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Framing Cognitive Machines: A Sociotechnical Taxonomy

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Abstract—Aims: we propose a sociotechnical taxonomy for the analysis of socio-economic disruptions caused by technological innovations. Methodology: a transdisciplinary principled approach is used to build the taxonomy through categorization and characterization of technologies using concepts and definitions originating from cybernetics, occupational science, and economics. The sociotechnical taxonomy is then used, with the help of logical propositions, to connect the characteristics of different categories of technologies to their socio-economic effects, for example their externalities. Results: we offer concrete illustrations of concepts and uses, and an Industry 5.0 case study as an application of the taxonomy. We suggest that the taxonomy can inform the analysis of opportunities and risks related to technological disruptions, specially of those that result from the rise of cognitive machines.

Keywords — sociotechnical taxonomy, technological disruptions, technological innovations, automatic, autonomous, physical technology, cognitive technology, skill-enhancing, skill-replacing, externalities, Industry 5.0, cognitive machines, artificial intelligence, occupational science

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I. INTRODUCTION

Over time, theories on technological disruptions have undergone evolution and change, as scientists tried to understand this complex phenomenon and had to adapt their thinking to ever-changing observable patterns regarding its socio-economic impacts. This is unsurprising, as technological progress is best comprehended through the lens of complexity theory, which takes in consideration aspects such as emergence, path dependence, multiple equilibria, nonergodicity, nonlinearity, and phase transitions. [1]–[3].

In social sciences in particular, the difficulties associated with the complexity of the subject have been compounded by the reliance on narrow mono-disciplinary, reductionist, productivist and economistic approaches [4]. It is our understanding that this way to proceed is ineffective and leads inevitably to intellectual dead-ends. A transdisciplinary approach is necessary due to the complex nature of the phenomenon. Moreover, exactly because of the lack of transdisciplinarity, the study of technological disruptions lacks comprehensive categorization and characterization.

With this in mind, we propose in this article a sociotechnical [5], [6] taxonomy that helps to frame studies of technological disruptions, allowing for a deeper understanding of the process of socio-economic change and evolution caused by technological innovations, such as those created during the last few decades by the emergence of cognitive machines. For that, technologies are categorized according to perspectives originating from cybernetics, economics and occupational science [7]. We further extend the taxonomy to incorporate Vinge's suggestion that technologies have physical and cognitive characteristics [8], [9]. Notice that Vinge originally called these characteristics "weak superhumanity" and "strong superhumanity" and applied them to technological entities. Vinge's characteristics should not be confounded with Searle's [10] concepts of weak and strong artificial intelligence [11].

The development of a transdisciplinary taxonomy becomes even more important when, as we argue in a previous article [4], and in disagreement with most of the existing reductionist economics literature on technological disruptions, one considers that the socio-economic effects of skill-replacing technological innovations are not caused by human characteristics such as "low skills" and "low cognition," or by task characteristics such as "routine" or "simplicity," but instead by the cybernetic characteristics of the innovations in a given context. We therefore propose that technologies need to be categorized and characterized according to the transdisciplinary taxonomy developed in this article.

The article is organized as follows: we first present the objectives of the study and its methodology. Then we proceed to the discussion, followed by the presentation of a case study that applies the taxonomy to the analysis of Industry 5.0 [12]. We conclude by offering some speculative thoughts on how the taxonomy brings to light opportunities and risks created by the disruptions of the socio-economic fabric due to the emergence of cognitive technological innovations, as exemplified by current concerns related to the unmanaged and unregulated deployment of artificial intelligence cybernetic technologies.

II. OBJECTIVES

The main objective of this article is to propose a sociotechnical taxonomy that allows researchers to frame studies of socio-economic disruptions resulting from technological innovations such as those created by the rise of cognitive machines.

III. METHODOLOGY

The theoretical methodology follows a principled approach to build a sociotechnical taxonomy through categorization and characterization of technologies using concepts and definitions originating from cybernetics, occupational science, and economics. Under a cybernetics perspective, the taxonomy divides technologies into noncybernetic and cybernetic, with the latter being subdivided into automatic and autonomous. Under an economics perspective it divides technologies into skill-enhancing and skill-replacing. Cybernetic technologies are then characterized according to

Vinge's two dimensions: physical and cognitive. Once the taxonomy is proposed, interconnections among categories and characteristics of technologies are developed based on logical propositions. As illustrations, we offer real-world examples of concepts and applications, including a discussion of the importance of the taxonomy in the context of industry 5.0.

IV. Discussion

In the next subsections we explore concepts that originate from cybernetics, occupational science, and economics and that we identify as being essential to the understanding of the socio-economic disruptions of technological innovations. By employing a transdisciplinary approach we avoid intellectual dead-ends typically found in social sciences. The economics literature for example overlooks the importance of cybernetics in the study of technological innovations and disruptions. Although it is possible to find examples of articles that are unquestionably aware of the developments in robotics, machine learning and artificial intelligence [13], we think that they systematically miss the point by adopting a narrow mono-disciplinary, reductionist, productivist and economistic view, not relying on other more relatable fields such as cybernetics and occupational science under a transdisciplinary perspective in order to improve the understanding of how technologies affect societies [4].

A. Noncybernetic, Automatic and Autonomous Technologies

Consider for example relatable concepts originating from cybernetics. Differently from the term technology, the term cybernetics has been used since ancient times to designate "good piloting." Ampère for example declared in his treatise on scientific classification that: "I name Cybernetics, from the word κυβερνητική, taken at face value, in a restricted sense, as the art of governing a vessel, and, when taken from usage among the Greek themselves, with the meaning otherwise extended, as the art of governing in general" [14].

The notion of cybernetics as art of governing comes back during the 20th century, initially in continental Europe, as the study of all social, physical and biological phenomena that involve self-governing systems, and then by the work of Norbert Wiener. He famously stated that "cybernetics attempts to find the common elements in the functioning of automatic machines and of the human nervous system, and to develop a theory which will cover the entire field of control and communication in machines and in living organisms" [15]. The field of cybernetics was central to the study and development of automatic technologies throughout de 20th century. Notice that automatic machines rely on self-governing mechanisms but do not embody significant amounts of cognitive capabilities.

This situation evolved when the field of artificial intelligence (AI) was defined and developed later. Following Moor, the Dartmouth Summer Research Project of 1956 is possibly the event that has set artificial intelligence as a promising scholarly field [16]. Participants followed on the original idea of McCulloch and Pitts, who declared that AI is a feasible technology because "the 'all-or-none' character of nervous activity, neural events and the relations among them can be treated by means of propositional logic" [17]. Since then we have seen the development of autonomous technologies and cognitive machines that, differently from automatic technologies, require strict ethical design standards due to the embodiment of decision-making capabilities [18].

Even though specific fields of cybernetics such as automation, information theory, machine learning and artificial intelligence do not follow necessarily the same epistemological principles, and do not always cover the same ground, they tend to intersect in what concerns socio-economic phenomena. We use therefore the term cybernetics in this article to represent the confluence of all its different fields in the creation of automatic and autonomous self-governing and cognitive technologies that have increasingly disruptive socio-economic effects [19]. In the sense of this article, these technologies typically follow algorithms (routines), which can range from static to adaptive, and simple (e.g. automation) to complex (e.g. artificial intelligence). As examples: thermostats embody static and simple cybernetics, while facial recognition software embodies adaptive and complex cybernetics.

In summary, we divide technologies, technological artifacts, and technological innovations into three categories based on concepts originating from cybernetics: noncybernetic (e.g. a hammer), automatic (e.g. a steam centrifugal governor) and autonomous (e.g. a planetary exploration rover).

B. Skill-Enhancing and Skill-Replacing Technologies

In the economics literature, technologies are typically divided into two groups according to how they interact with labor: skill-enhancing and skill-replacing [20]. As their qualifiers indicate, a skill-enhancing technology improves the given human skill that governs it, while a skill-replacing technology governs itself in the replacement of a human skill.

Notice that in our line of research we depart on multiple dimensions from the mainstream economics literature on skill-replacing technologies, e.g. [21]–[26], which sees in human characteristics ("low skills," "low cognition") or in task characteristics ("routine," "simplicity") the determinants of technologies' socio-economic effects. For us, it is the cybernetic characteristics of skill-replacing technologies (their ability to replace human skills) in a given context that determine their socio-economic effects. Moreover, based on knowledge originating from occupational science [7], we propose that studies of the socio-economic effects of technological innovations should not be narrowly concerned with the labor market, and should instead consider the effects of technological disruptions on all labor and non-labor human occupations [4].

C. A Sociotechnical Taxonomy

In order to better understand the relations between human skills, cybernetics, technological innovations, and their socio-economic effects, firstly we use a principled approach to define technologies according to a sociotechnical taxonomy inspired by [27] and [18] as follows:

Definition 1: a technology is cybernetic if it can self-govern, otherwise it is noncybernetic.

Definition 1.1: a technology is automatic if it is cybernetic but not capable of decision-making.

Definition 1.2: a technology is autonomous if it is cybernetic and capable of decision-making.

Having decision-making capabilities is a characteristic that involves advanced cognitive capabilities such as reasoning, learning, adapting, or environment transacting. Examples: a knife embodies noncybernetic technology, an alarm clock embodies automatic technology, and a self-piloting drone embodies autonomous technology.

Now, we propose the following alienation taxonomy of human skills [28]:

Definition 2: a human skill is currently alienable if it can be fully and adequately replaced by a current technology, otherwise it is currently inalienable.

As examples, certain human weaving skills are alienable because they can be fully and adequately replaced through automation technology, such as the one used in the 19th century Jacquard loom, while certain nurturing skills, such as those necessary for nursing a newborn, are inalienable because no current technology can fully and adequately replace them.

In general, and non-exhaustively, biological skills (such as mating skills), agency skills (such as wine choosing skills), emotional skills (such as delay of gratification skills), and soft skills (such as leadership skills) currently cannot be fully and adequately replaced by technologies, therefore are currently inalienable. Notice however that technological innovations can alienate previously inalienable human skills (see the weaving example above). The taxonomy is therefore state-of-the-art and context dependent.

The next definitions and proposition frame and clarify the previous subsection concepts originating from economics. With the help of Definition 2, we propose the following:

Definition 3.1: a technology is skill-replacing when it alienates a human skill.

For example, from an economics perspective, a dishwasher is a skill-replacing technology only when it is used to alienate human dishwashing skills. In addition, and following Kidd [29], we propose that:

Definition 3.2: a technology is skill-enhancing when it adapts a human skill into a more productive or effective skill.

Consider the example of a typewriter machine. It adapts writing skills into more productive or effective skills (typewriting). Nonetheless, writing skills remain necessary to govern the machine, so the latter skills remain inalienable.

Proposition 1: a technology can be skill-replacing, skill-enhancing or both, depending on the skill and the given context.

As an example, consider the skill of writing. A typewriter machine is: a skill-replacing technology in what concerns handwriting, a skill-enhancing technology in what concerns typewriting, and both simultaneously in what concerns writing.

D. Physical and Cognitive Characteristics of Technologies

The focus on the cybernetic characteristics of technological innovations allows us to introduce characteristics of technologies originally developed by Vinge [8]. As Vinge explains, "I call [the] 'fast thinking' form of superintelligence 'weak superhumanity'" (a physical technological improvement), while "'strong superhumanity' would be more than cranking up the clock speed on a human-equivalent mind" (a cognitive technological improvement).

More precisely, we offer the following definitions:

Definition 4.1: a physical technological innovation allows a new technology to perform with superior physical capabilities (e.g. superior speed or strength) at the same cognitive capability levels of the previous technology.

Definition 4.2: a cognitive technological innovation allows a new technology to perform with superior cognitive capabilities (e.g. superior reasoning, learning, adapting, or environment transacting) at the same physical capability levels of the previous technology.

Consider as an example the complex cognitive capabilities necessary for chess playing. On the one hand, a chess playing machine benefits from a more advanced physical technological innovation when it can play chess with the same cognitive capabilities of previous machines, but faster. On the other hand, a chess playing machine benefits from a more advanced cognitive technological innovation when it can play chess with superior cognitive capabilities, but at the same speed of previous machines. In the DC Universe©, a physically-enhanced human is *The Flash*, due to his "super-speed" skills [30], while a cognitively-enhanced human is *Batman*, due to his "genius-level intellect" skills [31].

Distinguishing between physical technological innovations and cognitive technological innovations is central to the understanding of the socio-economic effects of technological disruptions. For example, physical improvements in cybernetic technologies may displace labor because they increase the effective amount of labor supply, while cognitive improvements in cybernetic technologies may displace labor because they create superior cybernetic alternatives to human cognitive skills.

E. Interconnections Among Categories and Characteristics of Technologies

The combination of the four definitions above leads us to the following propositions:

Proposition 2.1: a skill-replacing technology is necessarily a cybernetic technology in what concerns the human skill that it replaces.

Human skills need to be governed. Therefore, to fully and adequately replace human skills, a technology must also self-govern, and if it self-governs, then it is cybernetic. Consider as an example an electronic calculator. As a technological artifact, it replaces alienable human calculation skills. It only replaces them because it automates calculations as a cybernetic technological artifact.

Proposition 2.2: a cybernetic technology is not necessarily a skill-replacing technology.

Cybernetic technologies can be used to complement or enhance other needed human skills or other technologies. For example, on one hand an automatic infrared targeting system does not replace human skills, because humans cannot see infrared light. On the other hand, it enhances human targeting skills as it complements other human skills needed for targeting.

Proposition 3.1: a skill-enhancing technology is necessarily a noncybernetic technology in what concerns the human skill that it enhances.

If a technology enhances a certain human skill, then these human skills are still employed for governance, and as such the technology is noncybernetic in what concerns these enhanced human skills. Notice however that the same technology could be cybernetic concerning other human skills that it replaces. For example, a financial accounting software is noncybernetic in what concerns the financial accounting human skills needed to operate it, but its software calculator component is cybernetic because it replaces alienable human calculation skills.

Proposition 3.2: a noncybernetic technology is not necessarily a skill-enhancing technology.

This proposition follows from the fact that a noncybernetic technology can be a component of a skill-replacing technology. As an example, optical lenses used in eyeglasses are a noncybernetic technological artifact and a skill-enhancing technology. But optical lenses are not a skill-enhancing technology when they are used as part of an automatic security camera.

Proposition 4: technological innovations may have physical and cognitive characteristics.

More precisely:

Proposition 4.1: Noncybernetic technologies may have physical characteristics but do not have cognitive characteristics.

Noncybernetic technologies do not self-govern, and as such do not recur to cognitive capabilities of any kind. They may however have physical characteristics, as these do not require self-governance. For example, a technological innovation that leads to sharper knives does not involve cognitive characteristics, but has superior physical characteristics (cuts faster or more precisely) compared to the previous technology.

Proposition 4.2: cybernetic technological innovations necessarily have cognitive characteristics.

As cybernetic technologies self-govern, they are able to replace human cognitive skills needed for governance, for example, the steam engine centrifugal governor [32], an invention that symbolizes the Industrial Revolution [33], replaces human cognitive skills needed for the stable functioning of steam engines.

Proposition 4.3: Autonomous cybernetic technological innovations significantly expand the scope and intensity of cognitive characteristics.

Automatic technologies may arguably have restricted endowments of cognitive characteristics, for example, a digital diary automates and replaces some memory skills at some basic cognitive level. But automatic technological artifacts do not have decision-making capabilities, hence their cognitive characteristics remain limited. The development of autonomous cybernetic technologies significantly expands and deepens cognitive characteristics available to innovations, magnifying and accelerating technological disruptions and setting in motion a process of socio-economic change like humanity has never experienced before.

F. Technological disruptions and externalities

In a narrow business administration context, technological disruptions have been defined as what happens when technological innovations are used by a startup challenger to displace firms detaining incumbent market power in a given industry [34], [35]. Originally a productivist and economistic concept, its meaning has been extended more recently to represent the more relevant disruptive impacts of technological innovations on broader socio-economic dimensions [36], [37].

In this article we update and frame the concept of technological disruptions so it more rigorously represents current uses in social sciences. Firstly, in order to escape from narrow productivist and economistic narratives, and in agreement with current use in the public debate arena, we extend it so it includes disruptions to all labor and nonlabor human occupations [4]. Secondly, we give it analytical value by framing it using language from externality theory.

For that, consider a broad definition of an externality as the costs or benefits imposed on an individual, organization or society by another entity that creates these costs or benefits, in other words, a situation where the private costs (or private benefits) to the entity differ from the social costs (or social benefits) imposed on (or granted to) another entity [38]. Notice that social costs (or benefits) are equal to private costs (or benefits) plus external costs (or benefits). We argue that:

Proposition 5: a technological innovation that involves a significant externality is necessarily disruptive.

On one hand, a technological innovation resulting from an entity's transaction should not be considered disruptive when its social costs (or social benefits) are equal to its private costs (or private benefits) because, by definition, there are no external costs (or external benefits) involved in such a transaction. On the other hand, if there are external costs or external benefits, and if they are significant, then it is clear that the socio-economic fabric is involuntarily disrupted.

Consider now the following propositions:

Proposition 5.1: any skill-replacement caused by a technological innovation externality is a cost to humans who are victims of skill alienation.

This proposition has its roots on the extensive social science literature that investigates the relations between technology and labor alienation [28]. We extend the discussion from labor alienation to skill alienation, and we interpret the phenomenon from an occupational science perspective [7] instead of an economics perspective, where the technological alienation of skills is a cost to its victims as it produces occupational injustice: occupational decline, occupational deprivation, occupational alienation, occupational imbalance, or occupational marginalization, and as any of those events are detrimental to well-being [39], [40].

Proposition 5.2: any skill-enhancement caused by a technological innovation externality is as an external benefit to humans who are granted enhanced skills.

This proposition follows from the wildly accepted theoretical and empirical assumption that research and development (R&D) creates positive externalities of many different varieties [41].

The latter three propositions lead to the following:

Proposition 6.1: if a skill-replacing technological innovation creates an externality, it is necessarily a negative technological disruption.

A skill-replacing technological innovation is created by its proprietor in the wish to obtain a private or social benefit. As long as the costs related to its skill-replacement function are born by the proprietor, no significant socio-economic disruption takes place. However, if the innovation creates an external cost that is related to its skill-replacing function, then the benefit-seeking proprietor transfers the innovation burden to the collective, therefore creating an external cost thus a negative technological disruption. For example, as a technological innovation a dishwasher machine does not create a technological disruption when used as a labor-saving device only by the proprietor of the technological artifact, but it creates a negative technological disruption to workers who earn a living from their alienated dishwashing skills.

Proposition 6.2: if a skill-enhancing technological innovation creates an externality, it is necessarily a positive technological disruption.

A skill-enhancing technological innovation is created by its proprietor in the wish to obtain a private or social benefit. As long as the benefits related to its skill-enhancement function are conferred only to the proprietor, no significant socio-economic disruption takes place. However, if the innovation creates an external benefit that is related to its skill-enhancing function, then the benefit-seeking proprietor transfers the innovation gain to the collective, therefore creating an external benefit thus a positive technological disruption. For example, as a technological innovation an online encyclopedia (such as Wikipedia) does not create a technological disruption when used only by the proprietor of the technological artifact, but it creates a positive technological disruption to users of the technology who have their intellectual skills enhanced by it.

G. A Sociotechnical Taxonomy Synthesis

To summarize the results in this section, consider first Table 1. Physical characteristics are possible in all technological innovation categories. Since immemorial times, humans have interacted with technological artifacts through their physical capabilities.

TABLE 1: A SUMMARY OF THE SOCIOTECHNICAL TAXONOMY FOR EXTERNALITY PRODUCING TECHNOLOGICAL INNOVATIONS

Sociotechnical dimension	**Category, characteristic, externality or skill**				
Cybernetics category	***Noncybernetic***	***Cybernetic (automatic & autonomous)***			
Economics category	***Skill-enhancing***	***Skill-enhancing***		***Skill-replacing***	
Vinge's characteristic	Physical	Physical	Cognitive	Physical	Cognitive
Externality	Positive	Positive	Positive	Negative	Negative
Affected human skill	Physical	Physical	Cognitive	Physical	Cognitive

As physical characteristics improve, they may offset human occupations of a physical nature, but still allow for humans to move to other labor and nonlabor occupations based on cognitive skills. For example, technological progress has pushed most of humanity out of agriculture towards industry, and then from industry towards services. This process of technological disruption is captured in a simplified way by the conjectural path of the yearly amount of technological innovations shown in Figure 1.

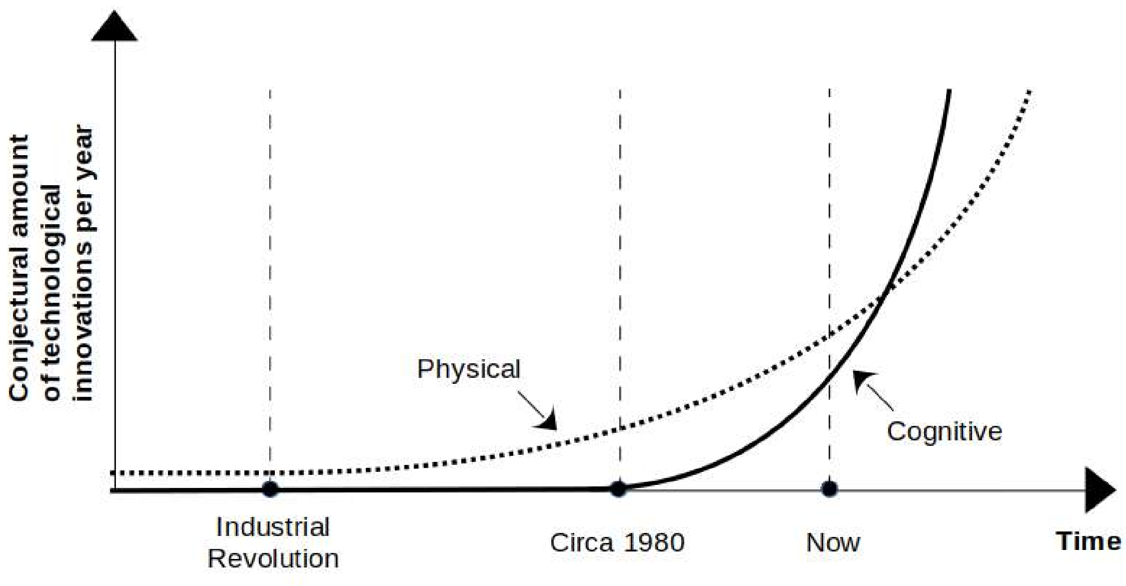

Fig. 1: Conjectural amount of technological innovations per year

The sociotechnical evolutionary path changes once cognitive innovations are introduced in the socio-economic system. Starting from the established evolutionary path of physical characteristics, there will be a point in time when cognitive characteristics start to evolve fast. We define this point in time as the occupational singularity [42]. Because of their cognitive and self-reinforcement nature (cognitive machines will accelerate the development of more advanced cognitive machines), we expect the evolution of cognitive technological innovations to only accelerate once the occupational singularity sets in. For the first time, technological artifacts will be able to replace complex human cognitive skills, and the process of replacement will only gain in intensity and scope with the passing of time. We can only speculate and theorize on how this new pattern will displace human labor and nonlabor occupations, as there is no historical precedent that can guide us in the understanding of this new phenomenon.

Data from the USPTO [43] shown in Figure 2 seem to validate such a conjecture: since around 1980 the number of cybernetic patents per year has been growing faster than the number of noncybernetic patents per year. The relative gap between these two categories has only been narrowing since then. The data does not directly represent Vinge's characteristics of cybernetic technological innovations, but given the evolution of cognitive technologies during the last few decades, we believe that this is evidence in favor of our conjecture that cognitive innovations are accelerating and becoming dominant, with complex socio-economic consequences that are hard to predict.

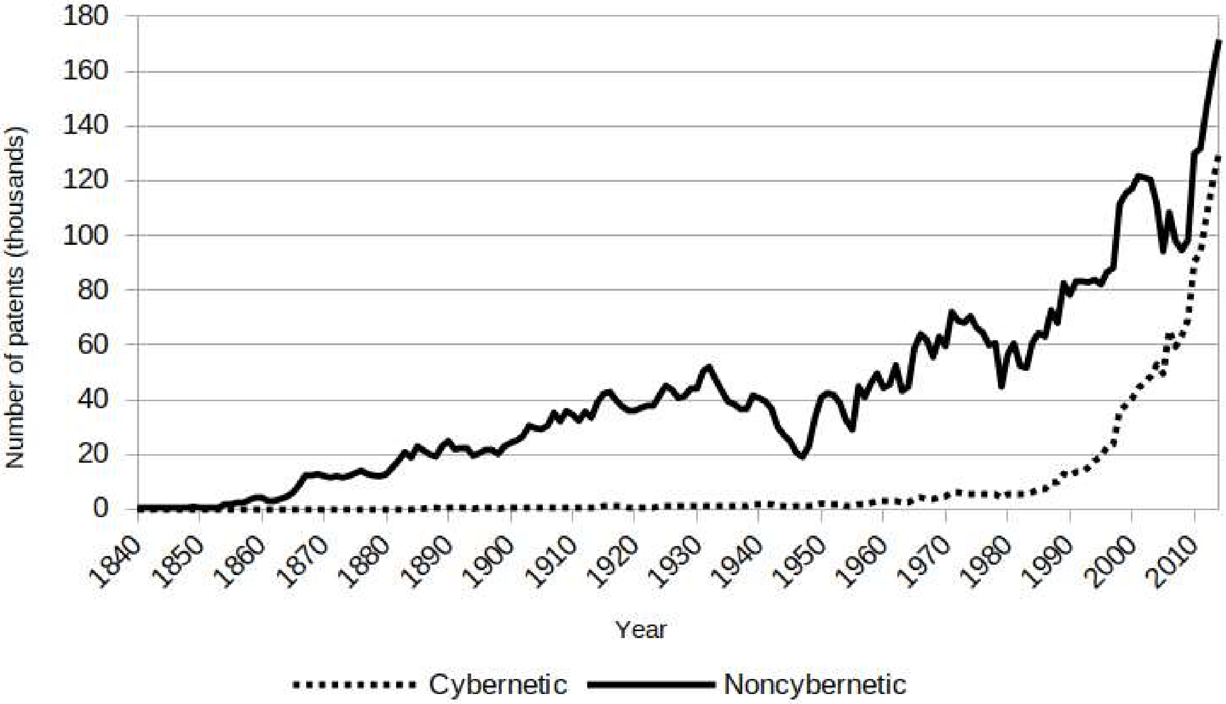

Fig. 2: Number of cybernetic and noncybernetic patents per year (USPTO)

Some pundits have been arguing that what we have been experiencing since the 80s is not new, that we have been witnessing another wave of technological progress identical to previous phases of the Industrial Revolution. We argue that this assessment is wrong, that instead we are experiencing an occupational singularity, as for the first time cognitive technological innovations are responsible for increasing and accelerating amounts of socio-economic disruptions.

V. Industry 5.0: A Case Study

In the recent literature about the latest stage of the Industrial Revolution that is now known as Industry 5.0 we commonly find the following triple bottom line as desired characteristics of future industrial developments: it must be sustainable, human-centric and resilient [44], [45]. The European Union for example declared in its recent report about Industry 5.0 [12] that "European industry is increasingly resilient and adapts itself to a new societal reality, in which production is required to respect the boundaries of our planet, and industry worker well-being is placed at the centre of the production process."

We believe that the current narrative about Industry 5.0 misses two essential points that are studied in this article. Firstly, it is necessary to bring the relatively new field of occupational science to the center of the discussion about industrial workers and end-users well-being. As some have pointed out before [46], [4], other social sciences are not as well equipped to offer policy advice concerning this vital aspect of industry's future. Secondly, as we showed in our proposed taxonomy, autonomous technologies will embody increasing amounts of cognitive technological innovations, which can be extremely disruptive compared to noncybernetic and automatic technological innovations employed in previous stages of the Industrial Revolution. Based on the findings of this article, we suggest that future research must consider how cognitive technological innovations create negative externalities that are detrimental to well-being or positive externalities that are an opportunity for the flourishing of Industry 5.0 in agreement with its triple bottom line. An example of how these ideas can be applied to remanufacturing is found in [47].

We argue therefore that we are living now in a new socio-economic environment that will be marked by an increasing number of technological innovations with cognitive characteristics that follow accelerating trajectories – an occupational singularity. This scenario is unique: for the first time in history humans will need to face a barrage of disruptions caused by technological innovations increasingly able to replace cognitive skills. We expect the challenges that it will create to become central to the future developments of Industry 5.0.

VI. Conclusion, Recommendations and Extensions

In this article we use cybernetics, occupational science and economics to study technological innovations and disruptions. We offer a series of definitions and propositions that help to clarify the relations between cybernetic categories such as noncybernetic, automatic and autonomous, and economic concepts such as alienable human skills and categories such as skill-replacing technologies and skill-enhancing technologies. We show, inspired by Vinge's work, that disruptive technological innovations may have two characteristics: physical and cognitive, and we propose that distinguishing between these two is essential to a better understanding of the socio-economic effects of technological innovations.

We speculatively suggest that cognitive innovations may lead to the accelerated displacement of meaningful human labor and nonlabor occupations [39] and has the potential to create politically and socially unsustainable outcomes [4], [48], specially in the case of skill-replacing cognitive technological innovations that produce large amounts of negative externalities. We define this moment in time as the occupational singularity. We believe that new approaches will be needed to address the detrimental effects of technological innovations on well-being and to channel them towards humanistic objectives [49].

Among possible extensions: autonomous technologies can be subdivided according to the cognitive capabilities they embody, for example, a technology may embody selective memory capabilities or environment transacting capabilities, which would then be tied to different types of socio-economic impacts. Technology affordances and constraints theory (TACT) [50] can also be introduced to establish the links between a technology category and its affordances and constraints. We intend to study these matters among others in our future investigations.

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