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Performance in the Workplace: a Critical Evaluation of Cognitive Enhancement

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Abstract The popular debates about the future organization of work through artificial intelligence technologies focus on the replacement of human beings by novel technologies. In this essay, we oppose this statement by closely following what has been developed as AI technologies and analyzing how they work, specifically focusing on research that may impact work organizations. We develop this argument by showing that the recent research and developments in AI technologies focus on developing accurate and precise performance models, which in turn shapes organizational patterns of work. We propose that the increased interest in the relationship between human cognition and performance will shortly bring human cognition to the focus on AI systems in workplaces. More specifically, we claim that the cognitive load measurement will shape human performance in manufacturing systems shortly.

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Introduction

The development of artificial intelligence (AI) technologies in the past several decades resulted in popular debates about its potential to "replace" human beings. This argument is even more frequently made in the debates about the future organization of work. These debates rely on a common tendency of evaluating any technological artifact as a thing on its own while abstracting from its determinations in sociohistorical formations. Those evaluations gain popularity in society as they are organized around specific moral judgments, for instance, whether a specific technology brings good or bad for humanity. We are closely acquainted with this reductionist (normative) organization of public debates over technology. However, it has notable (ideological) power in shaping critical evaluations of technologies, as well as commonsensical judgments in the broader public.

Shaping the debate around the technology as a thing itself ignores the critical evaluation that addresses the consequences as different actualizations of novel technologies. In order to develop a critical evaluation, this essay points out that we should closely follow what has been developed as AI technologies and analyze how they work, specifically

focusing on the research on and the use of AI technologies in workplaces.

The focus of the present study is the performance in the modern workplace, where a major goal is to increase productivity by putting pressure on the workers' capabilities. We use the term "performance" within the context of performance enhancement as the enabler and promoter of a faster, more efficient, and more productive accomplishment of tasks [1–3]. In that sense, we focus on the employee and the pressure on their performance rather than the environmental characteristics and the technologies used in the workplace, whether a factory or a home office for remote working.

Human Cognition and Performance in Workplaces

The arguments—focusing on AI technologies replacing human beings—are not able to elaborate on the overall shifts in social relations and organizations of work; instead, they solely consider the application of technology in the given organization of the work and impacts of this application on human beings (such as increasing the unemployment). Nevertheless, more emphasis is required on the radical transformation of human, work, and technology categories. We propose that the increased interest in the relationship between human cognition and performance, within the context of manufacturing, indispensably brings human cognition to the focus on AI systems in workplaces. More specifically, we claim that the cognitive load measurement will shape human performance in manufacturing systems shortly. For example, employers will start offering work contracts specifying working hours based on the employees' measured cognitive workload rather than following social practices that employ standard working hours. Hence, we should ponder a total reorganization of work, alongside social relations in a broader sense. Those changes in the workplace cannot be reduced to the invention of new technologies, but they have to be located in a more extensive process of social transformation.

To contribute to the broader discussion within the limits of this short essay, we point at two common misleading readings about the developments in AI technologies: first, we argue that the current technologies and research on AI do not follow the idea of AI as a substitute for human beings. Instead, they focus on developing accurate and precise models to predict the patterns of behavior, which in turn gain the capacity to shape those patterns. Second, focusing on the relationship between cognition and manufacturing within the context of AI research, we argue that AI technologies cannot be considered in opposition to the category of the human; instead, we point at the regime of the production of bodies in the workplaces that establish a new universalization of the category of the human that is no longer defined through its qualitative difference from technology (or nature), but through a quantitative measure of performance that could operate as the medium of reorganization of social differences (replacing or reshaping social categories such as age, race, gender). We claim that the operation of AI technologies in the workplace—as the new medium of control and reproduction of labor—forces us to rethink the organization of capitalist social relations by keeping the widely used concepts of human, work, and technology as wide-open questions.

AI Systems as Enhancers of Mind

A widespread debate around AI technologies has concentrated on the idea of whether these technologies would or could replace human beings or not. The essence of the idea is to reconsider the technology as a thing that could present human capabilities, thereby using it as a substitute for human beings. This argument instead reflects the earlier attempts to develop mechanisms that imitate human beings. A historical detour reveals that AI technologies do not address this substitution.[1] Nevertheless, most advances in

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[1] The origins of the mechanism idea can be traced back at least to the Middle Ages. For example, in the *Book of Knowledge of Ingenious Mechanical Devices*, Ismail al-Jazari (1136–1236) proposed autonomous system concepts, such as a drink-serving waitress, designed to imitate the behavior of a human waitress. The behavioral imitations of natural cognitive systems (i.e., humans or animals) included a wide variety of application domains and various types of mechanisms aimed at being autonomous agents. Some well-known examples include Giovanni de Fontana's (ca. 1395–ca. 1455) warfare machines, Leonardo da Vinci's (1452–1519) mechanical dove, Wolfgang von Kempelen's (1734–1804) chess player (viz. The Turk, 1769), Jacques de Vaucanson's (1709–1782) automata (viz. The Flute Player, The Tambourine Player and Digesting Duck, 1787), among many others, see Rosheim [4] and Koetsier [5] for extensive reviews of the history of robots and programmable machines. These historical examples show how the mechanism concept was developed through a tendency

today's AI may be conceived as originated from Alan Turing's (1912–1954) mind as a machine idea in the 1930s. Turing's conceptualization differs from the previous conceptualizations of mechanisms, which were behavioral imitations of humans by machines.

The idea of the mind as a machine was developed after the invention of calculating machines. Numerous mechanical calculators were designed and developed since the seventeenth century, including the ones by Blaise Pascal (1623–1662), Gottfried Leibniz (1646–1716), Charles Babbage (1791–1871), and Ada Lovelace (1815–1852) [5]. Despite their remarkable success as automata, their development did not lead to immediate strong claims about a relationship between the mind and the machine, leaving aside speculations about the machines' potential as intelligent devices. Alan Turing explicitly proposed automata as a framework for the mind [6, 7]. In the first half of the twentieth century, researchers attempted to apply computational frameworks to study the human mind, such as using logical calculus to study biological neurons [8].

The advances in the computation theory [9] and their implementations on computing machinery led to the emergence of artificial intelligence in the 1950s. Early AI programs addressed logical reasoning, such as the logic theorist [10], the geometry engine [11], and the checkers' player [12]. Following the development of knowledge-based systems in the 1970s, AI became popular in industry in the 1980s. The AI era was quite different from the previous attempts to devise imitating machines. The "AI as human substitute" idea did not last long within the mind-as-a-machine concept. Most AI researchers did not aim to design artificial agents that could think like humans (viz. strong AI). Therefore, the replacement of the human mind by artificial minds turned into a weak claim rather than an ultimate goal of AI. Instead, AI systems evolved as enhancers to the human mind, as in the case of machines collaborating with humans for improved task performance (human–machine teaming) and machines integrated with the human brain [13].[2]

The idea of enhancing the human mind through AI has been an outcome of the mind's conception as a machine. The presence of systematic patterns in human cognitive abilities, such as categorical similarities among individuals, has attracted attention in AI research, possibly more than differences between individuals, due to the compatibility of the former with the positivist conceptualization of the construction of scientific knowledge. In particular, the concept of computational cognitive modeling has been an appropriate venue for exploiting human cognitive abilities in a systematic manner [14]. The term "artificial" was introduced in connection with mind and intelligence in the 1950s, due to the belief that the human mind exhibits systematic patterns that computational models could reveal. Human cognitive modeling has been a popular domain of research due to its promise as applied research. In the 1980s, initial human cognition models were proposed as a methodological framework for designing human–computer interaction interfaces [15]. Despite a set of significant differences in underlying mechanisms, such as neural network models, symbolic models, and probabilistic models of cognition [16–18], they shared the same goal: investigating the human mind as a machine.

AI Systems as the Model of Performance in Workplaces

For the past two decades, the three-pillar debate about the imitation at a behavioral level, the design of AI agents as rational agents (e.g., the logic theorist [10]), and the design of the mind as a machine has been resolved in favor of AI systems that can model and predict human behavior. Machine technologies [25] have replaced the classical, rule-based AI algorithms by significantly improving the predictive accuracy in numerous domains, such as object recognition, without addressing the inner mechanisms of perception and cognition yet preserving behavioral-level accuracy. AI systems have been frequently criticized for being black box systems; they cannot respond to how they learn from data [26]. Nevertheless, in those

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Footnote 1 (continued)

to imitate human beings. A common conceptualization behind the idea of automaton was the imitation capability of the mechanisms rather than being a substitute for the universal category of the human.

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[2] See various authors [19–21] for the history of AI and introductory AI concepts, see Boden [22] for the history of the mind as a machine concept, and see Li et al. [23] for a comparative analysis of contemporaneous developments in cybernetics [24].

systems, the accuracy and precision of the predictions (i.e., the models' behavioral output) have been the key indicators of evaluating an AI system's success rather than assessing how it makes a prediction. More specifically, when applied to daily settings, today's AI systems act as recommenders that enhance information presentation to human users as a function of their history of actions.

Widely known examples for this operation include digital music and video streaming services, online video sharing, and social media platforms. In those services, a list of the content, such as a history of music clips, provides the data to the AI system (specifically, machine learning models), which in turn gains the capability of making efficient predictions about a user's taste of music represented by a user profile. The goal is usually to convince the user to subscribe to the service for a smooth user experience. That is an instance of exploiting metadata for personalization that employs tracking users' activity on the Internet. Therefore, the spread of the actualization of today's AI technologies builds on learning from the data provided by humans and thereby producing models that can make precise predictions on the patterns of behavioral forms (e.g., in this case, music tastes). The AI system aims at profiling the users through establishing machine-learning models: first, the user does not know the content beforehand to gain access. The patterns of preference become precise by accumulating the data not only from the individual user but also through the overall processing of collected data, such as web browser cookies and social media relations—which is beyond the direct access of any given individual. Second, the model gains the capacity of shaping the patterns of preference, even by producing novel ones. This example shows the tendency of developing models of patterns with the collection of and access to big data and shaping the patterns of behavior through AI models.[3]

We observe a similar tendency in the manufacturing context to establish precise and accurate models to increase performance. This tendency is evident in the increasing research published in academic journals. In manufacturing research, the human performer has been frequently investigated in terms of its relation to various aspects of cognition, including the cognitive aspects of the integration between humans and machines [27], the influence of the working conditions, and more generally, the influence of the manufacturing environment on the perception of the quality of working life [28–31]; job stress, work-related stress and mental health [31–33]; burnout and physical health [34, 35] and its physical, psychological, and occupational consequences [36]; and mental fatigue [37]. For the past decade, there has been intense interest in the relationship between performance and cognition in the workplace, under various names, such as mental workload [38, 39], cognitive load [40], and cognitive load assessment [41, 42], cyber-physical-human collaborative cognition for human-automation interaction [43] and human-centered connected factories [44], in addition to the common, contextual terms, such as human factors [45] and human systems design [46].[4]

Footnote 3 (continued)

tion on social media through profile-specific political propaganda. More recently, the potential integration of such tracking data with human physiological data, such as gaze and brain activity, created an urgent need for responsible brain-system integration [13].

[4] The increase in research focusing on cognitive performance is also observed in a Web of Science database query with relevant terms in the article publication titles. We used the following query to retrieve articles in the Web of Science Core Collection. The query searched articles with the terms "cognitive," "mental," or "workload" together with the terms "manufacturing" or "workplace" in their title: TI=((cognitive OR mental OR workload) AND (manufacturing OR workplace)). We found that the total number of publications almost doubles every five years since 2000. The number of articles $N=23$ in 2001–2005, $N=44$ in 2006–2010, $N=97$ in 2011–2015, and $N=248$ in 2016–2020. Those values reflect a steeper increase compared to the articles with the term "manufacturing" in their title, as well as the global increase in the number of publications for the past two decades.

[3] A relevant debate has been the privacy concerns about the exploitation of metadata for personalization. Internet users have been subject to various tracking methods, which include but are not limited to the use of cookies in browsers, mobile electronic system integration, such as tracking by the integration of face recognition tools into city surveillance cameras, and personalization through the integration of social media and mobile messaging services. Those tracking services had a significant impact on society, such as influencing user percep-

Frontiers of AI Technologies in Workplaces

In addition to this growing literature in manufacturing, a closer look at the recent efforts to integrate AI technologies into daily settings reveals how technological developments on multiple fronts would influence work organizations shortly. In the past decade, neuroimaging technologies have led to affordable brain monitoring technologies for estimating cognitive load and attention levels for the first time in history [47]. For the past three decades, neuroimaging technologies have employed electroencephalography (EEG) for detecting electrical activity in the brain using a set of electrodes attached to the scalp, magnetoencephalography (MEG) for recording magnetic fields produced by electrical currents in the brain, and functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) for detecting changes associated with blood flow. Functional near-infrared spectroscopy (fNIRS) has been developed as a noninvasive and relatively affordable optical neuroimaging technique measuring changes in hemoglobin concentration in the blood that flows through the brain. More specifically, optical imaging techniques have been already integrated into wearable devices, such as smartwatches, for detecting the changes in hemoglobin concentration in the blood, providing data about heartbeat rate and oxygen concentration. In addition, AI models have been developed to predict cognitive states, such as drowsiness and fatigue, by analyzing the data collected from the human body.

Those developments have also allowed decoding the brain activity into meaningful commands for machine interaction outside the laboratory environments, which led to brain computer interaction (BCI) technologies. BCI was developed initially for patients suffering from severe motor impairments [48, 49]. BCI has recently expanded to domains close to the manufacturing context, such as human–robot interaction [50]. The know-how has accumulated to implement neuroimaging technologies within classrooms and develop high bandwidth brain-machine interfaces to connect humans and computers by integrating affordable neuroimaging devices, such as fNIRS [51]. The ultimate goal is to integrate the human and the systems within the context of human–machine teaming research. In a BCI context, this integration aims at providing better interfaces that facilitate daily life interactions with computers. In an educational context, this setting aims at improving learning and teaching. In manufacturing, the recent developments may close the traditionally articulated gap between manufacturing robots that do not interact with humans (e.g., robot arms) and service robots that serve humans, particularly following the introduction of BCI-driven robots in workplaces.

Another area where AI technologies have been integrated into daily life settings is brain nerve stimulation. In a similar way to the development of brain computer interfaces, brain stimulation was developed for the treatment of diseases, such as Parkinson's disease [52] and epilepsy [53], as well as depression [54]. The technology has been known as deep brain stimulation, a surgical treatment that stimulates the brain with electrical impulses. More recently, brain stimulation has been employed for domains outside the context of disease treatment through affordable technologies that have been developed recently. For instance, transcranial direct current stimulation (TDCS) is an application of weak electrical current to nerves. Similarly, transcranial magnetic stimulation (TMS) is the induction of magnetic fields for stimulation. Recent studies show that brain stimulation in adults enhances language learning by improving speech category learning [55]. Similarly, various brain stimulation techniques have been shown to impact different types of decision-making, including risky decision-making processes [56]. These studies reveal the potential of brain stimulation enhancement as a novel cognitive enhancement, besides the traditional cognitive enhancement methods, such as pharmacological cognitive enhancement (PCE) [57]. AI technologies will be an embedded feature of BCI and stimulation technologies, given that AI has already been integrated into daily life settings on many fronts.

In summary, recent developments in AI technologies and their integration with BCI and brain stimulation technologies indicate the need to assess their potential use in various application domains. The need for scrutinizing the ethical implications of BCI-driven robots [57], brain computer interfaces in general, and brain stimulation [58] has already been recognized in the research community [13, 50, 59]. Nevertheless, discussing their impact on manufacturing life needs to ask novel questions that have not been debated before. What if an employee accepts a work contract that identifies working hours depending on the measured cognitive workload? What if the

employee decides to use brain stimulation enhancement to improve performance despite the uncertainties in brain stimulation effects in long-term use?

Conclusions

These questions address the relationship between an employer and an employee within the context of manufacturing life rather than being a debate about the capacity of the machine itself as a thing. Such questions make us think about the reorganization of work not through working hours but the performance models. For that reason, we have to develop a critical evaluation of the use of such technologies in workplaces. Pustovrh et al. [1] pointed out a similar relation between cognitive load and performance in the workplace. A direct implication of assessing cognitive load for performance measurement in the workplace is pharmacological cognitive enhancement (PCE) by individuals. Their argument reflects the other side of the same coin when observed in light of the developments in the field of AI technologies. The performance models developed through AI technologies do not simply reflect the current averages of the working capacity of the workers. They can optimize the capacity by producing specific models that would be imposed on the workers. Consequently, as PCE will be a necessity for individual workers, one can see the inevitability of the widespread diffusion of brain stimulation enhancers. However, this inevitability cannot be reduced to the qualities of AI technology without a critical analysis of the sociohistorical formation of the manufacturing life established upon performance today.

Those questions above do not necessarily lead us to concerns about whether AI technologies will replace human beings or not. However, they lead to some further open questions. The enhancement of performance through AI technologies makes us reconsider the category of the human itself. We are familiar with the modern construction of the category of the human in opposition to nature or technology. Nevertheless, with AI technologies, we can no longer draw clear lines between technology and the human. More importantly, we have to reconsider the formation of a new category of the human that could be universally imposed through the contemporary capitalist social relations based on performance. The examples above reveal the need for a broader, critical point of view to evaluate the relationship between AI and performance in the workplace. The widespread diffusion of performance enhancement mechanisms, may it be pharmacological cognitive enhancement or transcranial magnetic stimulation of the brain, seems inevitable shortly, not only in the workplace but also in schools and other daily settings, given that "performance" is being used as a key template to produce, measure, and evaluate social differences.

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