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DILEMMAS OF SOCIAL LIFE ALGORITHMIZATION – TECHNOLOGICAL PROOF OF EQUITY

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Purpose: The aim of the article is to describe and forecast possible dilemmas related to the development of cognitive technologies and the progressing process of algorithmization of social life.
Design/methodology/approach: Most of the current studies related to the Big Data phenomenon concern the level of efficiency improvement the algorithmic tools or protection against autonomization of machines, in this analysis a different perspective is proposed, namely – thoughtless way of using data-driven instruments, termed technological proof of equity. This study is to try to anticipate possible difficulties connected with algorithmization, which understanding could help to "prepare" or even eliminate the harmful effects we may face which will affect decisions made in the field of the social organization and managing organizations or cities etc.
Findings: The proposed point of view may contribute to a more informed use of cognitive technologies, machine learning, artificial intelligence and an understanding of their impact on social life, especially unintended consequences.
Social implications: The article can have an educational function, helps to develop critical thinking about cognitive technologies and directs attention to areas of knowledge by which future skills should be extended.
Originality/value: The article is addressed to data scientist and all those who use algorithms and data-driven decision-making processes in their actions. Crucial in this considerations is the introduction the concept of technological proof of equity, which helps to "call" the real threat of the appearance of technologically grounded heuristic thinking and it's social consequences.

Keywords: Big Data, algorithmization, data mining, data science, technological proof of equity.

Category of the paper: conceptual work.

1. Introduction

Smith and Harry Shum in the introduction to the publication by Microsoft under the telltale title *The Future Computed: Artificial Intelligence and Its Role in Society* claim: „digital technology powered by the cloud has made us smarter and helped us optimize our time, be more productive and communicate with one another more effectively. And this is just the beginning. Before long, many mundane and repetitive tasks will be handled automatically by AI, freeing us to devote our time and energy to more productive and creative endeavors. More broadly, AI will enable humans to harness vast amounts of data and make breakthrough advances in areas like healthcare, agriculture, education and transportation" (2018, p. 6). Those diagnoses are confirmed also in the reports by Deloitte, called *Tech trends 2020* (2020) and *Deloitte Global Human Capital Trends 2019* (Volini et al., 2019) which clearly emphasize the role of the analytics and cloud in data-driven decision-making processes as well as the increased importance of data management. Those tendencies comply with what James Bridle recognized as computational thinking, which means „the belief that any given problem can be solved by application of computation", but this kind of thinking have a unconscious level – "it internalizes solutionism to the degree that it is impossible to think or articulate the world in terms that are not computable" (Bridle, 2019, p. 4). In Bridle's opinion, the development of digital technologies with all their computational potential requires social actors to develop a critical - i.e. more conscious - attitude towards the way we use them (Bridle, 2019, pp. 4-6). His proposal should largely be treated pragmatically as the recommended actual broadening of the area of our agency which seems crucial from the management perspective. Here, the employed tools supporting the decision-making processes make sense provided they are able to make activities more effective instead of offering a false sense of that. This is why using broadly-taken computational technologies and social life algorithmization, including management, should be accompanied also by a broader, more critical reflection enabling to use those solutions consciously. It is required also because of the natural human proneness to employ cognitive simplifications which are often a source of false judgments. The fact this is not "cultural correctness", but a practical competence requirement, is corroborated by the diagnoses of Deloitte, according to which designing and organization management require conscious use of data management tools nowadays (Bannister, and Golden, 2020, pp. 23-41).

One of the basic concerns we have with respect to the technology as well as the wave of automation and algorithmization connected with it, taking place thanks to the development of the broadly-taken cognitive technologies, including machine learning, neural networks, natural language processing and what we term *artificial intelligence* (AI) (Ford, 2016) is how to protect from the autonomation of machines (Bostrom, 2016; Osika, 2017; Skinner, 2018). This article proposes to consider the opposite situation which seems highly legitimate given the progressing development of the computational thinking, i.e. the emancipation of the technology itself is as problematic as our thoughtless way of using it, applying a certain technological proof of equity. This is the thesis of those ponderations. Consequently, the objective of this article is the description and prognoses of any dilemmas we may face which will affect highly specific decisions made in the field of the social organization and managing organizations or cities etc.

The analysis will be theoretical. It will be based on the knowledge we already possess, e.g. the cognitive mechanisms recognized by psychologists and collected experiences of researchers in data analytics, enabling to verify the correctness of prediction tools (Schutt, O'Neil, 2014, p. 16). This reflection is to be a support for understanding and solution of future problems associated with the progressing algorithmic processes.

Performance of study tasks stipulated in this analysis requires, first and foremost, description of the algorithmization process itself, i.e. the way to understand it and the indication of mechanisms justifying the possible existence of the so-called technological proof of equity and, secondly, reference to some threats connected with the thoughtless trust to prognosticating and decision-making cognitive technologies.

2. Methods

This study uses critical analysis to identify potential dilemmas associated with the algorithmization of social life. The analysis referred to the mechanisms of heuristic thinking, well recognized in psychological research and accumulated experience of data scientist. Assumed that two aspects were crucial and study questions were formulated for them, namely:

1. Should we "defend" ourselves from the technological proof, i.e. what is the possible degree of threat it can pose?
2. Is it possible to reduce the impact of the technological proof?

3. Results

3.1. Algorithmization and technological proof of equity

Pedro Domingos in *Master Algorithm: How the Quest for the Ultimate Learning Machine will Remake Our World,* which have published in 2015, puts very adequate diagnosis of modern times: „we live in the age of algorithms. Only a generation or two ego, mentioninig the word algorithm would have drown a blank from most people. Today, algorithms are every nook and cranny of civilization. […] Algorithms combine with other algorithms to use the results of the other algorithms, in turn producing results for still more algorithms. Every second billions of transistors in billions of computer switch billions of times. Algorithms form a new kind of ekosystem – ever growing (Domingos, 2015, pp. 1-5).

Domingos' diagnosis makes us aware of the progressing algorithmization scope which is seemingly unquestionable now, as proved by the widespread use of cognitive technologies, i.e. machine learning, neural networks, robot automation, natural language processing and broadly-taken artificial intelligence which enable to shift from scattered, "impure" data to the structured set of specific steps enabling to obtain optimized results in virtually every area of our life. To put it most generally, those are the processes termed algorithmization. From the observation and stimulation of individual activity possible e.g. thanks to smartwatches, to designing cyber-physical systems popularly termed *smart factories* (Kagerman et al., 2013; Schwab, 2016; Morrar R., et al., 2017; Piccarozzi, Aquilani, Gatti, 2018).

It would not be possible to use algorithms to extract practical and theoretical knowledge or to prognosticate if it were not for what is called big data (BD) and datafication. It must also be mentioned those two phenomena are closely related. BD is about the innovative use of information which helps to understand the reality better, based on large data sets we have thanks to the digital potential of data collection, storage and processing. Three aspects of *big data* seem crucial. Those are the technical ability to analyze immense amounts of data which enables to consider its accuracy less important, the technical ability to organize data and the increased importance of correlations of key importance in *data mining* processes (Brynjolfsson, Mcafee, 2014; Dijk, 2014; Mayer-Schönberger, Cukier, 2014; O'Neil, Schutt, 2014). Datafication is the presentation of a specific phenomenon in a quantified form which may be subsequently listed in tables and analyzed (Mayer-Schoenberger, Cukier, 2013, p. 96; Śledziewska, and Włoch, 2020). Thus datafication refers to the tendency to "format" all areas of life mathematically (Dijk, 2014; Galliers, 2017), i.e. to present them in a quantitative framework (Manovich, 2001, pp. 27-30; Osika, 2015, pp. 72-74; Szpunar, 2019, pp. 11-22).

According to Yuval Noah Harari, the idea of the Turing machine was of key importance in those processes but only its development by computer scientists for many decades led to the contemporary advancement of digital algorithms (2018, pp. 467) which created a technological background enabling to carry out calculation on an unprecedented scale and to develop *data science*. Digitization is a flywheel of the big data, datafication and algorithmization revolution in a sense, as it provides a "language" to translate the real world into the *digital footprint* mathematically (Dijck, 2014; O'Neil, 2016; Schutt, O'Neil, 2014; Rudder, 2014; Jurgenson, 2014, Surma, 2017; Jones, 2019), while the *cloud* technology enables them to communicate and obtain metadata which, once analyzed, become a precious support in the decision-making processes and the new source of values.

In opinion Erik Brynjolfsson and Andrew Mcafee, this is what the second machine era consists in, i.e. "computers and other digital advances are doing for mental power – the ability to use our brains to understand and shape our environments – what the steam engine and its descendants did for muscle power" (Brynjolfsson, Mcafee, 2014, p. 10). The essence of technical solutions where the algorithms play a key role is supporting or even replacing human intellectual work, with particular emphasis on the decision-making processes which can be performed in real time based on the potential of data collection, storage and processing (Mayer-Schönberger, Cukier, 2014; O'Neil, Schutt, 2014; Yin, and Kaynak, 2015; O'Neil, 2017; Harari, 2018; Zysman, and Kenney, 2018; Śledziewska, and Włoch, 2020). The support it brings into our life, what we call data mining, i.e. extracting information from raw data (Han et al., 2012) is visible in many areas which we often term "smart", including e.g.:

- smart city — connected with the city organization enabling to optimize resource management and increase the quality of life in real time (Kummitha, 2019; Jonek-Kowalska et al., 2018);
- smart factory (Industry 4.0) — facilitating optimization of the production processes and adaptation to the market needs in real time (Kagerman et al., 2013; Schwab, 2016; Morrar R. et al., 2017; Piccarozzi, Aquilani, Gatti, 2018; Sobieraj, 2018, Osika, 2019c);
- smart medicine — supporting anti-pandemic activities, facilitating test performance, all forms of diagnostics, but also coordination of health care activities in real time (Tian et al., 2019);
- smart security — based on innovative technology which enables to improve individual and social security thanks to IoT (Kumar et al., 2019);
- smart ecology — supporting climate changes monitoring and counteracting their progress based on reasonable resource management (Jucevicius, Grumadaite, 2014);
- smart agriculture — optimized breeding and culturing thanks to using information technologies, enabling to coordinate activities in real time (Gębska, 2020; Wąs et al., 2020);
- etc.

Cognitive technologies are effective. This fact may become a trap one day, termed technological proof of equity here. To understand this phenomenon, we need to provide broader context enabling to accept the legitimacy of the proposed approach. Starting from late 20th century, many researchers, including Alvin Toffler, Nil Postman, Peter Drucker, Paul Virilio and Zygmund Bauman, stressed the digital technology introduction resulted in the accelerated growth of the quantity of data and information we have. We may say the world has never been so quantified in real time as it is now and it is e.g. thanks to it that we have a profound sense of our extensive knowledge of it, also in a purely practical dimension, e.g. management. However, a certain paradox is visible „today our knowledge is increasing at breakneck speed, and theoretically we should understand the world better and better. But the very opposite is happening. Our new-found knowledge leads to faster economic, social and political changes; in an attempt to understand what is happening, we accelerate the accumulation of knowledge, which leads only to faster and greater upheavals. Consequently we are less and less able to make sense of the present or forecast the future" (Yuval, Noah, Harari, 2017, e-book).

This means that despite our cognitive capabilities supported by the technology, we live in a state of uncertainty which always promotes use of cognitive mechanisms helping to cope with it. This includes all types of heuristics, i.e. simplified reasoning methods. Psychologists recognize a whole spectrum of heuristic cognitive strategies helping humans to cope with the information overload and uncertainty and enabling to formulate observations as well as to make sufficiently relevant decisions (Kanemen, 2011; Kenrick et al., 2014; Aronson et al., 2014). The pattern of those mechanisms' functioning is quite simple. In the situation of "cognitive" uncertainty we tend to resort to some higher instance which helps us restrain our cognitive dissonance. Sometimes, as in the case of the social proof of equity, we trust to the group infallibility and for the rule of authority this is somebody we trust because of high appraisal of their competences (Cialdini, 2007, pp. 114-166, 208-236) based on the analogy to the previous ones. For the technological proof of equity, it is entrusting thinking to algorithms, based on the rule that the calculations give this or that result (Osika, 2019a, p. 194). According to the studies, the efficiency of the above-mentioned proofs is immense. Historically, mass, unthinking basing on the beliefs of the majority or authority led us to social disasters and the experiments by Stanley Milgram or Solomon Ash confirmed their rules.

On the other hand, it seems obvious that when we have some tools to support us and alleviate our intellectual shortcomings, namely algorithmic models which help us cope with everyday problems, management, climate change prognostication, epidemics course controlling, we will be eager to use them and we will easily trust them to assess the decision accuracy. This is why Bridle encourages us „we don't and cannot understand everything, but we are capable of thinking. […] Technology is and can be a guide and helpmate in this thinking, providing we do privilege its output: computers are not here to give us answers, but are tools for asking questions" (2019, p. 6).

3.2. Technological proof of equity – possible dilemmas

If we think that it is possible to entrust thinking to algorithms unreflectively and, in the light of the above psychological mechanisms, the "entrusted thinking" becomes a realistic threat, its scale and possible consequences are indicated by Domingos again: "when algorithms become too intricate for our poor human brains to understand, when the interactions between different parts of algorithm are too many and too involved, errors creep in, we can't find them, and fix them, and algorithm doesn't do what we want. Even if we somehow make it work, it wings up being needlessly complicated for the people using it and doesn't play well with other algorithms, storing up trouble for later […]. Nevertheless we continue to build our tower of algorithms, with greater and greater difficulty. Each new generation of algorithms has to be built on the top of the previous ones and has deal with their complexities in addition to its own. The tower grows taller and taller, and it covers the whole world, but it's also increasingly fragile, like a house of cards waiting to collapse" (Domingos, 2015, pp. 1-5). Domingos warns us that the more we expand that ecosystem, the more dependent on it we become in our activities.

Algorithmization of certain areas of life enforces other and this, according to Domingos, may lead to the times when, thanks to deep machine learning and artificial intelligence exceeding human intellectual capacities, this system can no longer be controlled by us. It is worth noting that some scientific and business milieus have actually been awaiting it. This is the so-called singularity (Kurzweil, 2016; Bostrom, 2016; Osika, 2017; Skinner, 2018), perceived as a chance to solve the problems we need to cope with now, which Gregg Braden describes as the convergence of critical points and includes climate, population, energy and economic extremes (Braden, 2014; Osika, 2019b, p. 138).

Inevitably, this situation may entail many problems and this is seemingly what Domingos notes when he writes about the consequences of the complication increase and the collapse of that ecosystem. He suggests a solution entailing even more advanced algorithmization, i.e. focusing our activity on discovering/developing a master algorithm, ordering the activities of the other (Domingos, 2015). And even when we consider this perspective the most promising, we must at least try to face prognosticating the consequences of that solution and consider any emerging concerns.

Here, I suggest analyzing two aspects included in two study questions, namely:

1. Should we "defend" ourselves from the technological proof, i.e. what is the possible degree of threat it can pose?
2. Is it possible to reduce the impact of the technological proof?

3.2.1. The premises for "defend" ourselves from the technological proof

When attempting to answer the first question, the observations by Cathy O'Neil in *Weapons of Math Destruction. How Big Data Increases Inequality and Threatens Democracy*. In this work, the American mathematician analyzed the impact of algorithmic models on various aspects of social life, including education, employment, advertising, civic society etc., providing examples of their adverse activity and reminding simultaneously that no algorithmic model contains „all of the real world's complexity or the nuance of human communication. Inevitably, some important information gets left out. […] To create a model, then, we make choices about what's important enough to include, simplifying the world into a toy version, that can be easily understood and from which we can infer important facts and actions. We expect it to handel only one job and accept that it will occasionally act like a clueless machine, one with enormous blind spots" (2016, p. 20). O'Neil described a discriminatory role of the so-called *weapons of math deconstruction* (WMD), stressing how the algorithms or, more specifically, the opinions included in them, the approach and valuation of their creators affect the assessment of students' aptitudes, of the recruitment and selection participants, how they manipulate our choices etc. Algorithmization may contribute to the technological restraint of human freedom, generating the so-called "algorithmic prison" (Kleppman, 2017, p. 534). China and its Social Credit (Strittmatter, 2018) is the best example of that. All that is possible only thanks to the deep belief in the mathematics impartiality justifying the entrusted thinking.

In this context, the technological proof of equity may be an additional threat connected with a psychologically-founded sense of certainty where we have just higher or lower probability. Some researchers point to the existence of specific data interpretation conventions which is why its correct exploration requires analysis of both what we consider data in a given experiment and what interpretation methods we use to do it (Jones, 2019, pp. 6-12; Gitelman, Jackson, 2013). In the algorithmization framework, certain data use patterns can be recognized which should limit the trust to the result, e.g. Data decontextualization, i.e. using it in different context than the ones for which it was collected and processed; using quantitative data as substitute measures for complex phenomena; strategic and selective use of data to pursue particular interest; legitimation of the requested information based on the original data legitimation (Galliers el al., 2017, pp. 187-188).

One of the earliest examples of the technological proof may be the crises of 2008 when the employed algorithms "failed" and the unwavering belief in their risk assessment efficiency contributed to the financial market collapse (Brown, Whittle, 2020, pp. 70-75). Poorly developed algorithms are often blamed for that, but our belief in their reliability was equally if not more problematic. Just as for any type of heuristics, the absence of the critical/realistic reference to the grounds justifying the possible degree of certainty generates even greater uncertainty and a whole spectrum of adverse social and economic consequences, just like in 2008. Reducing our uncertainty with the "entrusted thinking", we contribute to its exponential growth and this should be deemed a conclusion related to the first study question.

3.2.2. Possible proposals to reduce the impact of the technological proof

As already mentioned, unreflective trust to the computational technology increases the risk level so we should rather focus on more conscious use of it. The fact that certain processes are not legible, which refers in particular to deep machine learning, does not mean we should ignore them, considering them to be "magical". This is why a correct data science experiment, i.e. grouping, organization into patterns and significant correlation (Mcllwraith et al., 2017) assume the participation of experts who are able to assess the legitimacy of data selection, models used and correlation. This requirement is not always respected (Galliers et al., 2017, pp. 187-188), but it is necessary. For those reasons, it seems it is impossible to eliminate the so-called "human factors" due to the intellectual flexibility and the ability to perceive dependencies in broad contexts which are considered characteristic of the human way of thinking (Harari, 2018) for the time being.

A valuable proposal is also to introduce new jobs, the so-called data translators or "datanauts" which observing the data "space" and explaining the meanings extracted from data to ensure their better use (*Translatorzy* 2018) but, first and foremost, helping to understand the essence of the processes taking place. This is again a "cumulated approach" to the *data scientists'* and experts' knowledge. It should be mentioned work devoted to such models has been initiated again and again (Kwiliński, 2019; Kuzior, 2019).

It is also necessary to ensure an in-depth approach to the so-called media education which is considered one of key competences nowadays (Bakhshi, 2017; Leopold, 2018). The very knowledge of the applications and their technical operation is not sufficient as the approach “I have an application and do not have to think anymore”, being the essence of the so-called computational thinking, is problematic (Bridle, 2019). A digital tool must be selected in connection with the awareness of what process is automated and what model is used to explore data, which requires improving data mining competences. This is particularly important when we know algorithms “skip” from one area to the other (O’Neil, 2016; Galliers et al., 2017, pp. 187-188). For example, epidemic-related algorithms are used to calculate viewing figures in the streaming services. Even if the social harm caused by it may seem negligible, the very existence of this practice entails the risk of inadequacy and unaware uselessness. Trusting the technology, we feel we are offered support in decision-making processes though actually the model examines a parameter of no importance in a given context. Control and actual efficiency can be obtained when the reason why we can afford the luxury of “thinking less” becomes clear, i.e. when we use tools suitable for a given situation and the employed model considers the vision and estimation-related values as much as possible. To understand the future, we do not need any *predictive analytics* and *prescriptive analytics*, but the adequate instruments where we know “what the data is about” and what contexts (variables, indexes) it considers, what opinion on the world in the mathematical language it contains (O’Neil, 2016). Concisely speaking, to be able to think less we need to think more which is the opposite of the technological proof of equity.

4. Discussion

One of the consequences of the emergence and widespread use of digital technology was the awareness of the amount of data that is generated, recorded and processed during its use, this phenomenon was defined as Big Data. This fact has allowed us to revive the ever-existing tendency to quantify reality, which involves a better understanding of the world, more influence on its shape (Brynjolfsson, Mcafee, 2014; Dijk, 2014; Mayer-Schönberger, Cukier, 2014; O’Neil, Yin, and Kaynak, 2015; O’Neil, 2017; Harari, 2018, Zysman, and Kenney, 2018, Śledziewska, and Włoch, 2020). Nowadays we are dealing with a similar situation, on the basis of the data collected through automated algorithmic processing we are trying to draw concrete conclusions about the functioning of reality, thus creating tools for "acting in the world", it concerns every aspect of our lives, in this sense we can talk about the progressing algorithmic processes (Dijck, 2014; O’Neil, 2016; Schutt, O’Neil, 2014; Rudder, 2014; Jurgenson, 2014, Surma, 2017; Jones, 2019, Manovich, 2001, pp. 27-30; Osika, 2015, pp. 72-74; Szpunar, 2019, pp. 11-22). Fascinated by the effectiveness of these instruments, we focus mainly on their "bright side" (Brynjolfsson, Mcafee, 2014; Schönberger, Cukier, 2014; Yin, and Kaynak, 2015; Kwiliński, 2019; Kuzior, 2019), but we need also critical thinking about this problem (Gitelman, Jackson, 2013; O'Neil, 2016; Galliers et al., 2017; Kleppman, 2017; Bridle, 2019, Osika, 2019a; Jones, 2019), allowing us to expose potential threats according to the simple rule that each "there are two sides to every story". The proposed technological proof of equity poses the questions of the consequences of the unreflective use of algorithms as a form of entrusted thinking. This way of addressing the problem is justified by the current psychological knowledge, but the study of its real impact requires in-depth analyses, including empirical ones. As it seems, empirical research should address more specific issues, helping to reveal the impact of the operation of technological proof of equity in such areas where we can already speak of the expanding influence of automated decision-making processes, for example in e-HRM (Volini et al., 2019). But also among data scientist to explore their level of awareness about the social implications of using their analytical tools. Perhaps this type of cognitive technology should be given similar descriptions as medication, in which users are made aware of the negative consequences of their use.

5. Summary

The development of machine learning, neural networks, natural language processing and AI make up processes connected with the social life algorithmization, i.e. using computational technologies for the so-called *data mining* which allows to go from the scattered, raw data to the organized set of specific steps enabling to predict risk and optimized future activities.

A condition of the effective use of those tools is their conscious use, i.e. understanding "what they do" and why they were used. However, this is not obvious due to the complexity degree of computational instruments. This complexity makes us assume more often than we know. This article proposes to consider the effects of the so-called computational thinking i.e. unreflective method of using computational technologies to which we ascribe high reliability degree without any grounds. The objective of this article is to describe any dilemmas we may face and which may have a highly practical dimension as they refer to the decisions connected with the society organization and management of organizations, cities etc.

This analysis was theoretical. Such terms as algorithmization and the technological proof in analogy to the social proof were defined. In the final section, an attempt at answering the questions if we should "defend" ourselves from the technological proof of equity, i.e. what the possible degree of threat it can pose is and if it is possible to reduce the impact of the technological proof was made. The answer to the first question was positive while the forms of defense were the need to apply expert intervention and the broadly-taken education within computational technologies.

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