between humans and AI at work (Guzman, 2017). As Wiener (1950) explained, the significance of machines for society is how they shape issues of communication and control. Workers' autonomy, for instance, often depends on how much they can understand and communicate with AI systems at work (Jarrahi et al., 2021). As the developing HMC literature has shown, there is a shifting degree of control imbued into technologies, ranging from low to high (Malone, 2018). The way that people conceptualise technologies also shapes how they make sense of and interact with them (Edwards, 2018). For instance, the more powerful technologies become, in relation to the individuals interacting with them, the more they get anthropomorphised (Waytz et al., 2010). We see this perception, for instance, in how AI applications for labour-control are often referred to as 'the boss' or the 'manager' (Adams-Prassl, 2019). Since individual and communal voices are heard distinctively, this chapter highlights the power differentials present in instances of development, customisation, and deployment of AI systems. Indeed, we must increasingly look at questions of how humans should act towards machines, and how machines should in turn act towards humans (Guzman & Lewis, 2020). In this sense, we argue that the aspect of polyvocal communication remains crucial in addressing some of the social issues related to the relationship of workers and AI systems.

Human-to-Machine Communication in AI Development

The first stage in the development of ML-based AI systems is creating datasets that will constitute the backbone of these technologies. Historically, data as a term emerged in the 17th century mainly as a rhetorical device to designate pieces of information independently of their veracity (Rosenberg, 2013). In the introduction to the edited collection 'Raw Data is an Oxymoron,' Gitelman and Jackson (2013) argue that data is never 'raw' and always 'cooked;' data is an abstraction of reality and processes of data creation comprise stages of collection, storage, processing, and interpretation. Similarly, D'Ignazio and Klein (2020) stress the importance of the social aspects of collecting and interpreting data and especially the power relations involved in these social processes. This process of 'datafication' involves the extraction, transformation, and interpretation of data from individuals, social relations, and natural phenomena (Mejias & Couldry, 2019).

In this chapter, we adopt a relational conceptualization of data as the product of meaning making. Data production for ML involves vast amounts of collaboration between humans, organizations, and technologies and such collaboration is always shaped by power differentials (Miceli et al., 2020, 2021). In this context, communication often takes the form of negotiation around the meanings that are ascribed to data, i.e., how each data point is interpreted in relation to a specific ML system, whose data is more profitable for marketing purposes, or what can a specific algorithmic model learn from what data. Working with data thus involves 'mastering forms of discretion' (Passi & Jackson, 2017).

To explore processes of AI development, we therefore focus on the *human-to-machine communication* that occurs in workplaces with the objective of producing data to train ML systems. This data can be communicated to ML systems, for example, via peripheral devices in the case of computers or through actuators and sensors present in other types of machines. Through input data, human workers set the tone of how ML systems make sense of the world. Later, ML systems will output predictions and classifications that carry those meanings created in the interaction with humans through data. By *human-to-machine communication* we thus refer to the meaning making involved in practices such as collecting, curating, and labelling data as well as its subsequent use to train and validate machine learning models.

Data work, i.e., the labour that goes into producing and maintaining datasets for AI, is a primary example of this type of *human-to-machine communication*. This type of work is carried out by AI developers, domain experts, outsourcing workers, and users of AI technologies. For example, in cases where AI has been deployed in healthcare, nurses, medical secretaries, and doctors input patient data into datasets that are ultimately fed into models (Møller et al., 2020). Users participate in data entry by using services (Terranova, 2000) and labelling data, for instance, through the solution of CAPTCHA tests where they transcribe text or select images according to predetermined labels (Justie, 2021). Most companies and research institutions, however, outsourced the labour and time intensive labelling process to workers worldwide through business process outsourcing (BPO) companies (Miceli et al., 2020) and digital labour platforms (Casilli & Posada, 2019; Newlands & Lutz, 2021). These forms of outsourcing data work involve low-paid independent contractors located, in many cases, in developing countries.

BPO companies usually specialize in one type of data annotation like semantic segmenting (i.e., the marking of objects in an image) and one type of application (e.g., computer vision). Conversely, platforms dedicated to data work function entirely online. As a subset of the larger gig economy (Woodcock & Graham, 2020), platforms serve as intermediaries between workers located in different geographies, usually working from their homes, and AI developers (Casilli & Posada, 2019). Tasks in online data work include the categorization of images, text, and video, inputting data in the form of text, video, audio, or images, and providing feedback to companies on the accuracy of AI algorithms (Casilli et al., 2019). Both in platforms and BPO companies, data work for ML is shaped by power dynamics (Gibbs et al., 2021; Miceli et al., 2020). Not only do power asymmetries affect labour and services relationships but they also shape the meanings that are ascribed to data and the communicative process that takes place between workers and systems in AI development.

Data annotation for supervised learning constitute a clear example of how power differentials shape meaning making between human workers and AI. The labels workers assign to data are instructed to them throughout hierarchical structures that leave almost no space for data annotators to exercise their own judgements and make sense of data on their own (Miceli, 2020). This top-down meaning imposition also embeds predefined interpretations onto datasets and, of course, on systems. As previous research has argued (Miceli & Posada, 2021) annotation instructions provided by machine learning practitioners to outsourced data annotators comprise narrow labels and include warnings that compel workers to follow orders. In this case, the influence of the most powerful actors (i.e., AI companies requesting the annotations) permeates datasets and models. Such instructions constitute a salient manifestation of the power differentials present in processes of meaning making among ML practitioners and data workers, and between them and AI systems. The sensemaking that human workers perform is a key element here: through practices of collecting, sorting, labelling, and cleaning training data, humans communicate their expectations to machine learning models.

Human-with-Machine Communication in AI Customisation

As discussed above, one of the primary mechanisms of AI adoption in work settings is through the use of third party AIaaS applications (Newlands, 2021b). However, this externalisation of AI development means that after AI services have been developed, they must be adapted and customised for the specific workplace setting (Vesa & Tienari, 2020). There is always a need for extra effort and time to align humans and algorithmic systems (Burton et al., 2020) and this is what Newlands (2021b) refers to as 'AI co-production', where organisations must engage in ongoing customisation and training of the AI service (Grønsund & Aanestad, 2020). Algorithmic systems do not exist outside of the organisational contexts within which they have been implemented (Kellogg et al., 2020) and the specific contexts of embedding shape the interplay between organisational actors and the AI, which in turn generates the communication paradigms eventually imposed on the workforce. We can observe this, for instance, through the customisation of 'digital employees' (Huang & Rust, 2018) where a considerable amount of human effort is involved in implementing specific AI applications into the organisation and keeping them running (Lyytinen et al., 2020).

Turning to a specific case, we can observe a high level of effort enacted in the customisation of chatbots to match the specific needs of the workplace (Baez et al., 2020). Chatbots enable rich interactions with people, triggering the view that they are social entities (Jörling et al., 2019; Wirtz et al., 2018). However, despite advances in natural language processing, chatbots remain incapable of making sense of nuance, of meaning, and of relationships (Pantano & Prizzi, 2020). Chatbots need to be actively trained through accurate input and predefined answers (Adamopolou & Moussiades, 2020; Følstad & Taylor, 2020). This process of chatbot training (Kvale et al., 2020) usually involves providing the chatbot with a predefined set of example phrases, while continuously adding, changing, and removing examples to gradually shape the chatbot's 'personality' (Liebrecht & van Hoojidonk, 2020).

As opposed to the initial training and development phases, the customisation stage allows us to observe a greater degree of interactive communication between the human workers and the AI in a mechanism of *human-with-machine communication*. This is because, at this stage, the specific 'voice' of the AI is being generated while simultaneously the 'voice' of the workers is being trained in how to appropriately talk to the AI. As with call centres, where workers develop certain scripts and a firm-specific personality (Sands et al., 2020), AI systems such as chatbots are also trained to portray a certain type of voice, usually by mimicking specific human workers (Luo et al., 2019). Referred to as the 'conversational human voice' (Kelleher & Miller, 2006), the development of a specific communication style that reflects human attributes such as informal speech, means that there is a greater sense of dialogue and mutual shaping between the worker and the machine.

This mutual dialogue, however, does not mean that humans and machines are considered equals and their relationship is devoid of a social context and power differentials. For instance, in the case of *human-with-machin*e *communication* in Amazon warehouses, Delfanti (2021) considers this relationship extractivist in nature, a form of 'machinic dispossession' in which the knowledge and behaviour of workers is expropriated and incorporated into machinery, in this case, the AI system. For Delfanti (2021), this relationship is one of 'dispossession' because, in the case of the warehouse, it occurs in a context of control by management through the use of technological tools to survey and discipline the workforce, which the author calls 'augmented despotism.'

Machine-to-Human Communication in AI Deployment

The use of AI has become ubiquitous in many workplaces because of the perceived increase in productivity, prediction, and coordination (Kellogg et al., 2020). However, AI can also perpetuate discrimination as demonstrated in the case of AI tools that offer algorithmic assessments of workforce (Rosenblat & Kneese 2014), and serve as a mechanism of control such as the case of Amazon warehouses (Delfanti, 2021) and data labour platforms (Miceli & Posada, 2021) described above.

After inputting information in an algorithm through *human-to-machine communication* and being affected by its customization through *human-with-machine communication*, algorithms generate outputs that its users perceive. This form of *machine-to-human communication* aids—but also influences—the actions of workers who are subject to algorithms in the workplace. Such algorithmic outputs are predefined by system developers and constitute, from a communication perspective, a top-bottom imposition. In this last section of the chapter, we will explore forms of machine-to-human communication through the lens of its influence over the labour process.

Labour process is a Marxian term defined as the transformation of *labour power* (i.e., the capacity –as opposed to the act–of working) into a *commodity* (i.e., a product destined to a market) following a series of *relations of production* (i.e., the relations involved in the reproduction of society) (Burawoy, 1979). Thus, labour process consists of the series of productive activities and the social relationships that surround them. The theory that has focused on the labour process looks into four different aspects of it (Thompson, 1990): the role of labour in capital accumulation, the reduction of skills (or 'deskilling') in the process, managerial control, and the conflictual (or 'antagonistic') relations between management and workers.

Based on this definition, the implementation of AI in the workplace does not only pursue productive outcomes: It also serves to control, transform, and intermediate the labour process. ML algorithms have transformative capabilities that influence behaviour. They are broadly opaque, characterized as a 'black box' (Pasquale, 2015), and are often mistaken as neutral and naturally derivative from data. However, as we have argued in the previous sections, the development of these algorithms is strongly shaped by power relations. Those power relations manifest in the deployment of such algorithms as mechanisms of control. In this vein, Kellogg et al. (2020) identify a number of ways in which algorithms manage workers by: restricting worker agency and recommending actions to *direct* workers, recording and rating workers to *evaluate* them, and replacing or rewarding them to *discipline* the workforce.

In the public sector, for example, governments worldwide are increasingly using different types of AI in workplaces across different civil services' agencies and subdivisions. One notable example is the use of machine learning algorithms to support decision-making in child welfare. In their work on the use of such algorithms in child maltreatment hotline screening, De-Arteaga et al. (2020) found that the civil servants' behaviour was influenced by the outputs of the system, even though not all workers adhered to the recommendations of the algorithm. That said, less experienced workers and in cases where overruling algorithmic decision-making requires managerial approval were less prone to contest outcomes which, in many cases, remained unexplained and difficult to understand (Saxena et al., 2021). When looking at the deployment of algorithms in the United Kingdom's welfare services, Redden et al. (2020) observed that their implementation followed neoliberal logics of austerity and displacement of risk on individual families. Thus, the guidance and predictions given by these tools were not only derived from existing data but also from political and logics defined by government agencies.

Worker evaluations by ML systems are present in many areas, but nowhere is as ubiquitous as in the on-demand gig economy. In cases such as ride-hailing, food-delivery or care work, workers' movements and activities are often tracked and evaluated in real time, based on metrics such as speed, navigation skills, or even politeness (Bucher et al., 2020; Newlands, 2020a). In gig work, the voice of the app is usually a monologue which dictates activity and provides feedback but does not open itself up to a sense of dialogue. In this way, the app is usually conceptualised as the 'boss' or the 'manager' (Adams-Prassl, 2019). Even outside the gig economy, AI has become a key tool for workplace monitoring such as in Amazon warehouses (Dzieza, 2020).

Technical and metricised forms of worker's evaluation, however, open up questions regarding how machines are communicating to human workers and to which extent workers can communicate back. An open question, for instance, surrounds whether non-human agents can give not only evaluations but also recognition (Laitinen, 2016). Indeed, this question is what Cappuccio et al. (2020) explore in their concept of 'pseudo-recognition' where 'most technological devices neither produce significant recognitive responses, nor solicit them in humans'. It is not possible, for instance, to develop good will or relational capacities with an algorithmic manager (Duggan et al., 2019), a concern which has important implications for how norms of communication will develop in the future between workers and AI systems.

Finally, AI systems can be used to discipline workers through machine-to-human communication. For instance, in the annotation platforms described in the AI development section, data workers are often expelled (or 'banned') from tasks when their responses do not comply with data previously labelled by clients or when they fail to repeat previous annotations in the same way (Posada, 2021). In some cases when productivity levels are lower than expected, workers can get fired or 'deactivated', which also occurs in other algorithmically mediated workplaces such as in data work platforms like Amazon Mechanical Turk (Berry, 2019), location-based gig work platforms like Uber (Rosenblat, 2019) or in supply chain warehouses managed by Amazon (De Stefano, 2020). Through punishment-and-reward mechanisms, AI algorithms manage workers behaviour to make them compliant with the expectations of rapidly expanding labour markets.

These examples of machine-to-human communication in the form of algorithmic management to guide, evaluate, and discipline workers show that AI has an increasingly important role in shaping labour processes. How AI communicates to workers is not neutral and not at all dependant exclusively on the machine's decision. It is part of hierarchical decision-making processes that involve, as seen in the examples, government policymakers in the case of the civil service and companies in the case of digital platforms. Instead of replacing workers altogether, artificial intelligence shapes labour-power and constrain workers' agency. In this context, several forms of resistance have been observed to counteract the power of algorithms in the workplace. Examples include 'gaming the system' or manipulating algorithms' inputs to generate a desired output (Newlands, 2021a; Petre et al., 2019), hacking tools and machines or performing *sousveillance* (Moore, 2019), as well as forms of organization, inquiry, and reappropriation of digital tools (e.g., Delfanti & Sharma, 2019). However, any form of resistance is reliant on a minimum level of understanding of how the system works, described by Jarrahi et al. (2021) as the development of 'algorithmic competencies'. Algorithmic competencies are also fundamental to challenge AI and avoid assuming that algorithmic decision making is always right (Bersin & Zao-Sanders, 2020). Educating workers in the intricacies of how AI works could open up contestation paths for them to "talk back," allowing machine-to-human communication in the workplace to become a two-way street.

Conclusion

In this chapter, we presented three moments in the relationship between workers and artificial intelligence systems. These are the *human-to-machine communication* that involves the meaning-making process of data production for AI development, usually through data work, the *human-with-machine communication* required for the constant improvement and customisation of AI, and the *machine-to-human communication* involved in the deployment of these systems in the workplace and the direction, evaluation, and discipline of workers. We argued that these moments are complementary, and it is often difficult to establish clear boundaries between them. For example, an outsourced data worker annotating image data through a platform can simultaneously be directed by the algorithmic manager and, through its interaction with it, improve its accuracy. Thus, the worker would be interacting with AI in the three forms mentioned above of communications simultaneously.

These different moments of human-machine communication in the workplace show a conflictual relationship between worker and machine since this communication not only serves to provide direction but also to discipline the workforce. However, these forms of communication are also related to instances of subversion, resistance, and co-creation when workers are instead placed at the forefront of the meaning-making process. Understanding how these interactions occur in different cases, notably from the perspective of workers, is fundamental when the benefits of artificial intelligence for humanity come into question.

Because human-machine communication occurs within social settings, a fundamental aspect of the three moments we describe in this chapter is the power relations enacted in the communication between workers, machines, and other actors involved in the labor process, notably management. Machines are never built autonomously, not even artificial intelligence. Human decision-making is present since the inception of the technology and, especially, in its deployment, even in models using deep neural networks challenging to scrutinise by developers. Thus, identifying the different voices that participate in meaning-making between workers and AI and making explicit which voices are heard more than others is crucial. This approach could point at moments when "meaning-making" becomes "meaning-imposition" and help to open contestation paths for workers to *talk back* and question data, systems, and algorithmic outputs.

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