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INDUSTRY 4.0: SELECTED ASPECTS OF ALGORITHMIZATION OF WORK ENVIRONMENT

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Purpose: The aim of the article is to describe and forecast possible difficulties related to the development of cognitive technologies and the progressing of algorithmization of HRM processes as a part of Industry 4.0.
Design/methodology/approach: While most of the studies to date related to the phenomenon of Industry 4.0 and Big Data are concerned with the level of efficiency of cyber-physical systems and the improvement of algorithmic tools, this study proposes a different perspective. It is an attempt to foresee the possible difficulties connected with algorithmization HRM processes, 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 managing organizations, especially regarding human resources management, in era of Industry 4.0.
Findings: The research of cognitive technologies in the broadest sense is primarily associated with a focus of thinking on their effectiveness, which can result in a one-sided view and ultimately a lack of objective assessment of that effectiveness. Therefore, conducting a parallel critical reflection seems even necessary. This reflection has the potential to lead to a more balanced assessment of what is undoubtedly "for", but also of what may be "against". The proposed point of view may contribute to a more informed use of algorithm-based cognitive technologies in the human resource management process, and thus to improve their real-world effectiveness.
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: This article is addressed to all those who use algorithms and data-driven decision-making processes in HRM. Crucial in these considerations is the to draw attention to the dangers of unreflective use of technical solutions supporting HRM processes. The novelty of the proposed approach is the identification of three potential risk areas that may result in faulty HR decisions. These include the risk of "technological proof of equity", overconfidence in the objective character of algorithms and the existence of a real danger resulting from the so-called algorithm overfitting. Recognition of these difficulties ultimately contributed to real improvements in productivity by combining human performance with technology effectiveness.

Keywords: Industry 4.0, HRM, e-HRM, algorithmization, data mining, data science.

Category of the paper: conceptual work.

1. Introduction

The expression Industry 4.0 (I 4.0) was originally used as a "working title" to describe the strategy for the development of computerization, which was presented by the German government at the trade fair in Hannover in 2011. The main assumptions of this strategy concerned the attempt to implement digital technologies in real manufacturing processes, leading to the creation of what's colloquially known as a *Smart Factory* (*Smart Factory*) (Schwab, 2016, p. 12; Morrar et al., 2017, p. 17; Piccarozzi el al., 2018; Marr, 2018, p. 2). The entrenched concept of this strategy was to use intensively developing digital technology to increase production efficiency while reducing costs. Over time, it turned out that both the title of the project and its main assumptions were strong enough to evolve into the terms we use to describe contemporary economic realities, by identifying them with the fourth industrial revolution, or as defined by Erik Brynjolfsson and Andrew McAfee in *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies,* the second machine age, in which "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. They're allowing us to blow past previous limitations and taking us into new territory" (Brynjolfsson, and Mcafee, 2014, p. 10).

The issues that focus interest around Industry 4.0 most often relate to the proposed *smart factory* models (Kagerman, 2013; Bunse et al., 2014; MacDougall, 2014; Wang, and Wang, 2016; Schwab, 2016; Morrar, 2017; Piccarozzi et al., 2018; Stock, and Seliger, 2019), often also paying attention to the social consequences of automation (Manyika et al., 2011; Manyika, et al., 2013; Brynjolfsson, and Mcafee, 2014; Schwab, 2016; Manyika et al., 2017; Harari, 2018; Osika, 2019; 2020; 2021). Nevertheless, it is obvious for all researchers dealing with these issues, that regardless of the increasingly expanding areas of activity, that may be subject to automation in production processes, it is impossible to completely eliminate human labor. This realization means, that the emerging work environment will force the need to change human resources management, and its future form will require rethinking and the inclusion of new contexts (Zysman, and Kenney, 2018). Already, one can see growing trends in this regard, which relate to one of the many technical solutions that make up Industry 4.0: we are talking here about the computational potential of digitality, known as Big Data (Yin, and Kaynak, 2015; Wang, and Wang, 2016, p. 6; Structural transformation…, 2019, p. 6). With such solutions as: The Internet of Things, data mining, data science and deep machine learning, data analytics equips people with tools, allowing them to make more rational decisions and effectively solve problems, including those related to the work environment. Algorithms are key to these processes, as they create a methodical backup, facilitating transitions from dispersed, 'contaminated' data to an ordered set of specific steps that allow for obtaining optimized effects in virtually every field from which the data have been processed. In this respect, it seems obvious that the availability of such tools is associated with their widespread use, leading to them developing into the dominant form of action, and this is how the concept of algorithmization should be understood. It is a progressive process of assigning specific tasks to digital tools, which are algorithms. As Pedro Domingos notes, „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), this trend is confirmed by many researchers (Mayer-Schönberger, and Cukier, 2013; O'Neil, and Schutt, 2014; O'Neil, 2016; Harari, 2018; Kwilinski et al., 2019, Kuzior et al., 2019).

On the other hand, we must be aware that the algorithms under development are derived from models that, contrary to the mathematical – or objective – nature of the tools, are not neutral, as they contain hidden assumptions of their designers, elements of their culture, their cognitive schemes and prejudices, etc. Therefore, in view of the intensifying tendency to algorithmize social life, it seems necessary to conduct analyzes to better understand the extent of the impact of this form of "entrusted thinking". Obviously, it is not possible to analyse all aspects related to the widespread implementation of cognitive solutions within HRM, so it is proposed to pay attention to three main research problems and consequent questions, namely: What if we stop critically refer to algorithmically developed conclusions? What if we do not understand that algorithmic models are only the opinions of people written in the language of mathematics? What if we don't understand that, each algorithm can "over-fitted"?

The purpose of the discussion is a preliminary description of the risk consequences that we have to face when algorithmizing the work environment, i.e. identifying areas of influence of mathematical tools and indicating possible negative consequences resulting from their use. Understanding these issues requires a general recognition of the role an analyst can play in Industry 4.0, while it is also necessary to specify in more detail the activities related to human resource management, in which Big Data can be used, and to realize potential problems arising therefrom.

Emphatically, considerations are not about building a technophobic attitude, but rather about discovering possible "system gaps" causing that the system would, contrary to expectations, not fulfill its optimizing function, primarily in order to be able to eliminate them before they become common practice.

2. Methods

The study makes use quality content analysis (Berlson, 1952; Flick, 2010; Mayring, 2014) and critical analysis (Jakkola, 2020). To assess the degree of algorithmization processes in HRM availed data harvested in *Global Human Capital Trends 2019* (Volini el al., 2019), which is the result of empirical research, published in 2019 year, the report covered 30 countries, surveyed 9453 people, employed in varied industries (Volini el al., 2019, pp. 14-16). The categorization uses in content analysis concerned only issues related to HR cloud, which the report by Deloitte places in the main HRM trend. The recognition made by Deloitte is crucial as it allowed predicting in which direction trends in HRM processes will develop, and the experience of the COVID 19 pandemic time confirmed their validity and intensified their implementation. However, from the point of view of the emergence of the trend itself in the HRM process, the report analyzed seems sufficient, and it has also been confirmed randomly in other Deloitte's reports (Global Human Capital Trends, 2020; Global Human Capital Trends, 2021). However, further reports focused on other aspects of HRM, so the one from 2019 that directly addresses the issues examined is use.

Second research was a critical analysis of a risk connected with algorithmization of work environment, to research used the cognitive mechanisms recognized by psychologists and accumulated experience of data scientist. Three types of risk are identified: technological proof of equity, simplifying of algorithms, and overfitting of algorithmic model. Three research questions were asked:

- What if we stop critically refer to algorithmically developed conclusions?

This question will allow to analyze the tendency, typical of the cognitive orientations, recognized by psychologists, to use intellectual shortcuts to offset a sense of uncertainty when faced with difficulties in assessing the reliability of information or making decisions. In this case, technology is to be the guarantor, so it is worth asking – is it justified?

- What if we do not understand that algorithmic models are only the opinions of people written in the language of mathematics?

The purpose of this question is to examine how far it is reasonable to understand algorithms as tools that objectively identify states of affairs.

- What if we don't understand that, each algorithm can "over-fitted"?

In a sense, this research question is a continuation of the previous one, because if we accept the partially subjective nature of algorithms, we must try to recognize what might influence their inadequacy resulting in ineffective performance. Such a factor may be the data scientist overfitting pointed out.

3. Results

3.1. Theoretical framework

3.1.1. Industry 4.0

As mentioned earlier, Industry 4.0 is considered to be the implementation of the concept of a smart factory, i.e. a form of production organization, in which complex cyber-physical systems control physical processes (MacDougall, 2014; Schwab, 2016; Morrar et al., 2017; Piccarozzi et al., 2018; Miśkiewicz, and Wolniak, 2020) and the production activities undertaken are automated, minimizing to a large extent the participation of people in production processes, thus allowing shortening of the production time and reduction of its cost. First and foremost, smart factory is based on various forms of connectivity, such as: Internet of People (social and business networks); Internet of Things (intelligent mobility and sensor data); Internet of Services (intelligent networks and logistics). Other applied solutions are robotization and automation of manufacturing processes, as well as the introduction of autonomous manufacturing and processing systems on production lines with full control of the process, while 3D printing allows the so-called additive manufacturing. An important supplement to the cyber-physical system being built is the use of cloud computing structures; creation of analytical and calculation systems, made possible by Big Data (BD), artificial intelligence, and deep machine learning. Innovative business models, such as *freeeconomics* or *sharing economy* are the culmination of these technological changes (Rifkin, 2015), because *mass customization*, i.e. the creation of custom-made products on a mass scale, is an important aspect of the functioning of smart factories. It is this factor, that is considered key in relation to Industry 4.0 – maintaining low costs with high individuality of product features, allowing to maximize the level of adaptation to market needs, while optimizing the consumption and reorganization of resources that the company already has. The combination of all these elements allows you to create „the embedded manufacturing systems […] vertically networked with business processes within factories and enterprises and horizontally connected to dispersed value networks that can be managed in real time – from the moment an order is placed right through to outbound logistics. In addition, they both enable and require end-to-end engineering across the entire value chain" (Kagerman et al., 2013, p. 5).

Naturally, all of the aforementioned technological solutions play a significant role, but it is BD analyzes that seem to be key in coordinating activities due to their potential for obtaining, storing, correlating and analyzing data that can also take place in real time (Lee, and Kao, 2014; Manyika et al., 2011; Henke, 2016; Wang, and Wang, 2016; Structural transformation…, 2019). As many authors point out, the use of Big Data is becoming a source of new values in business, mainly due to decisions that are more rational, because they are based on specific information (Yin, and Kaynak, 2015; Wang, and Wang, 2016; Alcacer, and Cruz-Machado, 2019). „Systematic guidance can be provided by BD for related production activities within entire product lifecycle, achieving cost-efficient running of the process and fault-free, and help managers on decision-making and/or to solve problems related to operation" (Alcacer, and Cruz-Machado, 2019, p. 904). BD potential is characterized by dimensions that help to understand the wide application of digital operations in Industry 4.0, including, first of all, the possibility of working on a very large *volume* of data – expressed in many terabytes or even petabytes. Secondly, a wide *variety* of data (video, audio, texts, etc.) can be analyzed, generated by the multidimensional content of data fields, related to structural heterogeneity in the data set. Thirdly, the *velocity* of analysis regarding both the speed of their generation and their analysis. Fourthly, the *veracity* of data, which often comes from sources recorded in real time. Fifthly, the possibility of targeted data recording (*vision*), allowing to work on relatively "clean" data. Sixthly, data *verification* related to the data life cycle, which involves constant data updates. Seventhly, *validation*, i.e., testing the compliance of the data used with the estimation; in other words, testing whether the data "tells" us what is needed to make specific decisions, e.g. to eliminate the possibility of *overfitting* of the system or working on data that is no longer relevant to the analyzed phenomena. Eighthly, analysis of data *variability* in terms of its flow, where, due to the technical possibility of correlating dimensions, another category of data measurement is obtained. Ninthly, the *value*: this dimension relates to the assignment of a specific economic value to the analyzed data (Mayer-Schönberger, and Cukier, 2013; Yin, and Kaynak, 2015; Gandomi, and Haider, 2015; Alcacer, and Cruz-Machado, 2019; Gajdzik, and Wolniak, 2021). The afore-described dimensions show how broadly applicable BD analyzes can be in modern management. They also bring forward a new decision-making potential, where high-risk choices made as part of management activities are supported by information from data supplied and processed in real time. Moreover, these processes allow the development of operating procedures or algorithms that can be successfully used in similar situations. The strong advantage of Big Data-based tools is their universal use within all functions typical of the management process, i.e. planning, organizing, directing and controlling (Medina, 2006, p. 6). This applies to all stages of production, including those that belong to human resources management, i.e. „the process through which management builds the workforce and create the human performances that the organization needs" (Boxall, and Purcell, 2016, p. 7).

3.1.2. Human resources management

As part of HRM, more detailed, operational functions are implemented, which include: employment, human resource development, remuneration, human relations, working conditions, motivation and industrial relations (Boxall, 2007; Mwaniki, and Gathenya, 2015; Shrama, 2016). The employment is implemented through such activities as: job analysis, human resource planning, recruitment, selection, placement. Human resources development is a process of evaluation, training and career planning, while remuneration requires job evaluation, wage and salary administration and incentives. Human relations apply to such activities as motivating, developing leadership skills, improving quality of work life etc.

Working conditions concern care for measurable and immeasurable aspects of work, such as health, safety and comfort of employees. Actions taken in the area of working conditions refer directly to the sphere of motivation and a sense of job satisfaction. This is yet another very significant operational function implemented within HRM (Mwaniki, and Gathenya, 2015; Shrama, 2016, pp. 9-10). Given the point of view adopted in these considerations, it is important to recognize what scope of activities, described above and implemented under HRM, can be subjected to algorithmization processes, i.e. which can be covered by the so-called e-HRM, which is defined as planning, implementation and application of information technology for HRM (Strohmeier, 2007). These activities are closely related to human resources information systems (HRIS), which we can define as algorithmic procedures for collecting, storing, searching and validation of data relevant to HRM processes (Bondaruk, and Ruël, 2013; Stone et al., 2015; Angrave et al., 2016; Bondaruk, and Brewster, 2016; Marler, and Parry, 2016). The implementation of IT systems for HRM activities has been ongoing since the late 1990s and there are a number of studies dealing with this issue (Withers, 2010; Bondaruk, and Ruël, 2013; Bondaruk, and Brewster, 2016; Marler, and Parry, 2016; Eneizan et al., 2018; Zysman, and Kenney, 2018; Parry, and Battista, 2019), but it has now become clear that "information systems have a deep effect on HRM. IT transformed human resources processes and practices mainly in terms of how organizations collect, store, use, and disseminate information" (Silva, and Silva Lima, 2018, p. 114). This applies to all stages of production, including those that belong to human resources management, i.e. „the process through which management builds the workforce and create the human performances that the organization needs" (Boxall, and Purcell, 2016, p. 7).

Considering that HR activities shape the working environment in a given enterprise to the greatest extent, an important question arises in a given organization on how BD analytics and related algorithms are used in HRM, i.e. to what extent we can talk about the algorithmization of the human resource management process.

3.2. Quality content analysis

To assess the degree of algorithmization processes typical of HR activities, such as recruitment, selection, turnover and performance management used quality content analysis of main trends of HRM, harvested in *Global Human Capital Trends 2019* (Volini el al., 2019). Research published in this report covered 30 countries, in total 9453 people were surveyed, employed in industries such as: professional services, financial services; energy, resources & industrials; technology, media & telecom; government & public services; life sciences & health care; consumer and others (Volini el al., 2019, pp. 14-16). The categorization used in content analysis concerned only issues related to HR cloud, and it included: HR cloud – trend importance at all, trend importance by region, trend importance by industry; shift toward becoming a strategic HR function; better data and workforce insights report by Deloitte places informatization in the main HRM trend. HR cloud in report is defined as: "HR technology […], considering cloud as a foundation and exploring innovative new platforms, automation, and AI-based tools" (Volini el al., 2019, p. 7), therefore directly refers to processes associated with algorithmization. Figure 1 below shows the rated of the importance of this issues all respondents.

Figure 1. HR cloud importance by all respondents. Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

In *Global Human Capital Trends 2019* 74% of respondents assess HR cloud as important and very important, 21% called it one of the tree most urgent topics (Volini el al., 2019, p. 13). Table 1 and 2 below shows the rated of the importance of this problem by region and by industry.

Table 1.
Trend importance by region

	Africa	Asia	Central and Eastern Europe	Latin and South America	Middle East	Nordic countries	North America	Oceania	Western Europe
HR cloud	82%	75%	71%	78%	85%	68%	75%	77%	68%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 2.
Trend importance by industry

	Professional services	Financial services	Energy, resources & industrials	Technology, media & telecom	Government & public services	Life sciences & health care	Consumer
HR cloud	73%	79%	74%	76%	72%	70%	76%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Research shows that the dominant trend in HR activities in 2019 should be considered the spread of subscription-based standardized BD platforms in HR systems, also made available by such technology giants as Google, Microsoft, IBM and LinkedIn (Cheng, and Hackett, 2019). These platforms allowed to integrate various forms of HR software, thus ensuring an improvement in data handling and their "functionality" resulting from the wider potential of data mining available to the organization. With them, it became possible to optimally manage vacation reserves, create consistent and comprehensive employment histories, ensure optimal staffing, match competences to new company strategies, plan training, analyze training effectiveness, identify areas that require additional training, correlate competences and test the effectiveness of incentive programs that allow maximum matching of motivators, creating employee benefit reports, managing recruitment projects, monitoring employee behavior, algorithmizing employee profiles and assessing the effectiveness of standard employee behavior – to mention only some of the most significant changes. Therefore, the organization's expectations towards HR cloud systems also increased. Selected indicators regarding these expectations are shown below.

Table 3.
Shift toward becoming a strategic HR function

Actual	Expected
44%	61%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 4.
Better data and workforce insights

Actual	Expected
40%	60%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 5.
Easier to use, less training needed

Actual	Expected
35%	59%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 6.
Increased HR tech innovation

Actual	Expected
32%	59%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 7.
Ease of updates and new releases

Actual	Expected
38%	59%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 8.
Lower cost of ownership

Actual	Expected
33%	59%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

Table 9.
Consolidated view

Actual	Expected
48%	57%

Source: Own elaboration on the *Deloitte Global Human Capital Trends 2019*.

The presented results help to realize what role in HRM practice begins to be attributed to BD analytics and how significant the parameters typical for its "logic" are becoming, i.e. collecting, storing and processing data based on the use of algorithms, including predictive and prescriptive ones, probabilistic rather than deterministic, as we want to see them (Cheng, and Hackett, 2019). Naturally, the main motive of these activities is the optimization of decisions, but shouldn't we consider whether the hopes placed in these tools are too optimistic, despite the growing market for these services (Cheng, and Hackett, 2019)? This is one of the issues worth analyzing, also to understand "what sort of world will we build with platforms, data, and intelligent tools?" (Zysman, and Kenney, 2018, p. 57). There are also purely pragmatic considerations, such as whether there are rational premises for the fact that "entrusted thinking" will allow us to optimize our actions? This is all the more important, especially in the context of the implementation of Industry 4.0, which is intended to automate production and management processes.

3.3. Critical analysis

Victor Mayer-Schönberger and Kenneth Cukier, in *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (2013), try to convince us how BD and the algorithmization of many aspects of our life are an opportunity to improve its quality (McAfee, Brynjolfsson, 2013). However, HRM researchers often question the value of analytics-driven software for decision making or warn that using analytical models is only a management fad (Angrave et al., 2016; Cheng, and Hackett, 2019). Similar cautions are formulated by researchers dealing with BD issues (O'Neil, and Schutt, 2014; O'Neil, 2016). A possible problem is worth investigating. Naturally, this critical analysis will be anticipatory, as verification requires empirical research, and consequently, a longer process of use that allows assessing the possible impact. However, in forecasting, we can use the knowledge we already have, wherein cognitive mechanisms recognized by psychologists will be used. We can also use the accumulated experience of researchers in the field of data analytics, such as those who can extract significant formulas from data, but also verify the correctness of tools used for prediction (Schutt, and O'Neil, 2014, p. 16). But first, we need to provide an concept of model for knowledge discovery from data, we use basis description of this process, understanding it as an iterative sequence of the following steps: raw data taking; data cleaning; data integration; data selection; data transformation; data mining; pattern evaluation; knowledge presentation (Han et al., 2012, pp. 6-8). Figure 2 below illustrate this model.

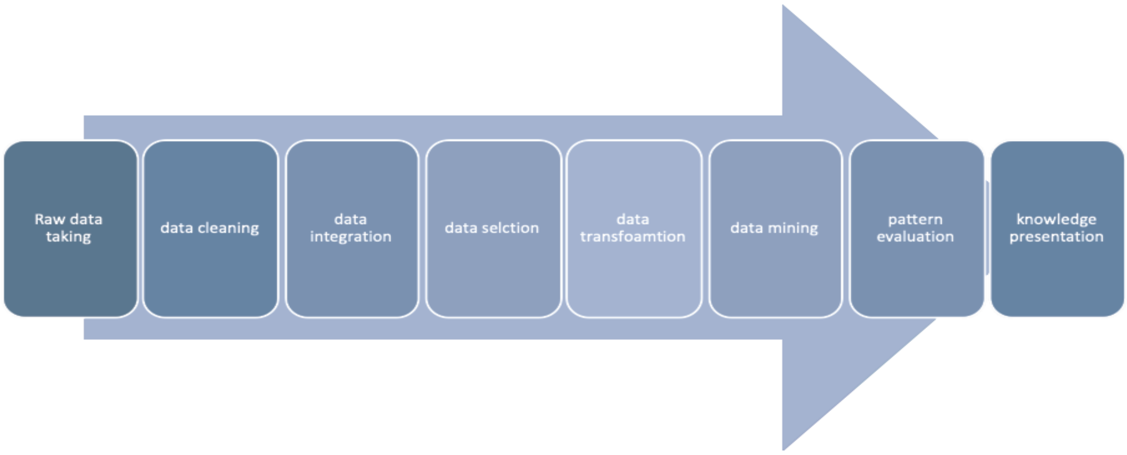

Figure 2. Model knowledge discovery from data. Source: Own elaboration on the Han J., Kamber M., Pei J. (2012), *Data Mining: Concepts and Techniques*. Amsterdam, Boston, Heidelberg, London, New York, Oxford, Paris, San Diego, San Francisco, Singapore, Sydney, Tokyo: Elsevier.

The steps of Knowledge Discovery in Databases, short KDD, in many models is similar and, because of systematic structure of method, they give very strong suggestion to be objective, create the "aura of objectivity" (Reynolds, 2016; Jons, 2019) which seems helpful for each process of decision. In spite of this, some threads may give rise to doubts, in this analysis selected three, these are cognitive patterns guiding our mode of action, the potential risk of using technological support in decision-making processes and possible consequences limiting the system's innovation and the resulting lack of adaptation of the strategy to changing environmental conditions. Secondly, the limited potential of the algorithmic models themselves (Mauboussin, 2012; Schutt, and O'Neil, 2014; O'Neil, 2016) and, thirdly, the susceptibility of the models to "excessive learning", known as overfitting, or a situation in which, after using a certain set of data to estimate the model, the resulting model does not reflect reality and becomes useless as a decision support tool (Griffiths, and Christian, 2016; Schutt, and O'Neil, 2014; Domingos, 2015).

Table 10.
Critical analysis – potential risks

Question	Description	Potential risk
What if we stop critically refer to algorithmically developed conclusions?	Psychological tendency to using heuristic cognitive mechanisms as the strategy of handling information overload (Kaneman, 2011; Kenrick et al., 2014; Aronson et al., 2014).	Using "technological proof of equity" in decision-making process in HRM – uncritical trust in algorithms
What if we don't understand that, algorithmic models are only the opinions of people written in the language of mathematics?	All algorithmic models are only simplifying the real world (Mauboussin, 2012; Schutt, and O'Neil, 2014; O'Neil, 2016).	Using inadequate data to predict and incorrect decision-making process in HRM
What if we don't understand that, each algorithm can "over-fitted"?	All algorithmic models have tendencies to over-fitted, it means that "model does not generalize well from observed data" (Ying, 2018), because of using the detail and noise data (Griffiths, and Christian, 2016; Schutt, and O'Neil, 2014; Domingos, 2015).	Using inadequate algorithmic model to predict and inefficient decision-making process in HRM

Source: Own elaboration.

3.3.1. Technological proof of equity

Psychologists dealing with perception issues have long recognized the entire spectrum of heuristic cognitive mechanisms that help people cope with information overload, which, as confirmed by our limited mental capabilities, create the need for simplifying, effortless strategies (Kaneman, 2011; Kenrick et al., 2014; Aronson et al., 2014), to make observations and make sufficiently accurate decisions. It seems obvious, that when we get tools in the form of algorithmic models that help supplement our deficiencies, we will be happy to use them, and we will gladly give them priority in assessing the accuracy of decisions as "technological proof of equity" (Osika, 2019; 2021). The same sources also tell us that there is a strong cognitive tendency to consolidate patterns, hence such emphasis is placed on developing critical thinking skills (Nussbaum, 2010). Can we, therefore, expect that, despite some natural tendencies, we will be able to critically refer to algorithmically developed conclusions? We already hear rumors that it is necessary.

3.3.2. Simplifying of algorithms

In *Weapons of Math Destruction. How Big Data Increases Inequality and Threatens Democracy,* American mathematician Cathy O'Neil analyzes the impact of algorithmic models on various aspects of social life, including restrictions on access to work or the dissemination of harmful HR practices. She recalls the obvious truth for the creators of algorithmic models – „no model can include 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). But whether users of predestination models have this awareness is a rhetorical question. What makes algorithmic models so unreliable, according to O'Neil, is the quality of the data used, which very often is only indirect in nature, that is, there is no direct result relation between the data, but the relation is "implicit". Because algorithmic models are the opinions of people written in the language of mathematics, who are backed by motives of specific people and the goals of specific organizations, they cannot be considered universal (O'Neil, 2016).

3.3.3. Overfitting of algorithmic model

Another difficulty is the lack of feedback in the evaluation of the algorithm's effectiveness, and since the models relate to changing reality, they should also be dynamic, i.e. they must be subject to constant verification. Data scientists point out one of the basic threats of "overfitting the model" when it no longer reflects the estimated relationships due to the change in reality (Griffiths, and Christian, 2016, pp. 155-159; Ying, 2019). For example, employees adapt to procedures, but these do not optimize work efficiency and, instead of being eliminated, persist. Considering the above, algorithmization of the work environment should not be treated as a tendency that allows to fully automate activities undertaken within HRM as a supplement to

Industry 4.0. Dedicated HR applications, using estimation models used in BD exploration, provide valuable assistance in tedious and routine processes, such as collecting basic data in recruitment or creating employment history of employees, as well as sorting this data, but these systems must be supported by the expert knowledge of HR specialists to the effects of data mining, actually, allowing making the most optimal decisions, and in this sense the human factor from HRM processes seems indelible. We will not lose control if we employ greater awareness to create the algorithms that serve us (Krauss, 2015; Kleppman, 2017; Osika 2020; 2021).

4. Discussion

Since the 1980s, we have been dealing with the intensive development of both theoretical reflection and practical activities under Human Resource Management (HRM) (Boxall, 2007, p. 50; Kaufman, 2007, p. 34; Cowling, 2011; Mwaniki, and Gathenya, 2015; O'Riordan, 2017, p. 7), which in the „broadest sense it may be taken to denote all aspects of recruitment and hiring, planning, development and reward, the human side of the organization of work and of the employment contract, HRM has also been taken to incorporate a strategic dimension" (Cowling, 2011; Collings et al., 2019, p. 2). As Michael Armstrong points out – "human resource management is a strategic, integrated and coherent approach to the employment, development and well-being of the people working in organizations" (Armstrong, 2016, p. 7). At the same time, many researchers paid attention to the fact, that this reflection and applied practices are embedded in specific social, economic and technological contexts, and therefore require continuous updating (Kaufman, 2007; Withers et al., 2010; Bondaruk, and Brewster, 2016; Johanson, and Szamosi, 2019, p. 27). The algorithmization of work environment and changes made in this respect within HRM were accepted as one of such contexts in these considerations. According to the assumptions made earlier it is a matter of recognizing the degree of use of BD analytics in the human resources management process, but also highlight potential risk of this trend such as technological proof of equity, simplifying made by algorithms and overfitting of algorithmic model. This reflection is to be a support for understanding and solution of HR problems associated with the implementation of HR cloud, and in the future that issues requires in-depth and more empirical research (Cheng, and Hackett, 2019; Osika, 2020). It should be stressed that this reflection has become particularly important in view of the very strong acceleration of the trends described here, forced by the Covid-19 pandemic and the implementation of HRM process automation related to remote working, therefore the subject matter undertaken in the article is a practical necessity and not a theoretical quibble.

The significant threads in the discussion on e-HRM in the context of Industry 4.0, which have been described in this article, should be considered to diagnose the areas of potential risk of the impact of technological solutions on the human way of using them, which is largely the result of, on the one hand, our mental limitations (Kaneman, 2011; Kenrick et al., 2014; Aronson et al., 2014) – technological proof of equity (Osika, 2019; 2020; 2021), but also the limitations of technology, which, contrary to our hopes, has areas of imperfection (Griffiths and Christian, 2016; Schutt, and O'Neil, 2014; Domingos, 2015; O'Neil, 2016; Krauss, 2015; Kleppman, 2017; Ying, 2019; Osika, 2021).

5. Summary

Klaus Schwab in *The Fourth Industrial Revolution* pointed that "we must have a comprehensive and globally scared view of how technology is changing our lives and those of future generation, and how it is reshaping the economic, social, cultural and human context in which we live" (Schwab, 2016, p. 8). It was recognized, that Industry 4.0 and the automation processes associated with it would not fulfill their effective function, unless they were supplemented with "human" support in decision-making processes. Technical solutions, such as: the Internet of Things, data mining, data science and deep machine learning, form the core of cyber-physical systems, allowing us to coordinate their activities, but, at the same time, complete automation of processes can create distortions in achieving goals that are assumed by people and for the people. The purpose of the discussion was to describe the role of BD analytics in Industry 4.0 and the scope of HRM algorithmization. t was important because the most of the researchers focus on the positive application of e-HRM tools. The present discussion had the opportunity to objectify the view by also highlighting areas of risk. The analysis noted several consequences associated with the use of mathematical tools for HRM processes, while it included potential negative aspects, such as: the impact of technological proof of equity, succumbing to the subjectivism "sewn" into algorithms by its designers, or the overfitting of the algorithms. As it seems, this reflection should be considered particularly important in the context of the changes in the HRM process that had to take place in the face of the Covid-19 pandemic, which is why this issue has gained currency. However, the risk areas identified in this consideration should be thoroughly investigated, for example: what extent is the support of e-HRM systems widely used?: are the results recognized indiscriminately, is their effectiveness evaluated? What is the human versus algorithmic involvement in decision making? Only by obtaining answers in the course of research will it be possible to assess to what extent the identified risks affect the effectiveness of HRM activities.

References

1. Alcacer, V., and Cruz-Machado, V. (2019). Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing System. *Engineering Science and Technology, an International Journal*, *22*, pp. 899-919, https://doi.org/10.1016/j.jestch.2019.01.006.
2. Amstrong, M. (2016). *Amstrong's Handbook of Strategic Human Resource Management.* London: Kogan Page.
3. Angrave, D. et al. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal, 26(1),* pp. 1-11.
4. Aronson, E. et al. (2014). *Pearson New International Edition. Social Psychology.* London: Pearson.
5. Berlson, B. (1952). *Content Analysis in Communication Research.* New York: Hafner.
6. Bondaruk, T., and Brewster, C. (2016). Conceptualizing the future of HRM and technology research. *The International Journal of Human Resource Management*, *27, 21,* pp. 2652-2671, https://doi.org/10.1080/09585192.2015.1091980.
7. Bondaruk, T., and Ruël, H. (2013). The Strategic Value of e-HRM: Results from an exploratory study in a governmental organization. *The International Journal of Human Resource Management*, *24(2),* pp. 1-24, https://doi.org/10.1080/09585192.2012.675142.
8. Boxall, P. (2007). The Goals of HRM. In: P. Boxall, J. Purcell and P. Wright (eds.), *The Oxford Handbook of Human Resource Management* (pp. 48-67). Oxford-New York: Oxford University Press, DOI:10.1093/oxfordhb/9780199547029.001.0001.
9. Boxall, P. and Prucell, J. (2016). *Strategy and Human Resource Management.* London: Palgrve Macmillian (e-book).
10. Boxall, P., Purcell, J. and Wright, P. (eds.) (2007). *The Oxford Handbook of Human Resource Management.* Oxford-New York: Oxford University Press.
11. Brynjolfsson, E., and McAfee, A. (2014). *The Second Machine Age. Work. Progress, and Prosperity in a Time of Brillant Technologies.* London-New York: W.W. Norton & Company.
12. Bunse, B. et al. (2014). *Industrie 4.0: Smart Manufacturing for Future.* Berlin: Germany Trade&Invest.
13. Cheng, M.M., and Hackett, D.R. (2019). The critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review, 31,* p.100698, https://doi.org/10.1016/j.hrmr.2019.100698.
14. Christian, B., and, Griffiths, T. (2016). *Algorithms to Live By: The computer Science of Human Decisions.* New York: Henry Holt and Company.
15. Collings, D.G. et al. (2019). Human Resource Management: A Critical Approach. In: D.G. Collings, G.T. Wood, L.T. Szamosi (eds.), *Human Resource Management: A Critical Approach* (pp. 1-24). New York: Routledge.

16. Collings, D.G., Wood, G.T., and Szamosi, L.T. (ed.) (2019). *Human Resource Management: A Critical Approach.* New York: Routledge.
17. Cowling, A. (2011). Developing a strategy for Human resources. In: A. Cowling and C. Mailer (eds.), *Managing Human Resources* (pp. 5-20). New York: Routledge.
18. Cowling, A., and Mailer, C. (ed.) (2011). *Managing Human Resources.* New York: Routledge.
19. Domingos, P. (2015). *Master Algorithm: How the Quest for the Ultimate Learning Machine will Remake Our World.* New York: Basic Books.
20. Eneizan, B. et al. (2018). Effect of technical support and trust on the adaption of electronic human resource management: Evidence from developing countries. *International Journal of Applied Research, 4(7),* pp. 31-40.
21. Flick, U. (2010) *An Introduction To Qualitative Research.* London-Thousand Oaks-New Delhi-Singapore: SAGE Publications.
22. Gajdzik, B., and Wolniak, R. (2021). Digitalization and Innovation in the Steel Industry in Poland-Selected Tools of ICT in an Analysis of Statistical Data and a Case Study. *Energies*, *14(11),* 3034, https://doi.org/10.3390/en14113034.
23. Gandomi, A., and Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*, pp. 137-144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007.
24. Han, J., Kamber, M., and Pei, J. (2012). *Data Mining: Concepts and Techniques*. Amsterdam-Boston-Heidelberg-London-New York-Oxford-Paris-San Diego-San Francisco-Singapore-Sydney-Tokyo: Elsevier.
25. Harari, Y.N. (2018). *21 Lessons for the 21st Century.* London Jonatan: Cape.
26. Henke, N. et al. (2016). *The Age of Analytics. Competing in a Data-Driven World.* Brussels-San Francisco-Shanghai: McKinsey & Company.
27. Jaakkola, E. (2020). Designing conceptual articles: four approaches. *AMS Review*,*10*, pp. 18-26.
28. Johnson, P., and Szamosi, L.T. (2019). HRM in Changing Organizational Context. In: D.G. Collings, G.T. Wood, L.T. Szamosi (eds.), *Human Resource Management*: *A Critical Approach* (pp. 27-48). New York: Routledge.
29. Kagerman, H. et al. (2013). *Recommendation for implementing the strategic initiative Industrie 4.0. Final report of the Industries 4.0 Working Group.* Frankfurt: National Academy and Science and Engineering.
30. Kahneman, D. (2011). *Thinking Fast and Slow.* New York: Farrar, Straus and Giroux.
31. Kaufman, B. (2007). The Development of HRM in Historical and International Perspective. In: P. Boxall, J. Purcell and P. Wright (ed.), *The Oxford Handbook of Human Resource Management* (pp. 19-47). New York: Oxford University Press.
32. Kenrick, D. et al. (2014). *Social Psychology: Goals in Interaction.* London: Pearson Education.

33. Kleppman, M. (2017). *Designing Data-Intensive Applications: The Big Ideas Behind Reliable, Scalable and Maintainable Systems.* Beijng-Boston-Farnham-Sebastopol-Tokyo: O'REILLY.
34. Krauss, L.M. (2015). What Me Worry. In: J. Brockman (ed.), *What to Think About Machines That Think.* New York: Harper Perennial (e-book).
35. Kuzior, A. et al. (2019). Sustainable Development of Organizations Based on The Combinatorial Model of Artificial Intelligence. *Entrepreneurship and Sustainably Issues, 7(2),* pp. 1353-1376.
36. Kwiliński, W. et al. (2019). Transparent cognitive technologies to ensure sustainable society development. *Journal of Security and Sustainability Issues*, *9(2),* pp. 561-570. DOI: 10.9770/jssi.2019.9.2(15).
37. Lee, J., and Kao, H-A. (2014). Servis Innovation and Smart Analytics for Industry 4.0 and Big Data Environment. *Product Services Systems and Value Creation. Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems*, DOI: 10.1016/ j.procir.2014.02.001.
38. MacDougall, W. (2014). *Industry 4.0. Smart Manufacturing for the Future.* Berlin: Germany Trade&Invest.
39. Manyika, J. et al. (2011). *Big Data: The next frontier for innovation, competition, and productivity.* McKinsey Global Institute.
40. Manyika, J. et al. (2013). *Disruptive technologies: Advences that will transform life, business and the global economy.* McKinsey Global Institute.
41. Manyika, J. et al. (2017). *A Future That Works: Automation, Employment and Productivity.* McKinsey & Company.
42. Marler, J.H., and Parry, E. (2016). Human Resource management, strategic involvement and e-HRM technology. *The International Journal of Human Resource Management*, *27*, pp. 2233-2255, https://doi.org/10.1080/09585192.2015.1091980.
43. Marr, B. (2018). The 4th Industrial Revolution Is Here – Are You Ready. *Forbs*, 13.08. 2018.
44. Mauboussin, M.J. (2012). The True Measures of Success. *Harvard Business Review*, *October*.
45. Mayer-Schönberger, V., and Cukier, K. (2013). *Big Data: A Revolution That Will Transform How We Live, Work, and Think.* London: John Murray.
46. Mayring, P. (2013). Q*ualitative Content Analysis. Theoretical Foundation, Basic Procedure and Software Solution,* Klagenfurt, p. 10. Retrieved from: https://www.ssoar.info/ssoar/bitstream/handle/document/39517/ssoar-2014-mayring-Qualitative_content_analysis_theoretical_foundation.pdf?sequence=1, 28.11.2021.
47. McAfee, A., and Brynjolfsson, E. (2013). Big Data: The Management Revolution. *Harvard Business Review*, *October*.

48. Medina, R.G. (2006). *Personnel and Human Resources Management.* Manila: Rex Book Store.
49. Miśkiewicz, R., and Wolniak, R. (2020). Practical Application of the Industry 4.0 Concept in a Steel Company. *Sustainability*, *12*, 5776, pp. 1-21.
50. Morrar, R. et al. (2017). The Fourth Industrial Revolution (Industry 4.0): A Social Innovation Perspective. *Technology Innovation Management Review, 7/11,* pp. 12-20.
51. Mwaniki, R., and Gathenya, J. (2015). Role of Human Resource Management Functions On Organizational Rerformance with reference to Kenya Power & Lighting Company – Nairobi West Region. *International Journal of Academic Research in Business and Social Science, 5/4,* pp 432-448.
52. Nussbaum, M. (2010). *Not for Profit. Why Democracy Needs the Humanities.* Princeton-Oxford: Princeton University Press.
53. O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy.* New York: Penguin Random House LLC.
54. O'Neil, C., and Schutt, R. (2014). *Doing Data Science: Straight Talk From the Frontline.* Sebastopol: O'Reilly Media.
55. O'Riordan, J. (2017). *The Practice of Human Resource Management.* IPA, An Foras Riarachain Institute of Public Administration.
56. Osika, G. (2019). Algorytmiczne narzędzia analizy zawartości mediów. Metametodologiczne refleksje. In: I. Hofman, D. Kępa-Figura (Eds.), *Współczesne media. Problemy i metody badań nad mediami*, *tom 2* (pp. 181-194). Lublin: Wydawnictwo UMCS.
57. Osika, G. (2019). Social Innovation as Support for Industry 4.0. *Scientific Papers of Silesian University of Technology, Organization and Management Series*, *141*, pp. 289-301.
58. Osika, G. (2020). Datafikacja środowiska pracy a prawa człowieka. In: A. Kuzior (Eds.), *Globalne konteksty poszanowania praw i wolności człowieka. Współczesne problemy i dylematy, tom 12,* (pp. 235-248). Gliwice: Wydawnictwo Politechniki Śląskiej.
59. Osika, G. (2021). Dilemmas of Social Live Algorithmization – Technological proof of Equity. *Scientific Papers of Silesian University of Technology, Organization and Management Series*, *151*, pp. 525-538.
60. Parry, E., and Battista, V. (2019). *The impact of emerging technologies on work: a review of the evidence and implications for the human resource function.* Emerald Open Research, published 28, Jan, pp. 1-13.
61. Piccarozzi, M., Aquilani, B., Gatti, C. (2018). Industry 4.0 in Management Studies: A Systematic Literature Review. *Sustainability*, *10/10,* 3821, https://doi.org/10.3390/su10103821.
62. Rifkin, J. (2015). *The Zero Marginal Cost Society. The Internet of Things, The Collaborative Commons, and The Eclipse of Capitalism.* New York: Martin's Press.

63. Schwab, K. (2016). *The Fourth Industrial Revolution.* Cologny-Geneva: World Economic Forum.
64. Sharma, F.C. (2016). *Human Resource Management*. SBPD Publications.
65. Silva, M.S.A., and Silva Lima, C.G. (2018). The Role of Information Systems in Human Resource Management. In: M. Pomffyova (ed.), *Management of Information System* (pp.113-126). IntechOpen, http://dx.doi.org/10.5772/intechopen.79294.
66. Stock, T., and Seliger, G. (2019). *Opportunities of Sustainable Manufacturiong in Industry 4.0*, *The Changing Nature of Work. World Development Report.* Washington: International Bank for Reconstruction and Development.
67. Stone, D. et al. (2015). The influence of technology on the future of human resources management. *Human Resources Management Review, vol. 25*, pp. 216-231.
68. Strohmeier, S. (2007). Research in e-HRM: Review and implications. *Human Resource Management Review, 17(1),* pp. 19-37, DOI: 10.1016/j.hrmr,2006.11.002.
69. *Structural transformation, Industry 4.0 and inequality: Science, technology and innovation policy challenges* (2019). United Nations Conference on Trade and Development, Trade and Development Board, Investment, Enterprise and Development Commission, Geneva, 11-15 November 2019.
70. Volini, E. et al. (2019). *Global Human Capital Trends 2019 Deloitte.* New York: Deloitte Insights (pdf).
71. Wang, L., and Wang, G. (2016). Big Data in Cyber-Physical System, Digital Manufacturing. *I.J. Engineering and Manufacturing*, *4,* pp. 1-8, DOI: 10.5815/ ijem.2016.04.01.
72. Withers, M. et al. (2010). *Transforming HR. Creating Value Through People.* Oxford: Elsevier.
73. Yin, S., and Kaynak, O. (2015). Big Data for Modern Industry: Challenges and Trends. *Proceedings of The IEEE*, *103/2,* pp. 143-146.
74. Ying, X. (2018). An Overview of Overfitting and its Solutions. *Journal of Phisics: Conf. Series, 1168*, pp. 1-6. DOI: 101088/1742-6596/1168/2/022022.
75. Zysman, J., and Kenney, M. (2018). The Next Phase in the Digital Revolution: Intelligent Tools, Platforms. *Growth, Employment*, *Communication of The ACM, 61*, pp. 54-63.